Tamkang University
淡江大學

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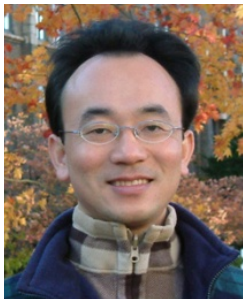
# 社群網路文字探勘與情感分析 (Text Mining and Sentiment Analytics on Social Media)

Time: 2016/05/10 (Tue) (12:00-14:00)
Place: 淡水校園覺生綜合大樓I501室

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2016-05-10

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中央研究院資訊科學研究所訪問學人

國立台灣大學資訊管理博士


Publications Co-Chairs, IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM 2013- )

Program Co-Chair, IEEE International Workshop on Empirical Methods for Recognizing Inference in TExt (IEEE EM-RITE 2012- )

Workshop Chair, The IEEE International Conference on Information Reuse and Integration (IEEE IRI)

# Outline

- 文字探勘技術
  (Text Mining Technologies)

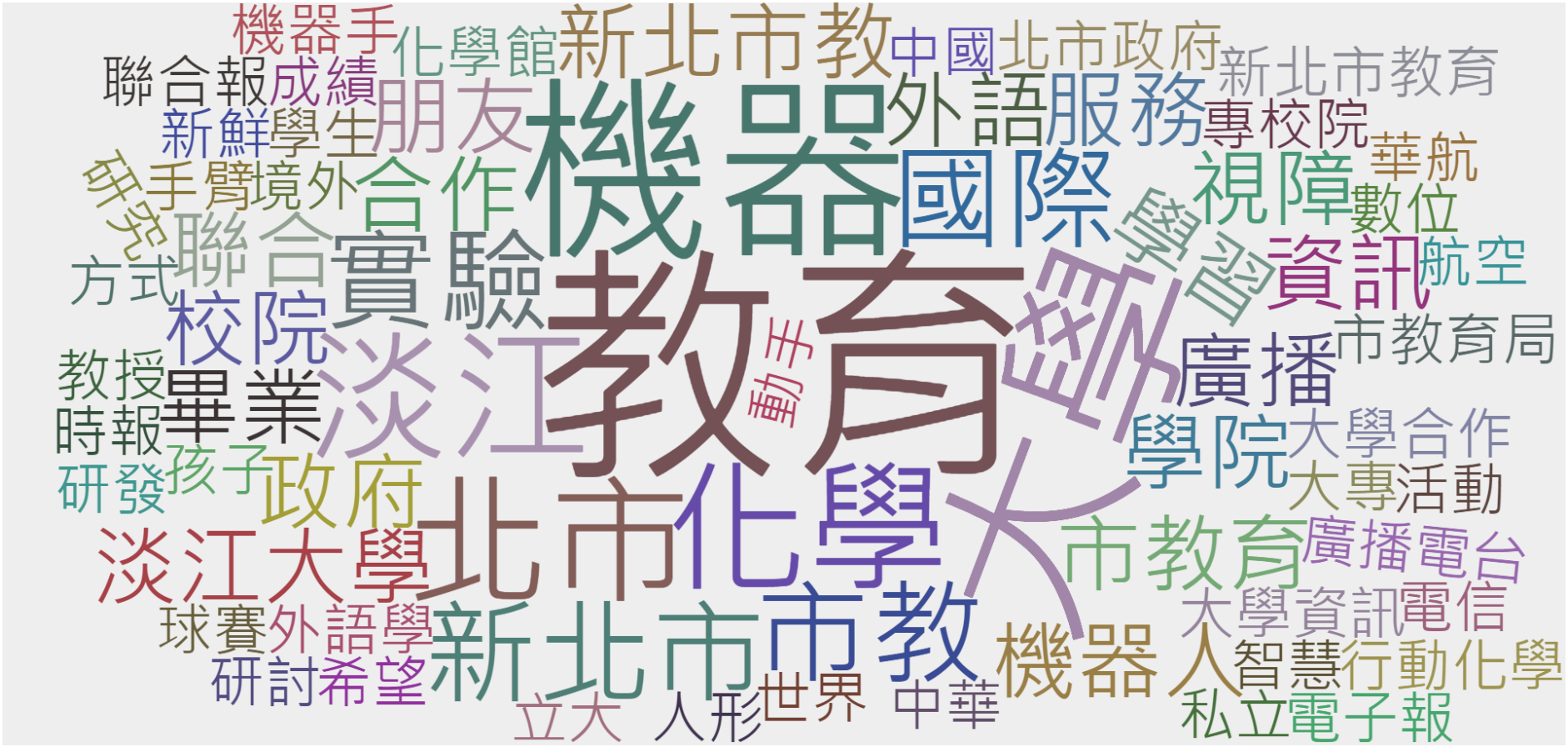
- 情感分析架構
  (Architectures of Sentiment Analytics)

