

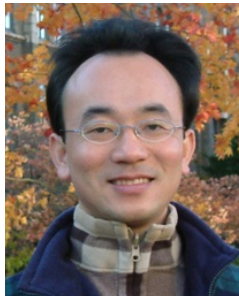
Practices of Business Intelligence

文字探勘與網路探勘 (Text and Web Mining)

1022BI07

MI4

Wed, 9,10 (16:10-18:00) (B113)



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2014-04-30



課程大綱 (Syllabus)

週次 (Week)	日期 (Date)	內容 (Subject/Topics)
1	103/02/19	商業智慧導論 (Introduction to Business Intelligence)
2	103/02/26	管理決策支援系統與商業智慧 (Management Decision Support System and Business Intelligence)
3	103/03/05	企業績效管理 (Business Performance Management)
4	103/03/12	資料倉儲 (Data Warehousing)
5	103/03/19	商業智慧的資料探勘 (Data Mining for Business Intelligence)
6	103/03/26	商業智慧的資料探勘 (Data Mining for Business Intelligence)
7	103/04/02	教學行政觀摩日 (Off-campus study)
8	103/04/09	資料科學與巨量資料分析 (Data Science and Big Data Analytics)

課程大綱 (Syllabus)

週次	日期	內容 (Subject/Topics)
9	103/04/16	期中報告 (Midterm Project Presentation)
10	103/04/23	期中考試週 (Midterm Exam)
11	103/04/30	文字探勘與網路探勘 (Text and Web Mining)
12	103/05/07	意見探勘與情感分析 (Opinion Mining and Sentiment Analysis)
13	103/05/14	社會網路分析 (Social Network Analysis)
14	103/05/21	期末報告 (Final Project Presentation)
15	103/05/28	畢業考試週 (Final Exam)

Learning Objectives

- Describe text mining and understand the need for text mining
- Differentiate between **text mining**, **Web mining** and **data mining**
- Understand the different application areas for text mining
- Know the process of carrying out a text mining project
- Understand the different methods to introduce structure to text-based data

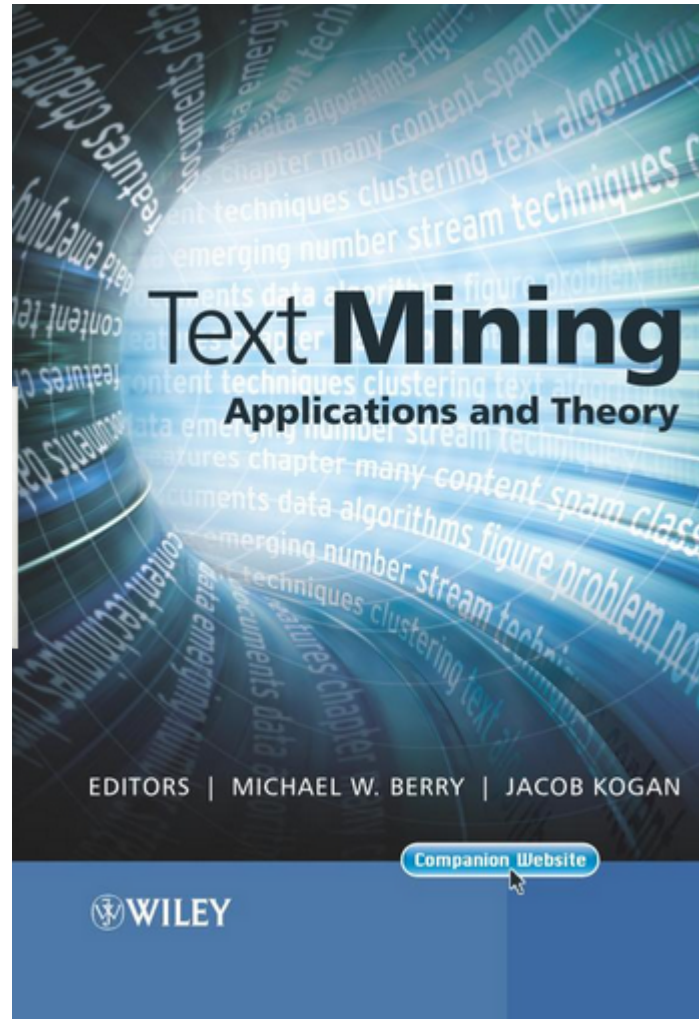
Learning Objectives

- Describe Web mining, its objectives, and its benefits
- Understand the three different branches of Web mining
 - Web content mining
 - Web structure mining
 - Web usage mining
- Understand the applications of these three mining paradigms

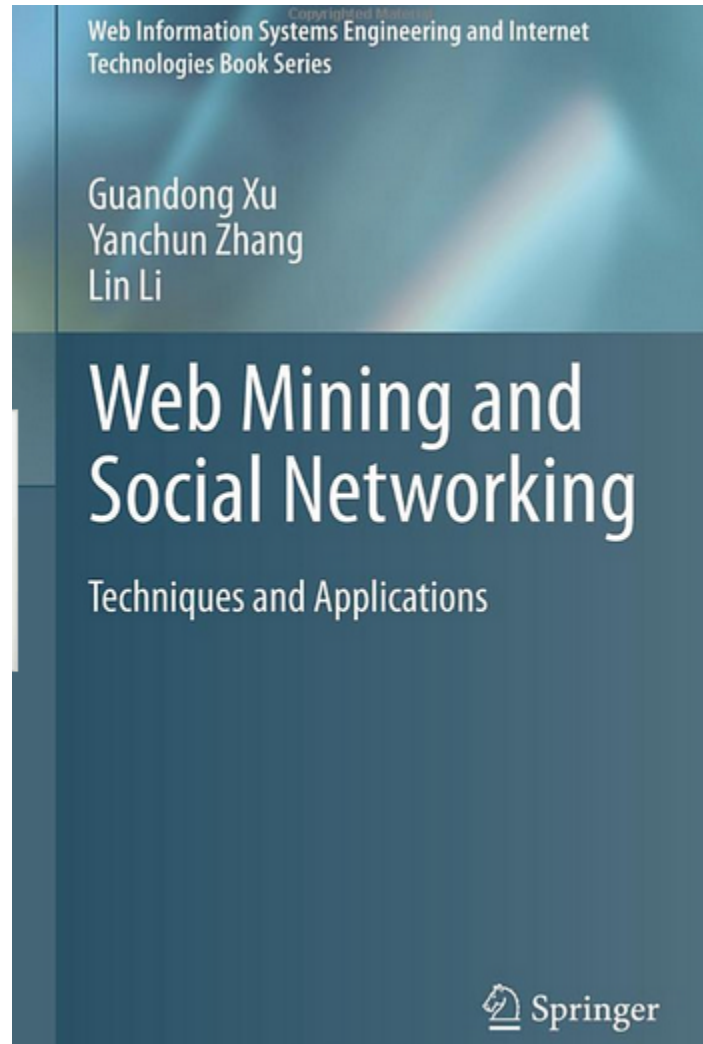
Text and Web Mining

- Text Mining: Applications and Theory
- Web Mining and Social Networking
- Mining the Social Web: Analyzing Data from Facebook, Twitter, LinkedIn, and Other Social Media Sites
- Web Data Mining: Exploring Hyperlinks, Contents, and Usage Data
- Search Engines – Information Retrieval in Practice

Text Mining



Web Mining and Social Networking



Mining the Social Web: Analyzing Data from Facebook, Twitter, LinkedIn, and Other Social Media Sites