# Data Scientist

# 資料科學家


Source: http://www.ibmbigdatahub.com/infographic/what-makes-data-scientist

# 淡江大學
# 媒體報導文字雲




淡江大學媒體報導：http://gdc.tku.edu.tw/TodayNews/summarymedia.aspx
HTML 5 文字雲：http://timdream.org/wordcloud/

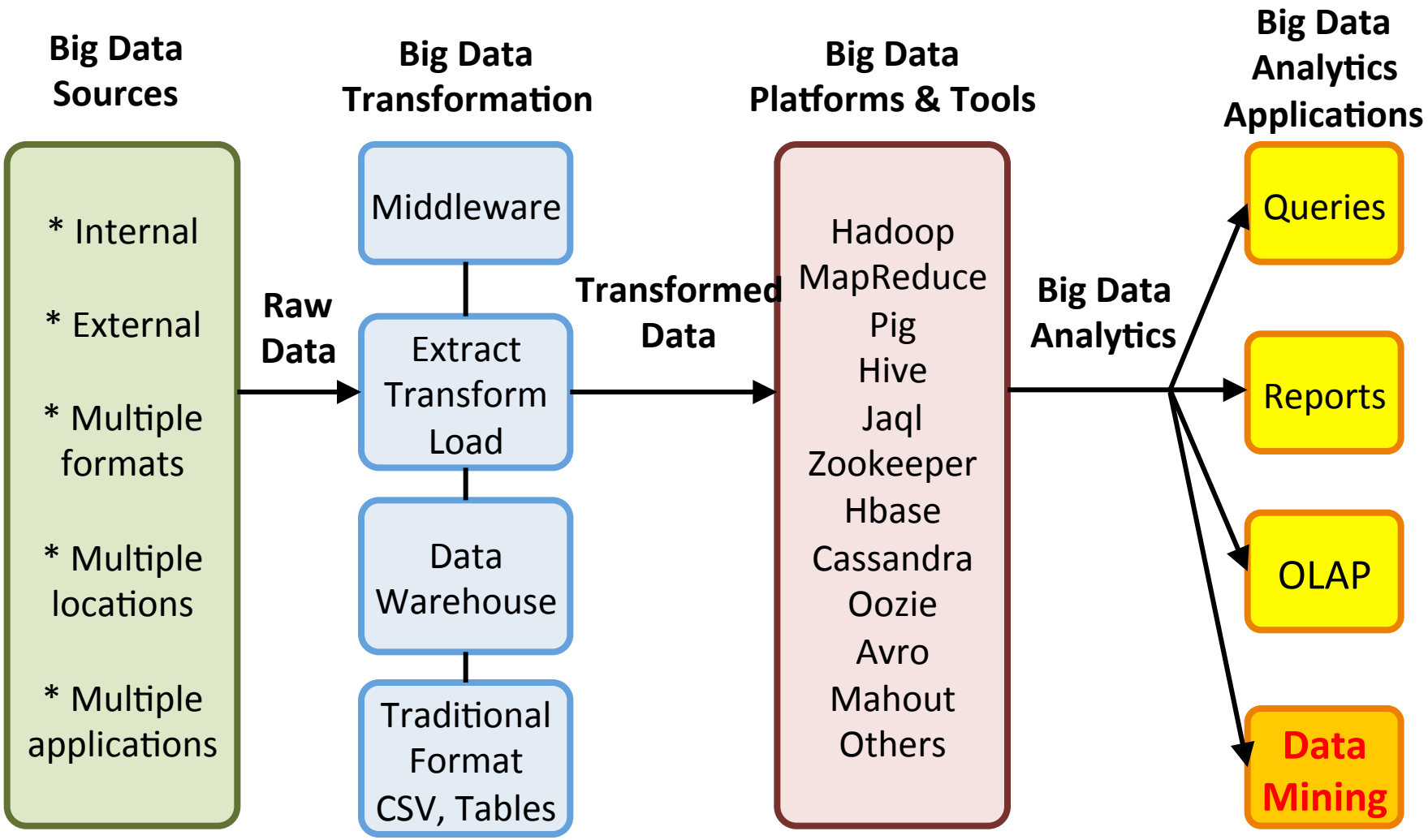
# 淡江大學媒體報導


淡江大學媒體報導：http://gdc.tku.edu.tw/TodayNews/summarymedia.aspx