*Analyzing Data from Facebook, Twitter, LinkedIn,
and Other Social Media Sites*

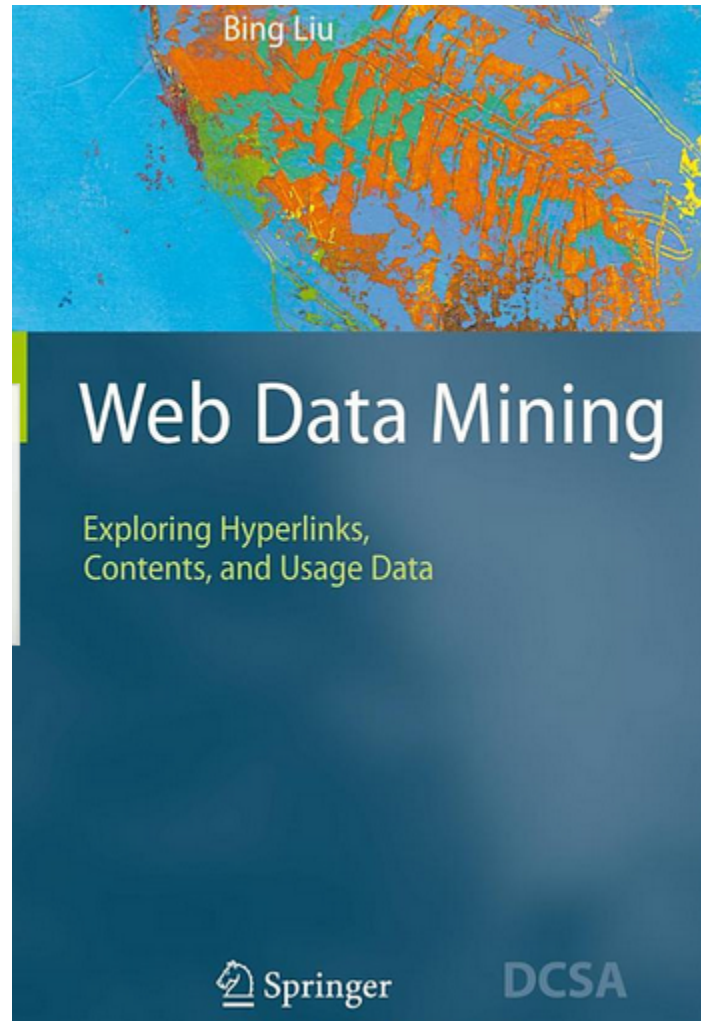


Mining the
Social Web

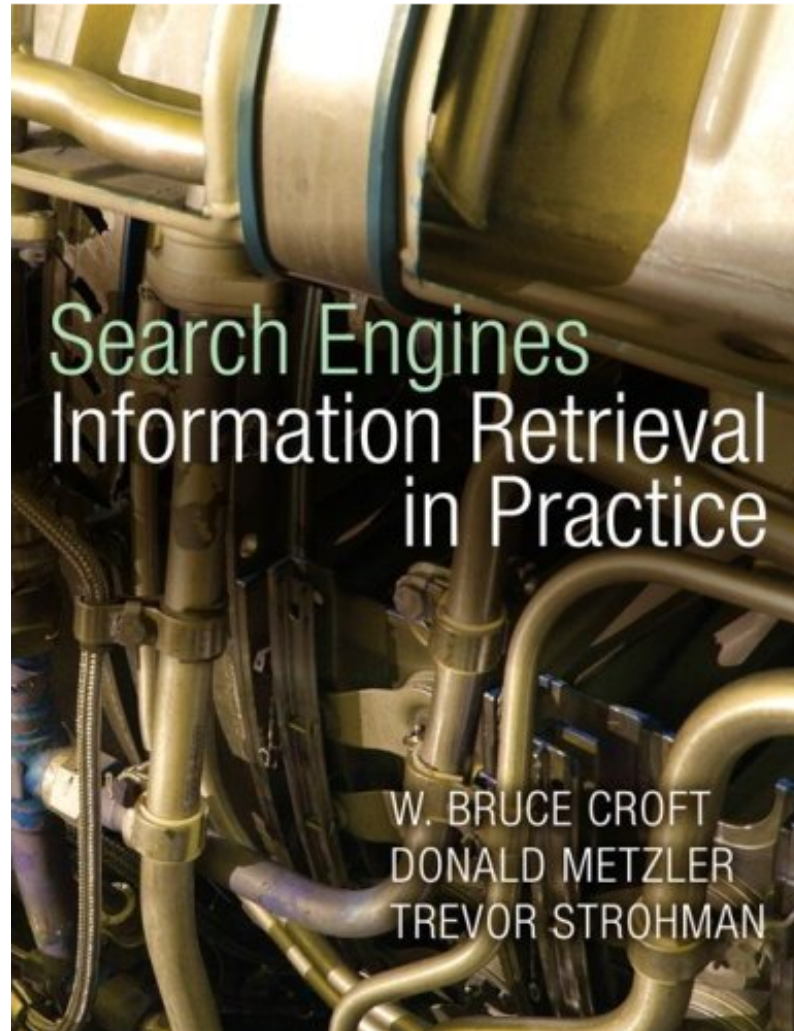
O'REILLY®

Matthew A. Russell

Web Data Mining: Exploring Hyperlinks, Contents, and Usage Data



Search Engines: Information Retrieval in Practice



Text Mining

- Text mining (text data mining)
 - the process of deriving high-quality information from text
- Typical text mining tasks
 - text categorization
 - text clustering
 - concept/entity extraction
 - production of granular taxonomies
 - sentiment analysis
 - document summarization
 - entity relation modeling
 - i.e., learning relations between named entities.

Web Mining

- Web mining
 - discover useful information or knowledge from the **Web hyperlink structure, page content, and usage data.**
- Three types of web mining tasks
 - Web structure mining
 - Web content mining
 - Web usage mining

Mining Text For Security...

Cluster 1

(L) Kampala
(L) Uganda
(P) Yoweri Museveni
(L) Sudan
(L) Khartoum
(L) Southern Sudan

Cluster 2

(P) Timothy McVeigh
(P) Oklahoma City
(P) Terry Nichols

Cluster 3

(E) election
(P) Norodom Ranariddh
(P) Norodom Sihanouk
(L) Bangkok
(L) Cambodia
(L) Phnom Penh
(L) Thailand
(P) Hun Sen
(O) Khmer Rouge
(P) Pol Pot

Text Mining Concepts

- 85-90 percent of all corporate data is in some kind of unstructured form (e.g., text)
- Unstructured corporate data is doubling in size every 18 months
- Tapping into these information sources is not an option, but a need to stay competitive
- Answer: text mining
 - A semi-automated process of extracting knowledge from unstructured data sources
 - a.k.a. text data mining or knowledge discovery in textual databases

Data Mining versus Text Mining

- Both seek for novel and useful patterns
- Both are semi-automated processes
- Difference is the nature of the data:
 - Structured versus unstructured data
 - **Structured data:** in databases
 - **Unstructured data:** Word documents, PDF files, text excerpts, XML files, and so on
- Text mining – first, impose structure to the data, then mine the structured data

Text Mining Concepts

- Benefits of text mining are obvious especially in text-rich data environments
 - e.g., law (court orders), academic research (research articles), finance (quarterly reports), medicine (discharge summaries), biology (molecular interactions), technology (patent files), marketing (customer comments), etc.
- Electronic communication records (e.g., Email)
 - Spam filtering
 - Email prioritization and categorization
 - Automatic response generation

Text Mining Application Area

- Information extraction
- Topic tracking
- Summarization
- Categorization
- Clustering
- Concept linking
- Question answering

Text Mining Terminology

- Unstructured or semistructured data
- Corpus (and corpora)
- Terms
- Concepts
- Stemming
- Stop words (and include words)
- Synonyms (and polysemes)
- Tokenizing

Text Mining Terminology

- Term dictionary
- Word frequency
- Part-of-speech tagging (POS)
- Morphology
- Term-by-document matrix (TDM)
 - Occurrence matrix
- Singular Value Decomposition (SVD)
 - Latent Semantic Indexing (LSI)

Text Mining for Patent Analysis

- What is a patent?
 - “exclusive rights granted by a country to an inventor for a limited period of time in exchange for a disclosure of an invention”
- How do we do patent analysis (PA)?
- Why do we need to do PA?
 - What are the benefits?
 - What are the challenges?
- How does text mining help in PA?

Natural Language Processing (NLP)

- Structuring a collection of text
 - Old approach: bag-of-words
 - New approach: natural language processing
- NLP is ...
 - a very important concept in text mining
 - a subfield of artificial intelligence and computational linguistics
 - the studies of "understanding" the natural human language
- Syntax versus semantics based text mining

Natural Language Processing (NLP)

- What is “Understanding” ?
 - Human understands, what about computers?
 - Natural language is vague, context driven
 - True understanding requires extensive knowledge of a topic
 - Can/will computers ever understand natural language the same/accurate way we do?

Natural Language Processing (NLP)

- Challenges in NLP
 - Part-of-speech tagging
 - Text segmentation
 - Word sense disambiguation
 - Syntax ambiguity
 - Imperfect or irregular input
 - Speech acts
- Dream of AI community
 - to have algorithms that are capable of automatically reading and obtaining knowledge from text

Natural Language Processing (NLP)

- WordNet
 - A laboriously hand-coded database of English words, their definitions, sets of synonyms, and various semantic relations between synonym sets
 - A major resource for NLP
 - Need automation to be completed
- Sentiment Analysis
 - A technique used to detect favorable and unfavorable opinions toward specific products and services
 - CRM application

NLP Task Categories

- Information retrieval (IR)
- Information extraction (IE)
- Named-entity recognition (NER)
- Question answering (QA)
- Automatic summarization
- Natural language generation and understanding (NLU)
- Machine translation (ML)
- Foreign language reading and writing
- Speech recognition
- Text proofing
- Optical character recognition (OCR)

Text Mining Applications

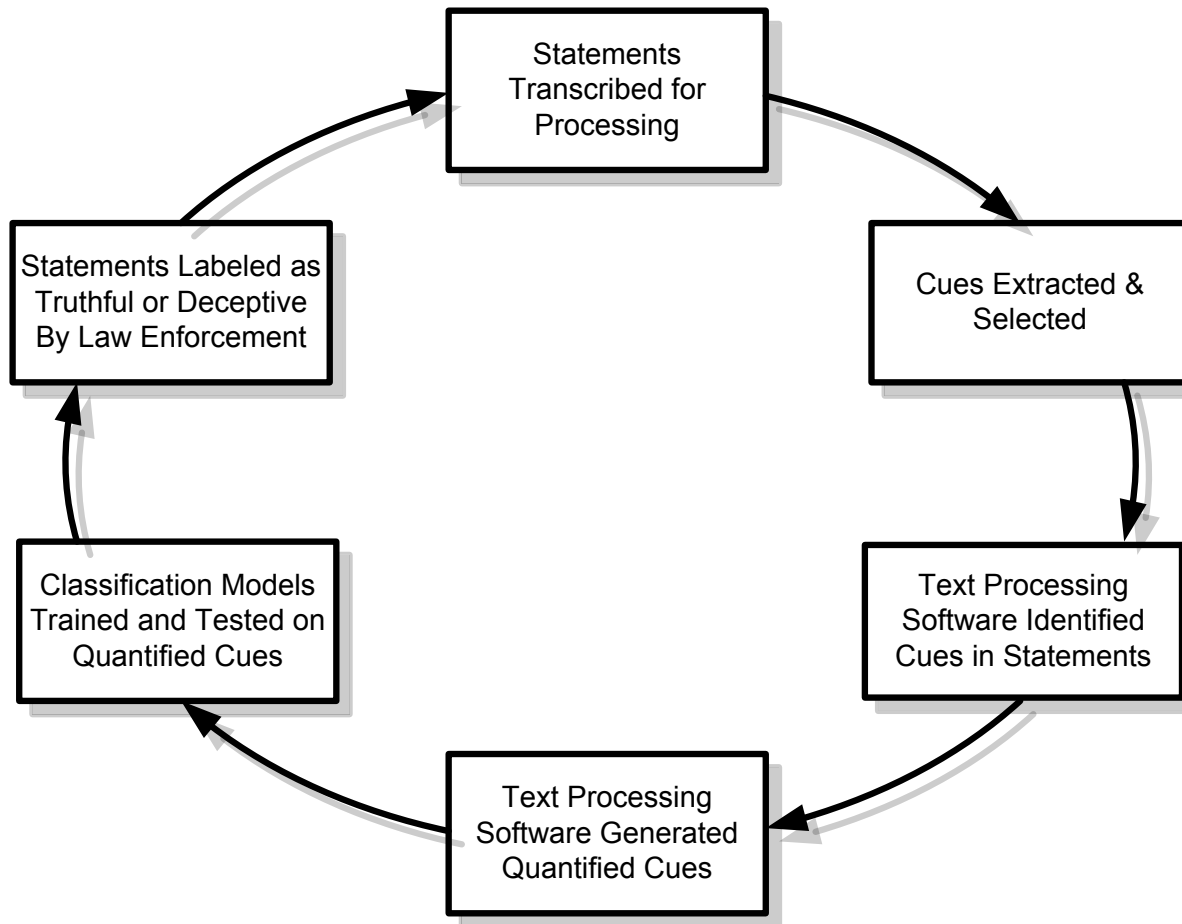
- Marketing applications
 - Enables better CRM
- Security applications
 - ECHELON, OASIS
 - Deception detection (...)
- Medicine and biology
 - Literature-based gene identification (...)
- Academic applications
 - Research stream analysis