# 淡江大學媒體報導關鍵字

- 淡江大學　共出現1173次
- 化學　共出現749次
- 台灣　共出現740次
- 教育　共出現606次
- 活動　共出現575次
- 學校　共出現550次
- 淡大　共出現522次
- 國際　共出現465次

# Architecture of Big Data Analytics



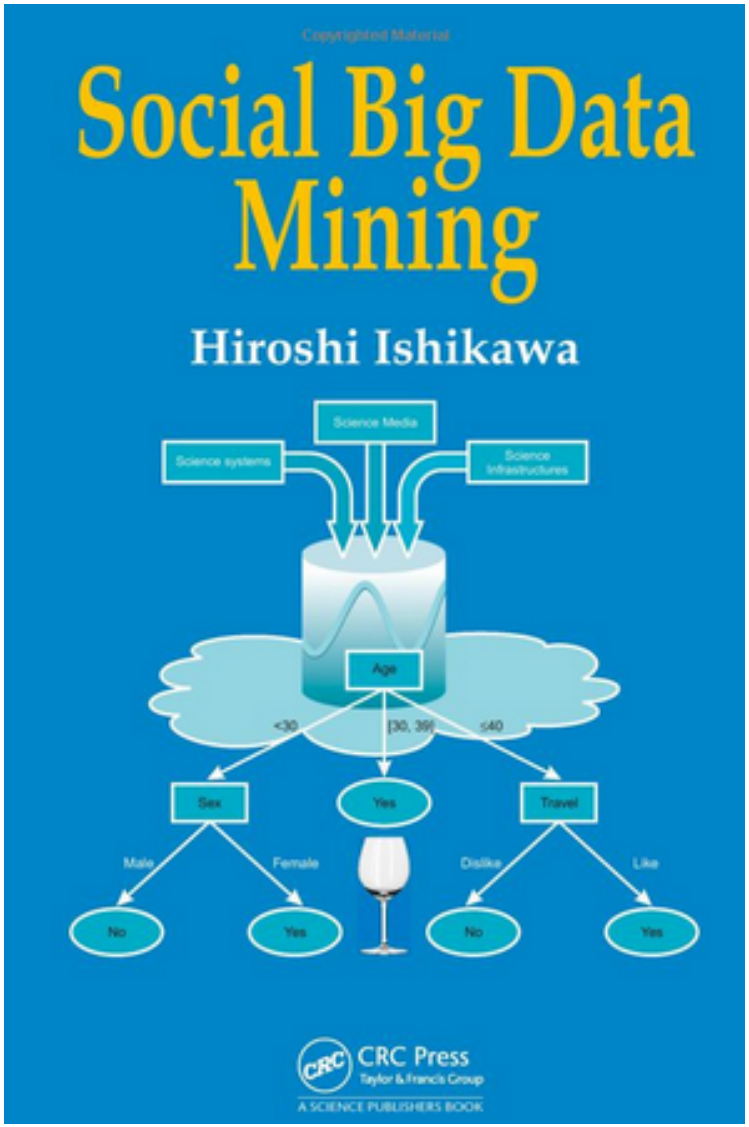

Source: Stephan Kudyba (2014), Big Data, Mining, and Analytics: Components of Strategic Decision Making, Auerbach Publications