Text Mining Applications

- Application Case: Mining for Lies
- Deception detection
 - A difficult problem
 - If detection is limited to only text, then the problem is even more difficult
- The study
 - analyzed text based testimonies of person of interests at military bases
 - used only text-based features (cues)

Text Mining Applications

- Application Case: Mining for Lies



Text Mining Applications

- Application Case: Mining for Lies

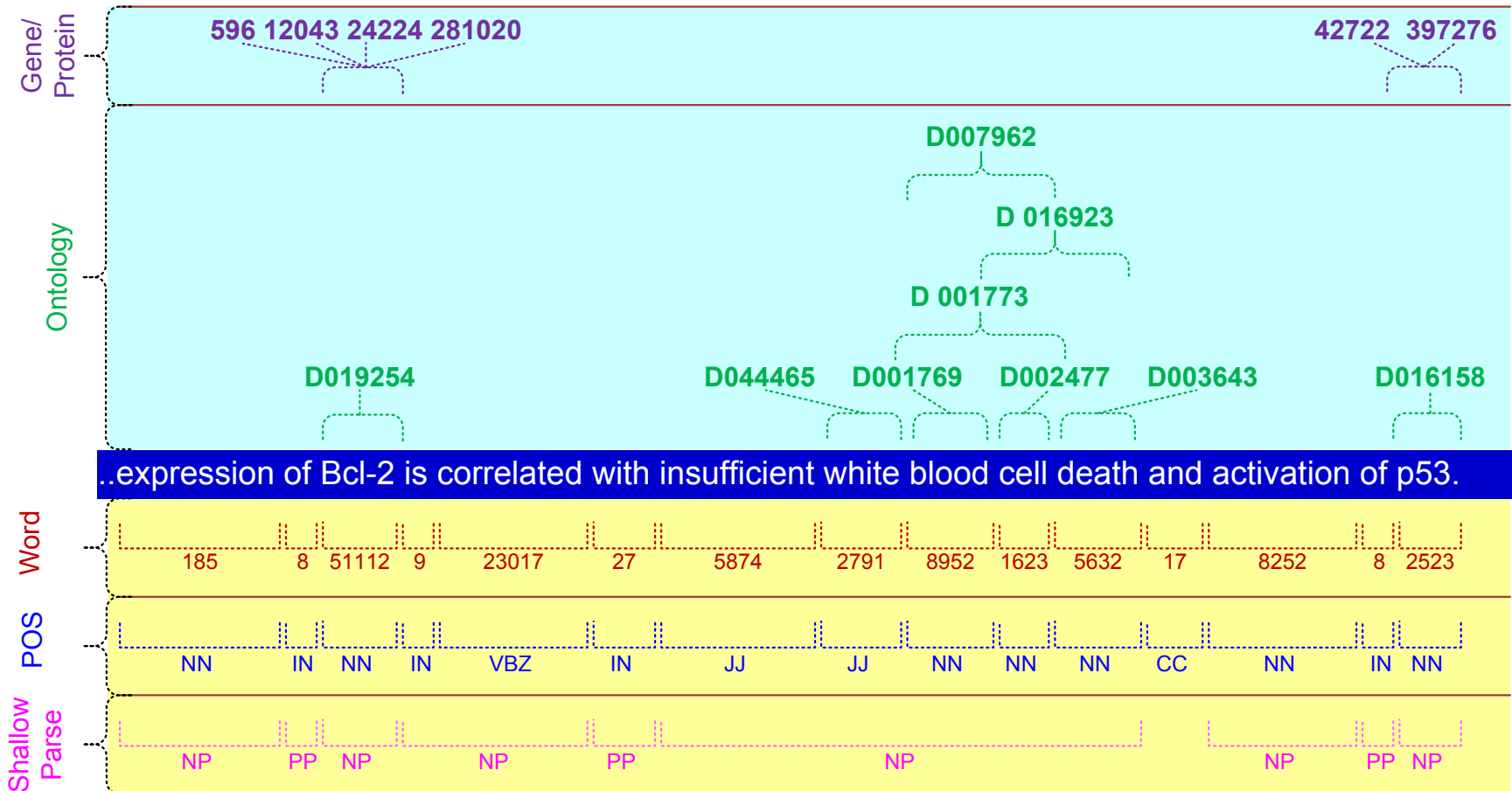
Category	Example Cues
Quantity	Verb count, noun-phrase count, ...
Complexity	Avg. no of clauses, sentence length, ...
Uncertainty	Modifiers, modal verbs, ...
Nonimmediacy	Passive voice, objectification, ...
Expressivity	Emotiveness
Diversity	Lexical diversity, redundancy, ...
Informality	Typographical error ratio
Specificity	Spatiotemporal, perceptual information ...
Affect	Positive affect, negative affect, etc.

Text Mining Applications

- Application Case: Mining for Lies
 - 371 usable statements are generated
 - 31 features are used
 - Different feature selection methods used
 - 10-fold cross validation is used
 - Results (overall % accuracy)
 - Logistic regression 67.28
 - Decision trees 71.60
 - Neural networks 73.46

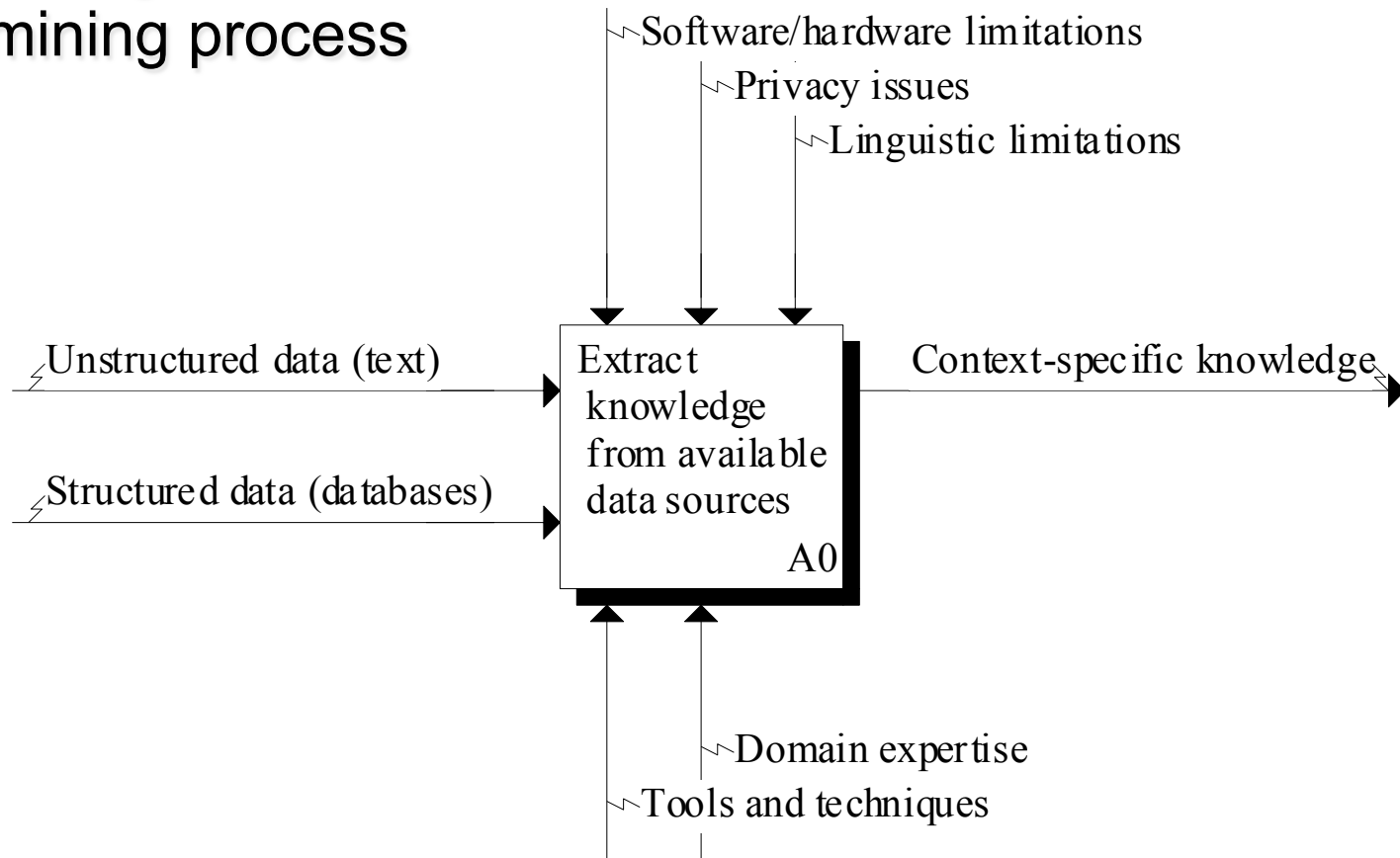
Text Mining Applications

(gene/protein interaction identification)