# Architecture of Big Data Analytics


Source: Stephan Kudyba (2014), Big Data, Mining, and Analytics: Components of Strategic Decision Making, Auerbach Publications

# Social Big Data Mining

(Hiroshi Ishikawa, 2015)



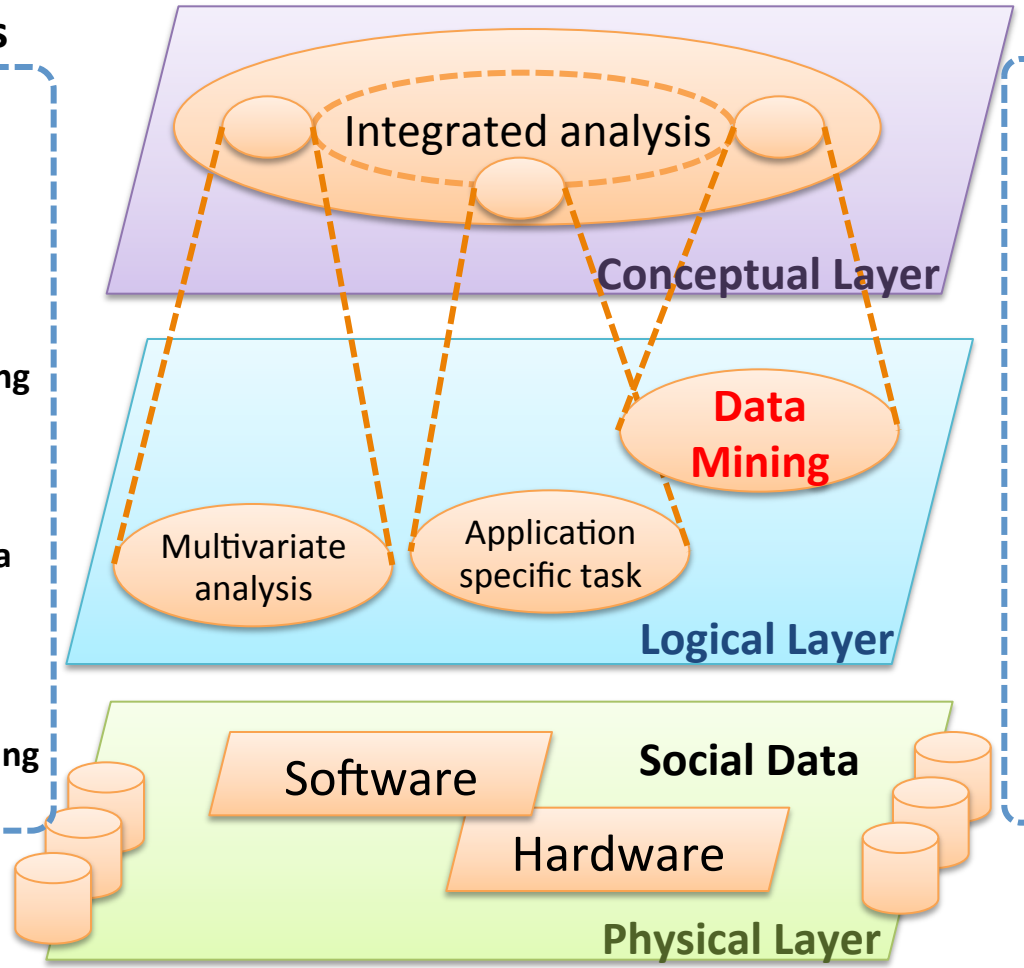

Source: http://www.amazon.com/Social-Data-Mining-Hiroshi-Ishikawa/dp/149871093X

# Architecture for Social Big Data Mining

(Hiroshi Ishikawa, 2015)

**Enabling Technologies**

- **Integrated analysis model**
- **Natural Language Processing**
- **Information Extraction**
- **Anomaly Detection**
- **Discovery of relationships among heterogeneous data**
- **Large-scale visualization**
- **Parallel distrusted processing**




**Analysts**

- **Model Construction**
- **Explanation by Model**
- **Construction and confirmation of individual hypothesis**
- **Description and execution of application-specific task**

Source: Hiroshi Ishikawa (2015), Social Big Data Mining, CRC Press

# Deep Learning

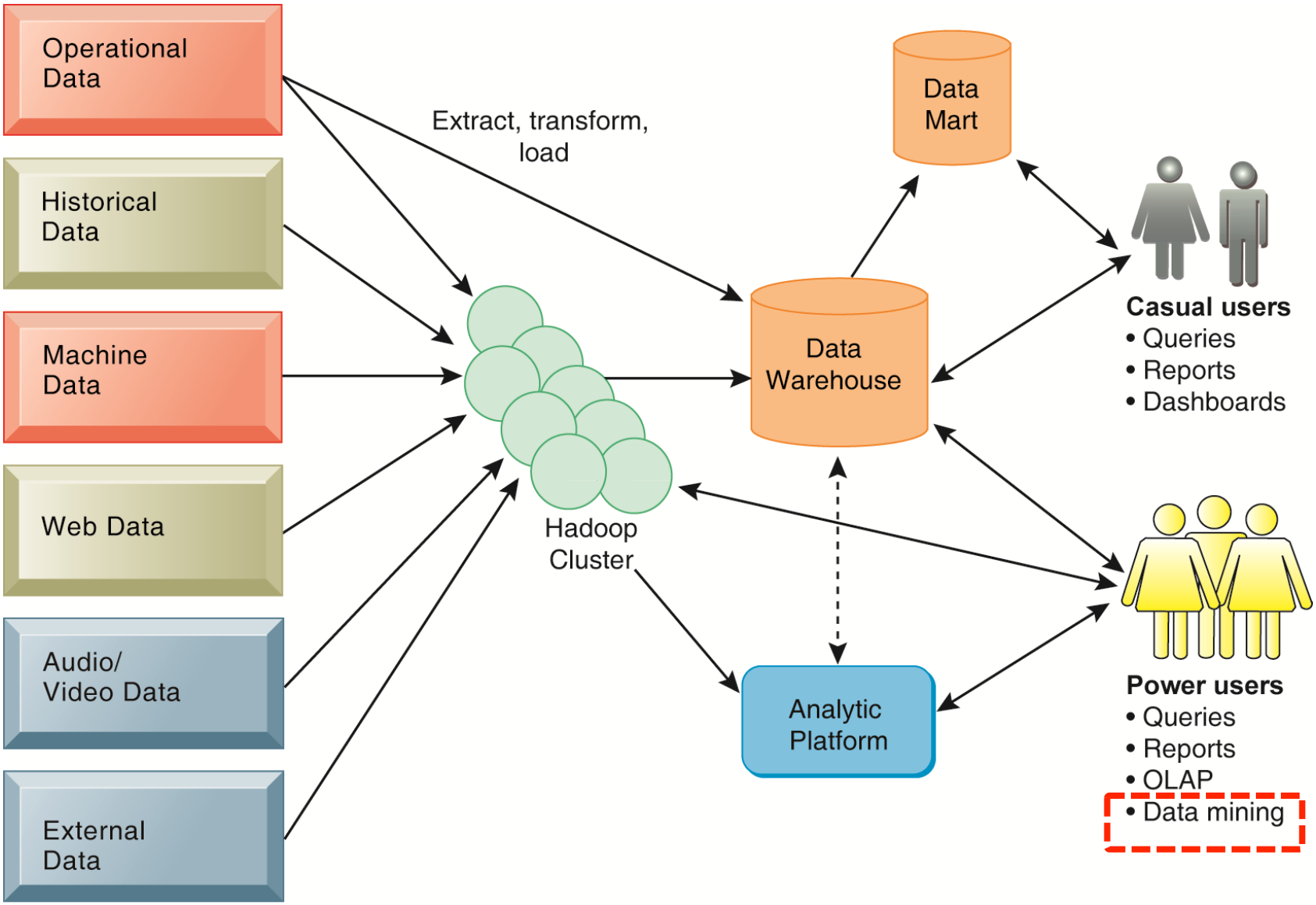
## Intelligence from Big Data

Source: https://www.vlab.org/events/deep-learning/