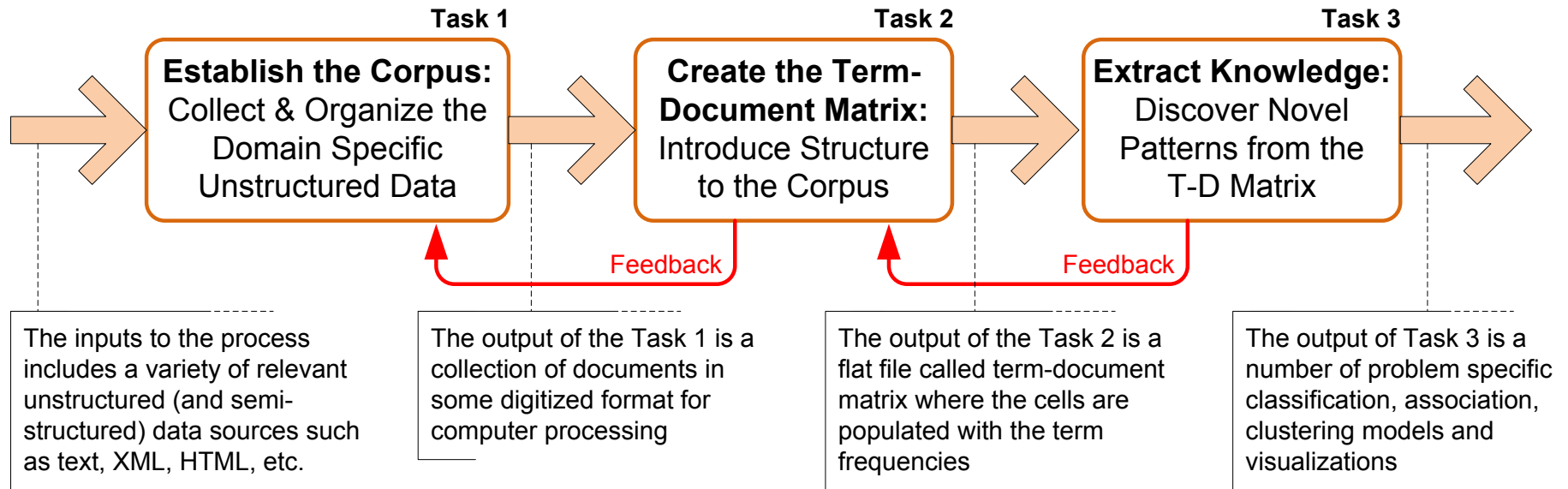


Text Mining Process

Context diagram for the text mining process



Text Mining Process



The three-step text mining process

Text Mining Process

- **Step 1:** Establish the corpus
 - Collect all relevant unstructured data (e.g., textual documents, XML files, emails, Web pages, short notes, voice recordings...)
 - Digitize, standardize the collection (e.g., all in ASCII text files)
 - Place the collection in a common place (e.g., in a flat file, or in a directory as separate files)

Text Mining Process

- **Step 2:** Create the Term-by-Document Matrix

Terms Documents	investment risk	project management	software engineering	development	SAP	...
Document 1	1			1		
Document 2		1				
Document 3			3		1	
Document 4		1				
Document 5			2	1		
Document 6	1			1		
...						

Text Mining Process

- **Step 2:** Create the Term–by–Document Matrix (TDM), cont.
 - Should all terms be included?
 - Stop words, include words
 - Synonyms, homonyms
 - Stemming
 - What is the best representation of the indices (values in cells)?
 - Row counts; binary frequencies; log frequencies;
 - Inverse document frequency

Text Mining Process

- **Step 2:** Create the Term-by-Document Matrix (TDM), cont.
 - TDM is a sparse matrix. How can we reduce the dimensionality of the TDM?
 - Manual - a domain expert goes through it
 - Eliminate terms with very few occurrences in very few documents (?)
 - Transform the matrix using singular value decomposition (SVD)
 - SVD is similar to principle component analysis

Text Mining Process

- **Step 3:** Extract patterns/knowledge
 - Classification (text categorization)
 - Clustering (natural groupings of text)
 - Improve search recall
 - Improve search precision
 - Scatter/gather
 - Query-specific clustering
 - Association
 - Trend Analysis (...)

Text Mining Application

(research trend identification in literature)

- Mining the published IS literature
 - MIS Quarterly (MISQ)
 - Journal of MIS (JMIS)
 - Information Systems Research (ISR)
 - Covers 12-year period (1994-2005)
 - 901 papers are included in the study
 - Only the paper abstracts are used
 - 9 clusters are generated for further analysis

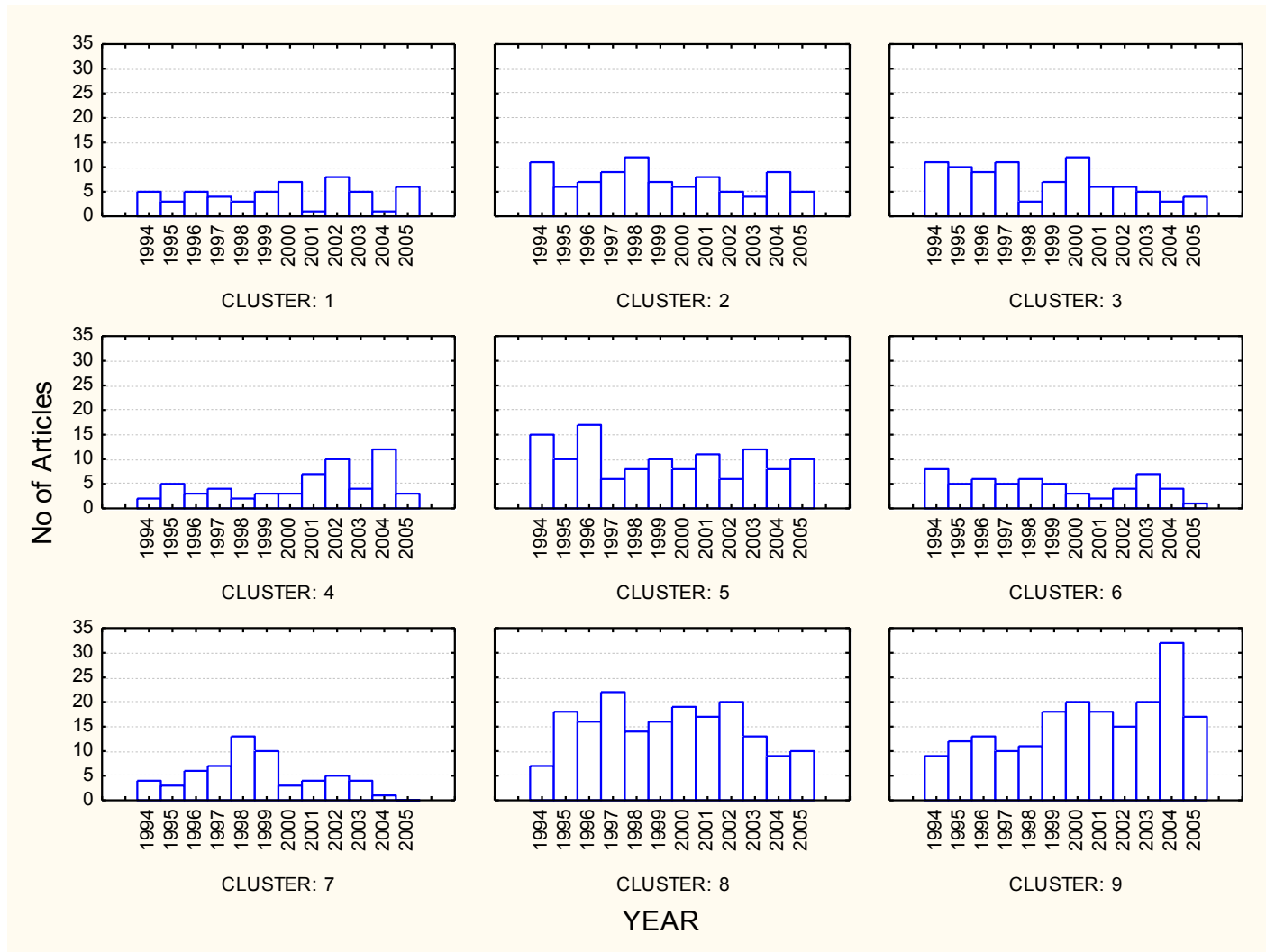
Text Mining Application

(research trend identification in literature)

Journal	Year	Author(s)	Title	Vol/No	Pages	Keywords	Abstract
MISQ	2005	A. Malhotra, S. Gosain and O. A. El Sawy	Absorptive capacity configurations in supply chains: Gearing for partner-enabled market knowledge creation	29/1	145-187	knowledge management supply chain absorptive capacity interorganizational information systems configuration approaches	The need for continual value innovation is driving supply chains to evolve from a pure transactional focus to leveraging interorganizational partner ships for sharing
ISR	1999	D. Robey and M. C. Boudreau	Accounting for the contradictory organizational consequences of information technology: Theoretical directions and methodological implications	2-Oct	167-185	organizational transformation impacts of technology organization theory research methodology intraorganizational power electronic communication mis implementation culture systems	Although much contemporary thought considers advanced information technologies as either determinants or enablers of radical organizational change, empirical studies have revealed inconsistent findings to support the deterministic logic implicit in such arguments. This paper reviews the contradictory
JMIS	2001	R. Aron and E. K. Clemons	Achieving the optimal balance between investment in quality and investment in self-promotion for information products	18/2	65-88	information products internet advertising product positioning signaling signaling games	When producers of goods (or services) are confronted by a situation in which their offerings no longer perfectly match consumer preferences, they must determine the extent to which the advertised features of
...