# The Evolution of BI Capabilities


Source: Turban et al. (2011), Decision Support and Business Intelligence Systems

# Business Intelligence (BI) Infrastructure




Source: Kenneth C. Laudon & Jane P. Laudon (2014), Management Information Systems: Managing the Digital Firm, Thirteenth Edition, Pearson.

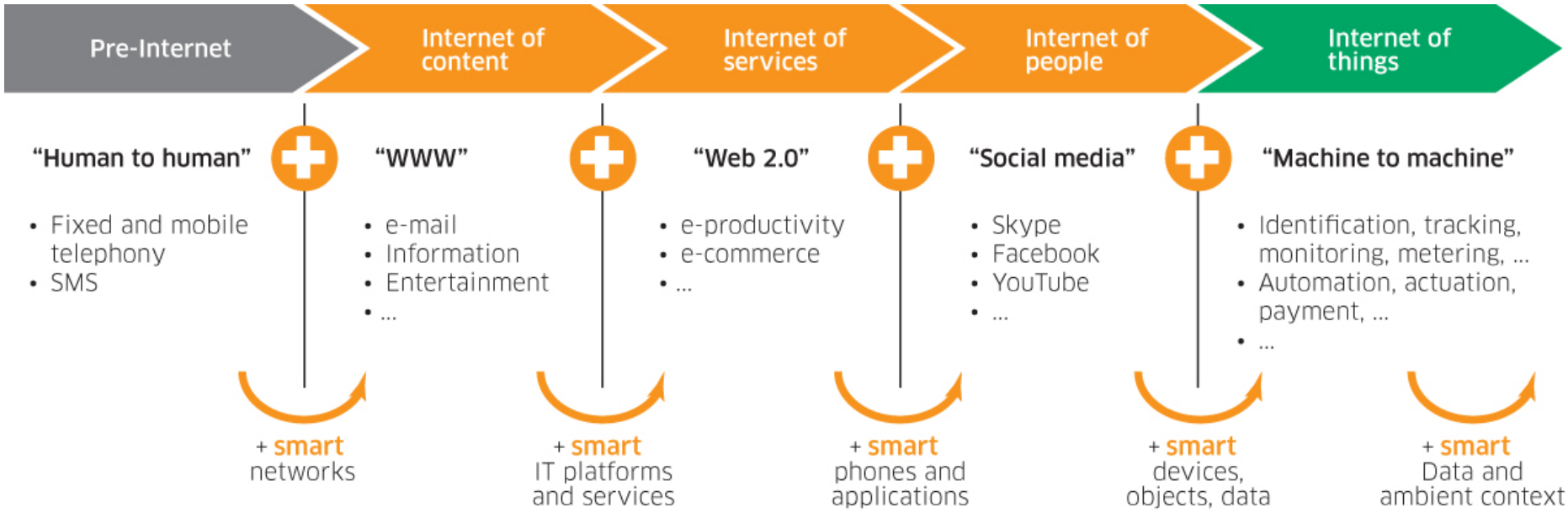
# Social Media


Source: http://hungrywolfmarketing.com/2013/09/09/what-are-your-social-marketing-goals/

# Internet Evolution

## Internet of People (IoP): Social Media

## Internet of Things (IoT): Machine to Machine




Source: Marc Jadoul (2015), The IoT: The next step in internet evolution, March 11, 2015
http://www2.alcatel-lucent.com/techzine/iot-internet-of-things-next-step-evolution/