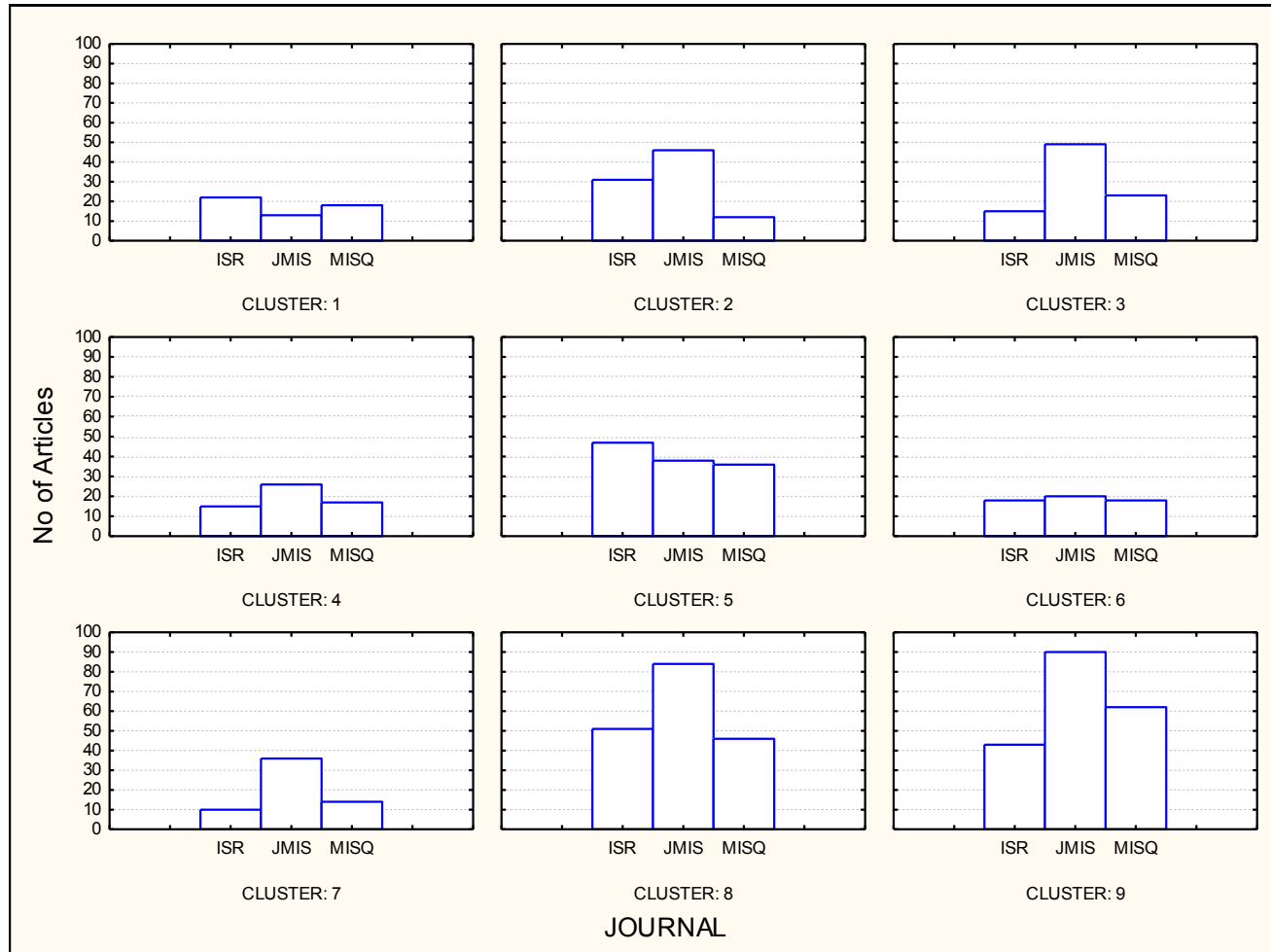
Text Mining Application

(research trend identification in literature)



Text Mining Application

(research trend identification in literature)



Text Mining Tools

- Commercial Software Tools
 - SPSS PASW Text Miner
 - SAS Enterprise Miner
 - Statistica Data Miner
 - ClearForest, ...
- Free Software Tools
 - RapidMiner
 - GATE
 - Spy-EM, ...

SAS Text Analytics

File: [input field]

I called up to **cancel** my card, because I have been **charged** an **annual fee** in every year and **complaining** about there being an **annual fee** on the card that my mother signed me up for when I was still under the age of 18. I inherited it. so I was **charged** this **late fee** again and, because I was under 18 that billing cycle I was **charged** a **late fee** on top of that, so I owe whatever my balance is. I was kind of expecting... I have called, because in previous years that this has happened I've called them and **complained** and was just really busy I wasn't able to handle this in a **timely manner**. I was **charged** an **annual fee charge**, which is basically the only **charge** on the card and asked to **cancel** and said that I **would pay** whatever that balance was. I **cancel** it. I was kind of expecting that they might offer again to **walk me through** the process of **canceling** the card.

Text Result: [selected] Graphical Result

Test in rule-based model result is Negative
Probability to be positive is 0.239% with confidence 99.549%
43 matches:
0 matches for product definitions:
9 matches for feature definitions:
No 0 (62-71): orion-Fees : annual fee

SAS® Text Analytics

SAS THE POWER TO KNOW.

0:16 / 4:50

SAS® Text Analytics Software Demo

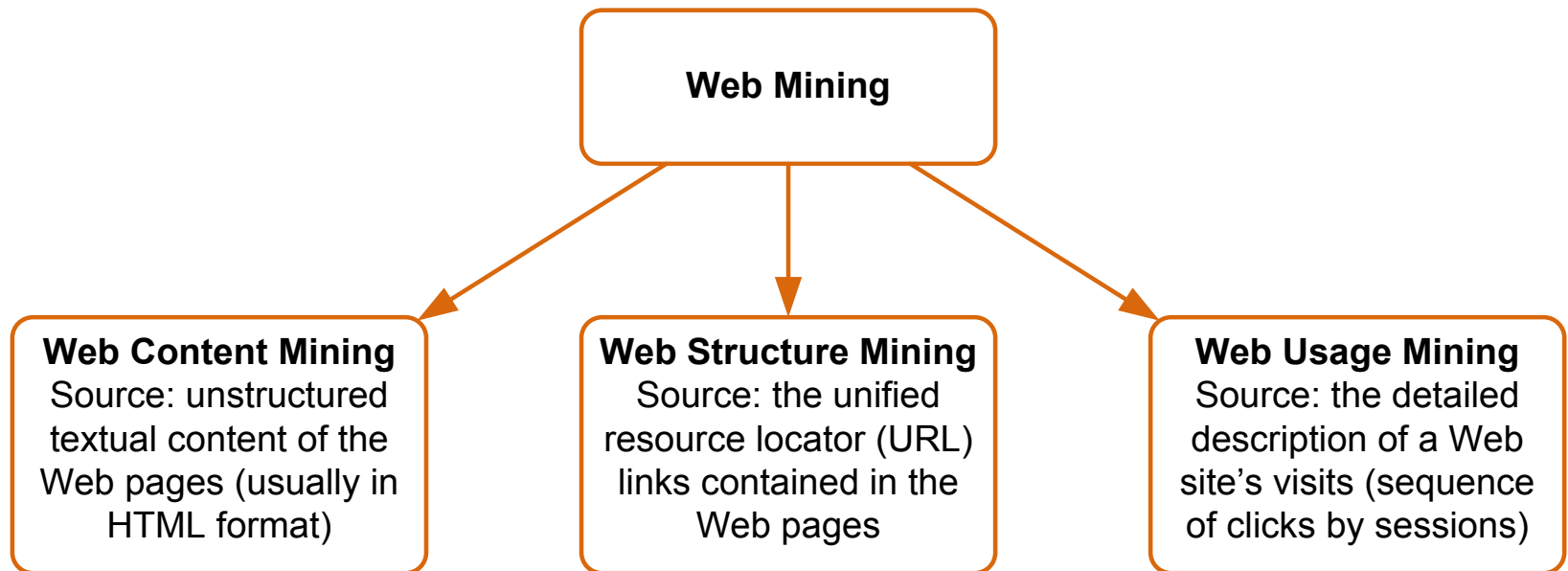


Web Mining Overview

- Web is the largest repository of data
- Data is in HTML, XML, text format
- Challenges (of processing Web data)
 - The Web is too big for effective data mining
 - The Web is too complex
 - The Web is too dynamic
 - The Web is not specific to a domain
 - The Web has everything
- Opportunities and challenges are great!

Web Mining

- Web mining (or Web data mining) is the process of discovering intrinsic relationships from Web data (textual, linkage, or usage)



Web Content/Structure Mining

- Mining of the textual content on the Web
- Data collection via Web crawlers
- Web pages include hyperlinks
 - Authoritative pages
 - Hubs
 - hyperlink-induced topic search (HITS) alg

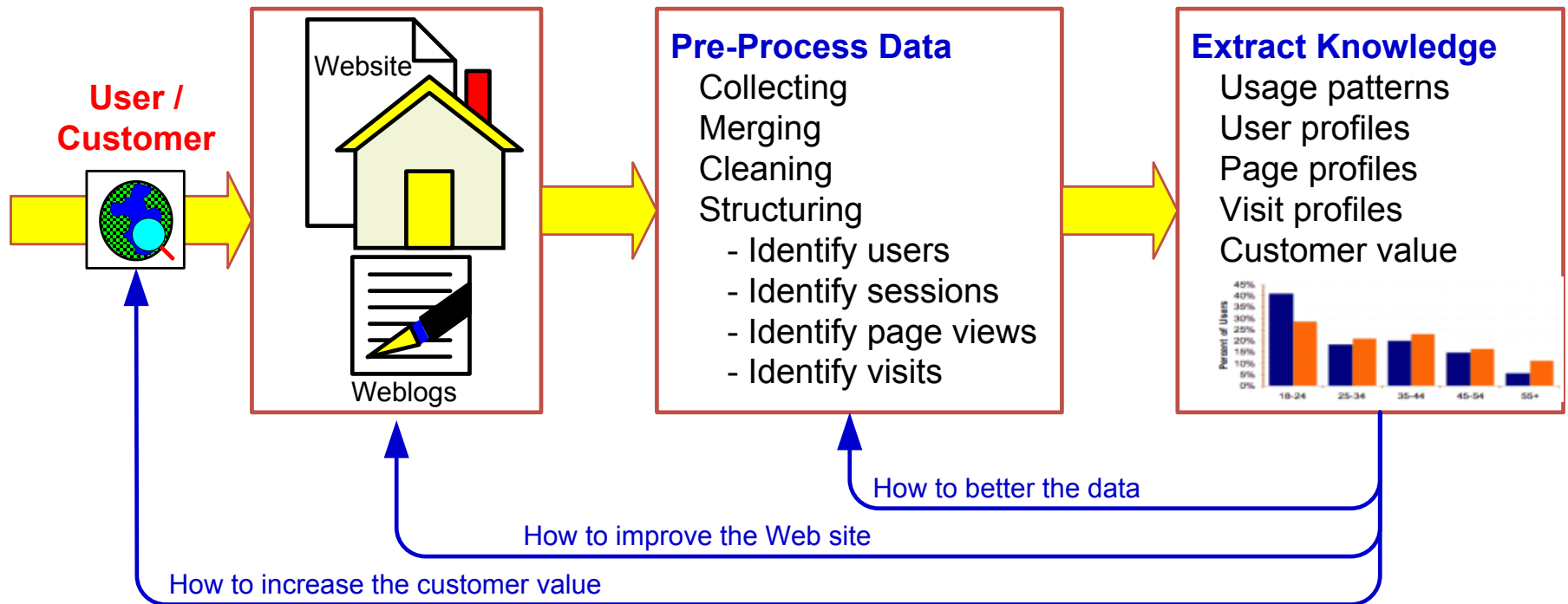
Web Usage Mining

- Extraction of information from data generated through Web page visits and transactions...
 - data stored in server access logs, referrer logs, agent logs, and client-side cookies
 - user characteristics and usage profiles
 - metadata, such as page attributes, content attributes, and usage data
- Clickstream data
- Clickstream analysis

Web Usage Mining

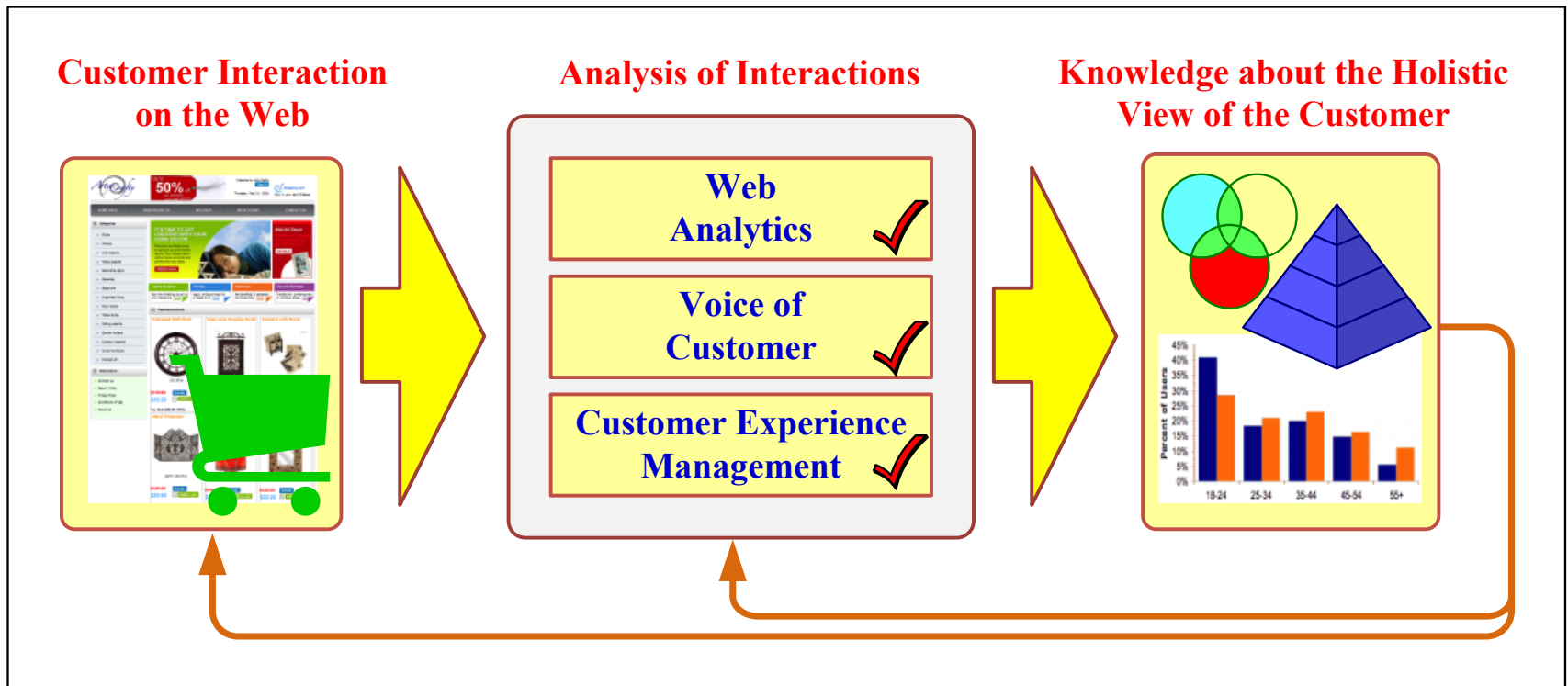
- Web usage mining applications
 - Determine the lifetime value of clients
 - Design cross-marketing strategies across products.
 - Evaluate promotional campaigns
 - Target electronic ads and coupons at user groups based on user access patterns
 - Predict user behavior based on previously learned rules and users' profiles
 - Present dynamic information to users based on their interests and profiles...

Web Usage Mining (clickstream analysis)



Web Mining Success Stories

- Amazon.com, Ask.com, Scholastic.com, ...
- Website Optimization Ecosystem



Web Mining Tools

Product Name**URL**

Angoss Knowledge WebMiner

angoss.com

ClickTracks

clicktracks.com

LiveStats from DeepMetrix

deepmetrix.com

Megaputer WebAnalyst

megaputer.com

MicroStrategy Web Traffic Analysis

microstrategy.com

SAS Web Analytics

sas.com

SPSS Web Mining for Clementine

spss.com

WebTrends

webtrends.com

XML Miner

scientio.com

Evaluation of Text Mining and Web Mining

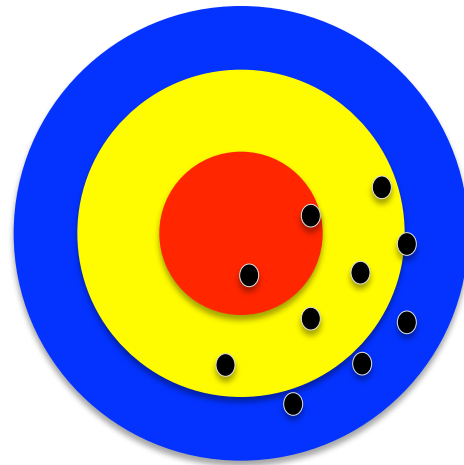
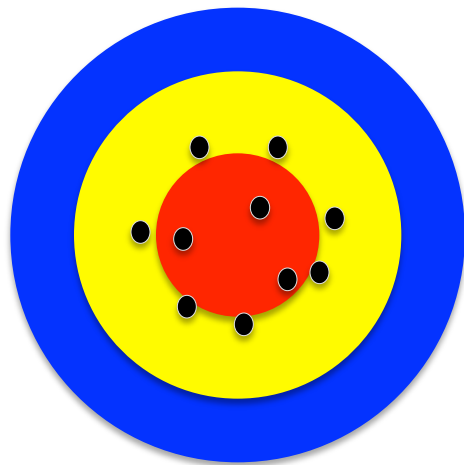
- Evaluation of Information Retrieval
- Evaluation of Classification Model (Prediction)
 - Accuracy
 - Precision
 - Recall
 - F-score

Accuracy

Validity

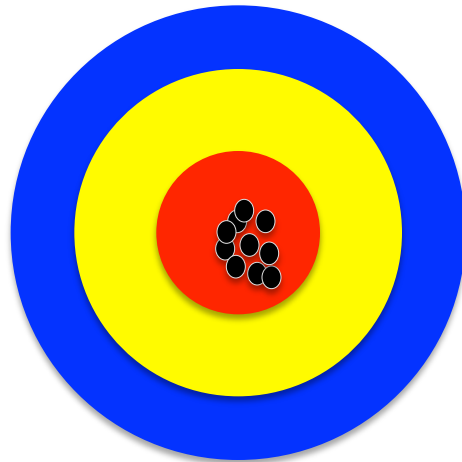
Precision

Reliability



Accuracy vs. Precision

A



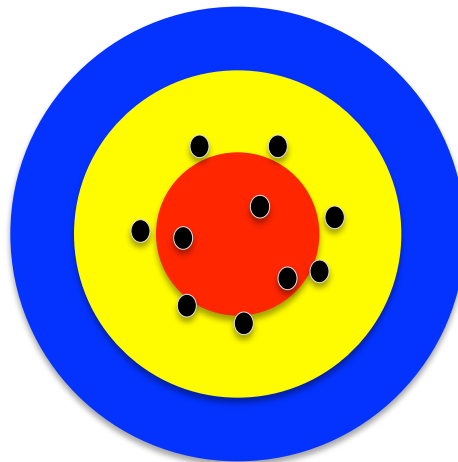
**High Accuracy
High Precision**

B



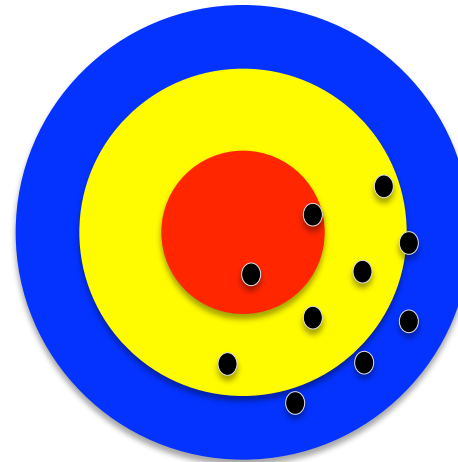
**Low Accuracy
High Precision**

C



**High Accuracy
Low Precision**

D



**Low Accuracy
Low Precision**

Accuracy vs. Precision

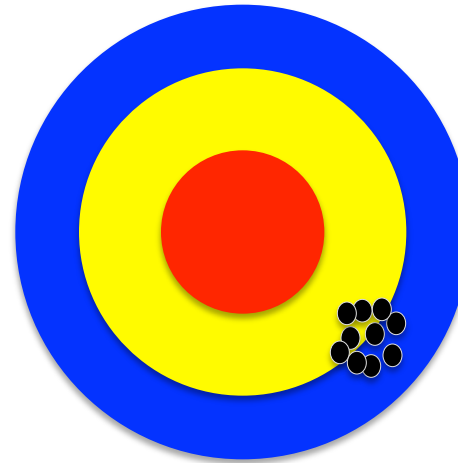
A



**High Accuracy
High Precision**

**High Validity
High Reliability**

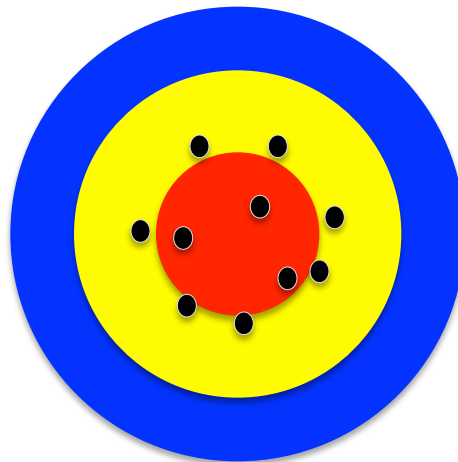
B



**Low Accuracy
High Precision**

**Low Validity
High Reliability**

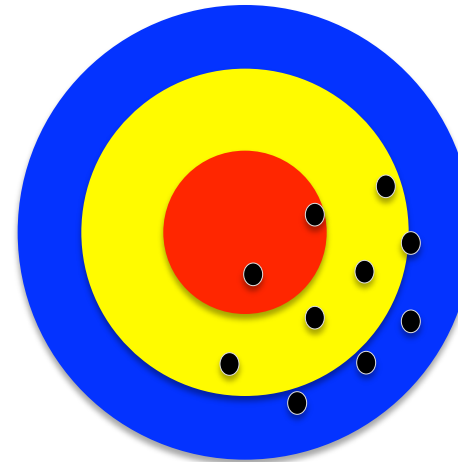
C



**High Accuracy
Low Precision**

**High Validity
Low Reliability**

D



**Low Accuracy
Low Precision**

**Low Validity
Low Reliability**

Accuracy of Classification Models

- In classification problems, the primary source for accuracy estimation is the **confusion matrix**

		True Class	
		Positive	Negative
Predicted Class	Positive	True Positive Count (TP)	False Positive Count (FP)
	Negative	False Negative Count (FN)	True Negative Count (TN)

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$True\ Positive\ Rate = \frac{TP}{TP + FN}$$

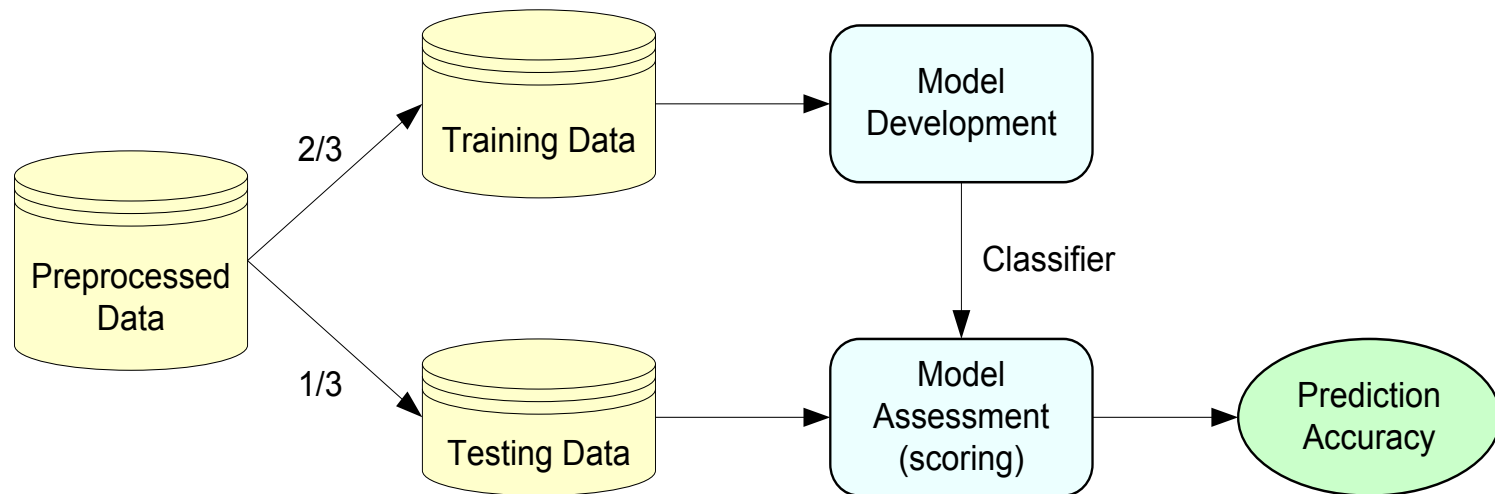
$$True\ Negative\ Rate = \frac{TN}{TN + FP}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

Estimation Methodologies for Classification

- **Simple split** (or holdout or test sample estimation)
 - Split the data into 2 mutually exclusive sets training (~70%) and testing (30%)

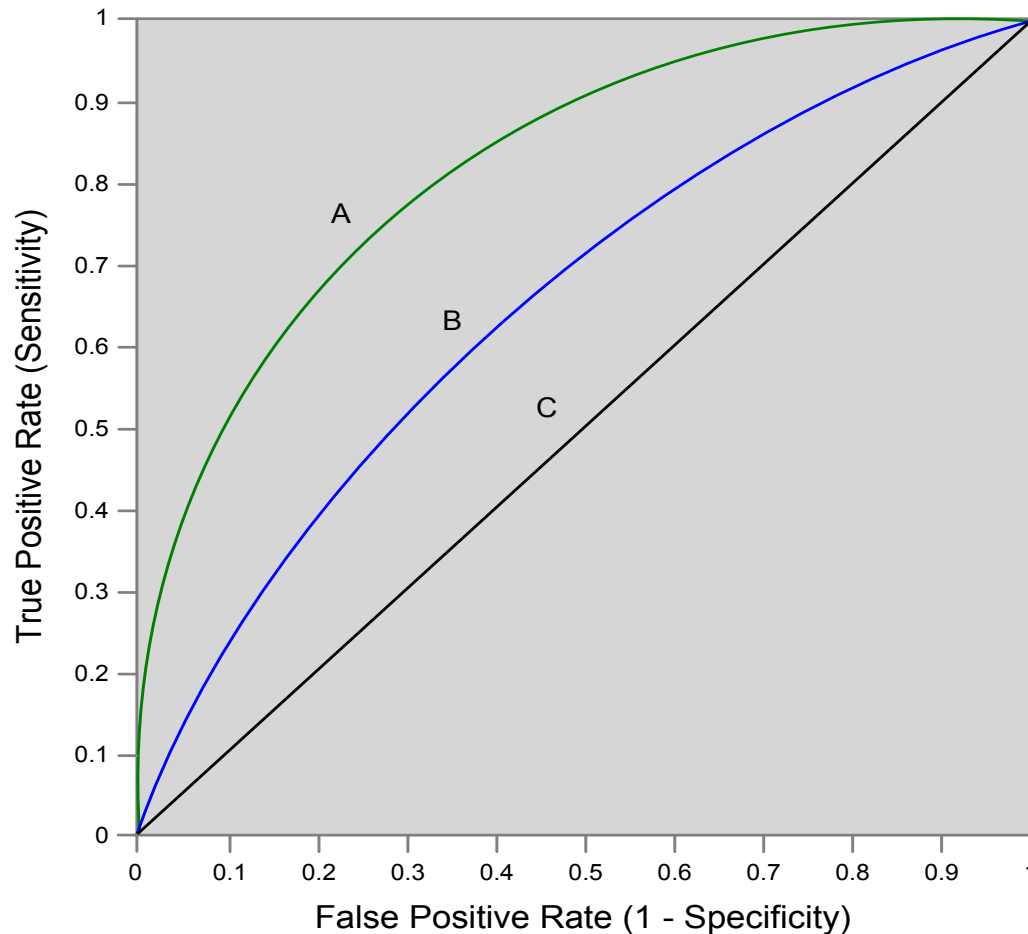


- For ANN, the data is split into three sub-sets (training [~60%], validation [~20%], testing [~20%])

Estimation Methodologies for Classification

- ***k*-Fold Cross Validation** (rotation estimation)
 - Split the data into k mutually exclusive subsets
 - Use each subset as testing while using the rest of the subsets as training
 - Repeat the experimentation for k times
 - Aggregate the test results for true estimation of prediction accuracy training
- Other estimation methodologies
 - Leave-one-out, bootstrapping, jackknifing
 - Area under the ROC curve

Estimation Methodologies for Classification – ROC Curve



		True Class (actual value)		total
		Positive	Negative	
Predictive Class (prediction outcome)	Positive	True Positive (TP)	False Positive (FP)	P'
	Negative	False Negative (FN)	True Negative (TN)	N'
total		P	N	

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$True\ Positive\ Rate = \frac{TP}{TP + FN}$$

$$True\ Negative\ Rate = \frac{TN}{TN + FP}$$

$$Precision = \frac{TP}{TP + FP}$$

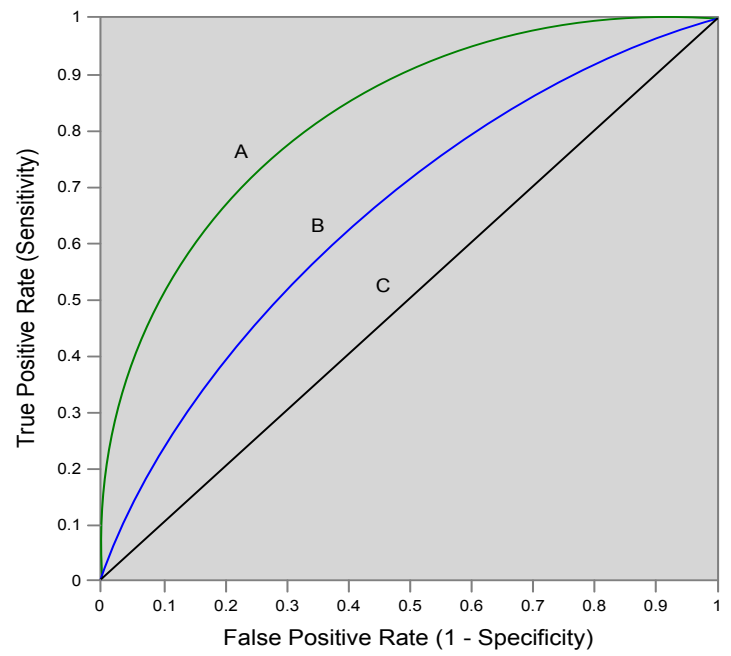
$$Recall = \frac{TP}{TP + FN}$$

$$True\ Positive\ Rate\ (Sensitivity) = \frac{TP}{TP + FN}$$

$$True\ Negative\ Rate\ (Specificity) = \frac{TN}{TN + FP}$$

$$False\ Positive\ Rate = \frac{FP}{FP + TN}$$

$$False\ Positive\ Rate\ (1 - Specificity) = \frac{FP}{FP + TN}$$



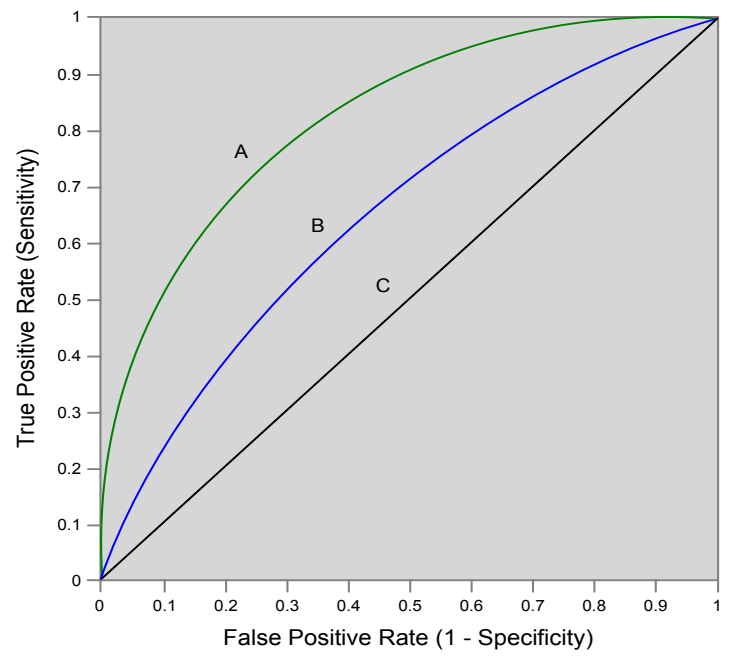
		True Class (actual value)		total
		Positive	Negative	
Predictive Class (prediction outcome)	Positive	True Positive (TP)	False Positive (FP)	P'
	Negative	False Negative (FN)	True Negative (TN)	N'
total		P	N	

$$\text{True Positive Rate} = \frac{TP}{TP + FN}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

$$\text{True Positive Rate (Sensitivity)} = \frac{TP}{TP + FN}$$

Sensitivity
 = True Positive Rate
 = Recall
 = Hit rate



		True Class (actual value)		total
		Positive	Negative	
Predictive Class (prediction outcome)	Positive	True Positive (TP)	False Positive (FP)	P'
	Negative	False Negative (FN)	True Negative (TN)	N'
total		P	N	

$$\text{True Negative Rate} = \frac{TN}{TN + FP}$$

Specificity

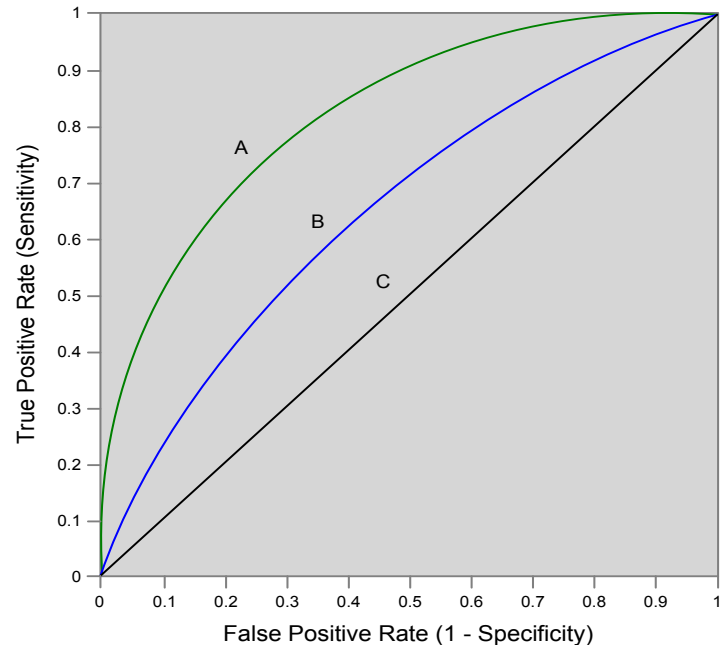
= True Negative Rate

= TN / N

= $TN / (TP + TN)$

$$\text{True Negative Rate (Specificity)} = \frac{TN}{TN + FP}$$

$$\text{False Positive Rate (1-Specificity)} = \frac{FP}{FP + TN}$$



		True Class (actual value)		total
		Positive	Negative	
Predictive Class (prediction outcome)	Positive	True Positive (TP)	False Positive (FP)	P'
	Negative	False Negative (FN)	True Negative (TN)	N'
total		P	N	

Precision

= Positive Predictive Value (PPV)

$$Precision = \frac{TP}{TP + FP}$$

Recall

= True Positive Rate (TPR)

= Sensitivity

= Hit Rate

$$Recall = \frac{TP}{TP + FN}$$

F1 score (F-score)(F-measure)

is the harmonic mean of precision and recall

$$= 2TP / (P + P')$$

$$= 2TP / (2TP + FP + FN)$$

$$F = 2 * \frac{precision * recall}{precision + recall}$$

A		
63 (TP)	28 (FP)	91
37 (FN)	72 (TN)	109
100	100	200

Recall

= True Positive Rate (TPR)
 = Sensitivity
 = Hit Rate

Specificity

= True Negative Rate
 = TN / N
 = TN / (TP + TN)

$$TPR = 0.63$$

$$Recall = \frac{TP}{TP + FN}$$

$$True\ Negative\ Rate\ (Specificity) = \frac{TN}{TN + FP}$$

$$FPR = 0.28$$

$$False\ Positive\ Rate\ (1 - Specificity) = \frac{FP}{FP + TN}$$

$$PPV = 0.69$$

$$= 63 / (63 + 28)$$

$$= 63 / 91$$

$$Precision = \frac{TP}{TP + FP}$$

Precision

= Positive Predictive Value (PPV)

$$F1 = 0.66$$

$$= 2 * (0.63 * 0.69) / (0.63 + 0.69)$$

$$= (2 * 63) / (100 + 91)$$

$$= (0.63 + 0.69) / 2 = 1.32 / 2 = 0.66$$

$$F = 2 * \frac{precision * recall}{precision + recall}$$

F1 score (F-score) (F-measure)

is the harmonic mean of precision and recall

$$= 2TP / (P + P')$$

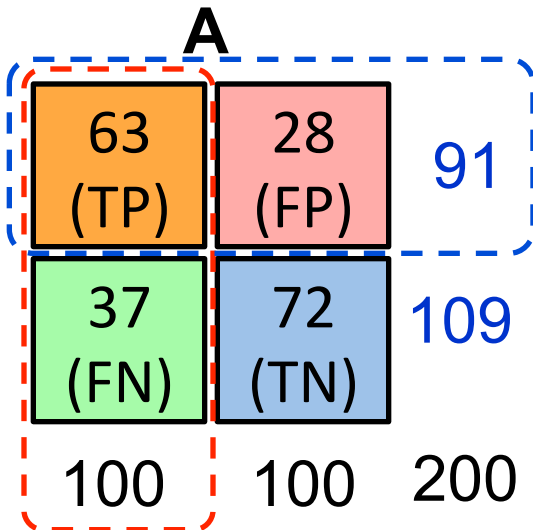
$$= 2TP / (2TP + FP + FN)$$

$$ACC = 0.68$$

$$= (63 + 72) / 200$$

$$= 135 / 200 = 67.5$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$



$$\text{TPR} = 0.63$$

$$\text{FPR} = 0.28$$

$$\begin{aligned} \text{PPV} &= 0.69 \\ &= 63 / (63 + 28) \\ &= 63 / 91 \end{aligned}$$

$$\text{F1} = 0.66$$

$$= 2 * (0.63 * 0.69) / (0.63 + 0.69)$$

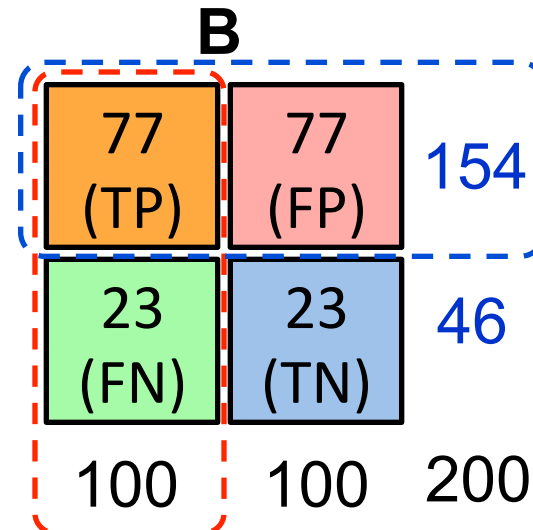
$$= (2 * 63) / (100 + 91)$$

$$= (0.63 + 0.69) / 2 = 1.32 / 2 = 0.66$$

$$\text{ACC} = 0.68$$

$$= (63 + 72) / 200$$

$$= 135 / 200 = 67.5$$



$$\text{TPR} = 0.77$$

$$\text{FPR} = 0.77$$

$$\text{PPV} = 0.50$$

$$\text{F1} = 0.61$$

$$\text{ACC} = 0.50$$

Recall

= True Positive Rate (TPR)

= Sensitivity

= Hit Rate

$$\text{Recall} = \frac{TP}{TP + FN}$$

Precision

= Positive Predictive Value (PPV)

$$\text{Precision} = \frac{TP}{TP + FP}$$

C

24 (TP)	88 (FP)	112
76 (FN)	12 (TN)	88
100	100	200

TPR = 0.24

FPR = 0.88

PPV = 0.21

F1 = 0.22

ACC = 0.18

C'

76 (TP)	12 (FP)	88
24 (FN)	88 (TN)	112
100	100	200

TPR = 0.76

FPR = 0.12

PPV = 0.86

F1 = 0.81

ACC = 0.82

Recall
 = True Positive Rate (TPR) $Recall = \frac{TP}{TP + FN}$
 = Sensitivity
 = Hit Rate

Precision
 = Positive Predictive Value (PPV) $Precision = \frac{TP}{TP + FP}$

Summary

- Text Mining
- Web Mining

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