# Emotions


Love

Anger

Joy

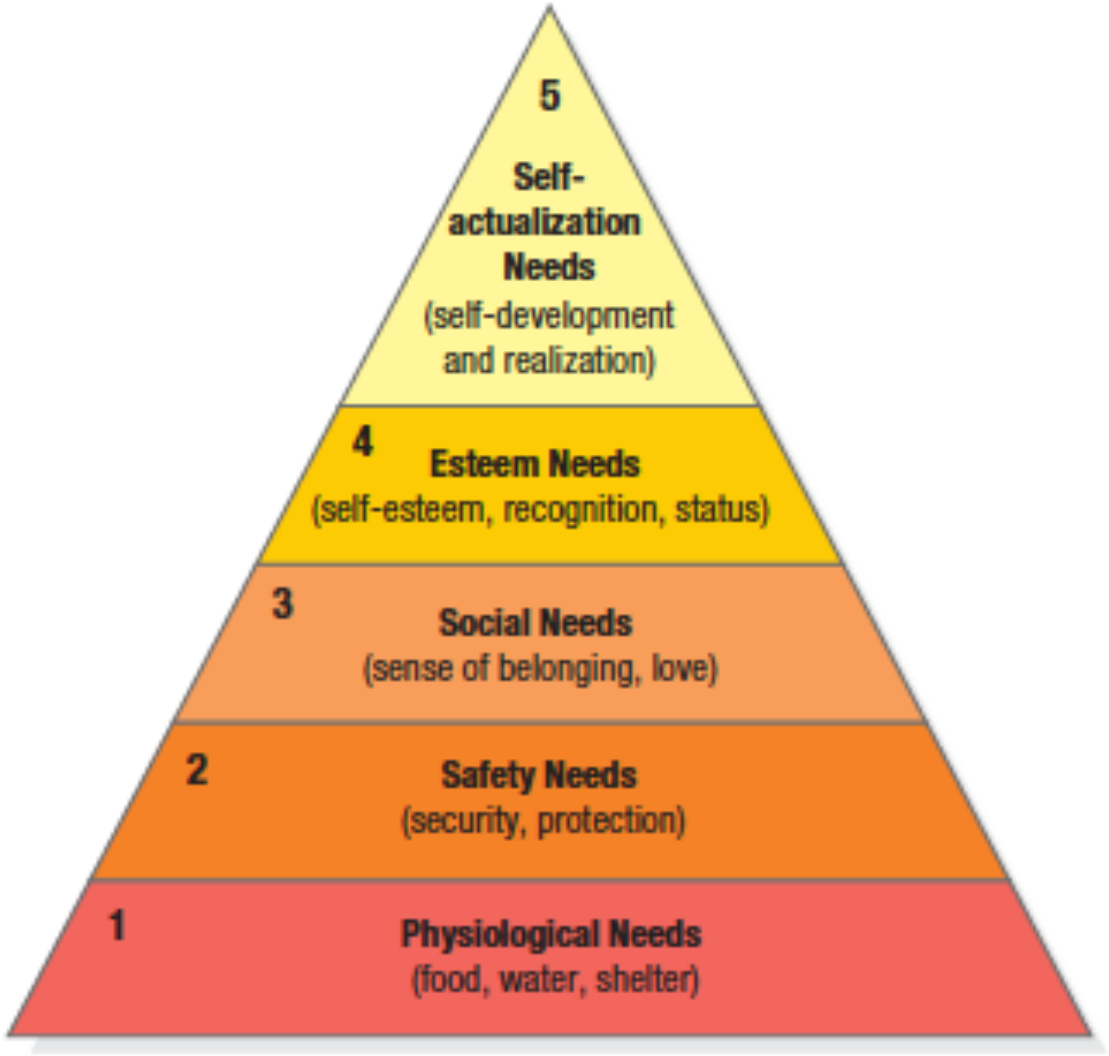
Sadness

Surprise

Fear

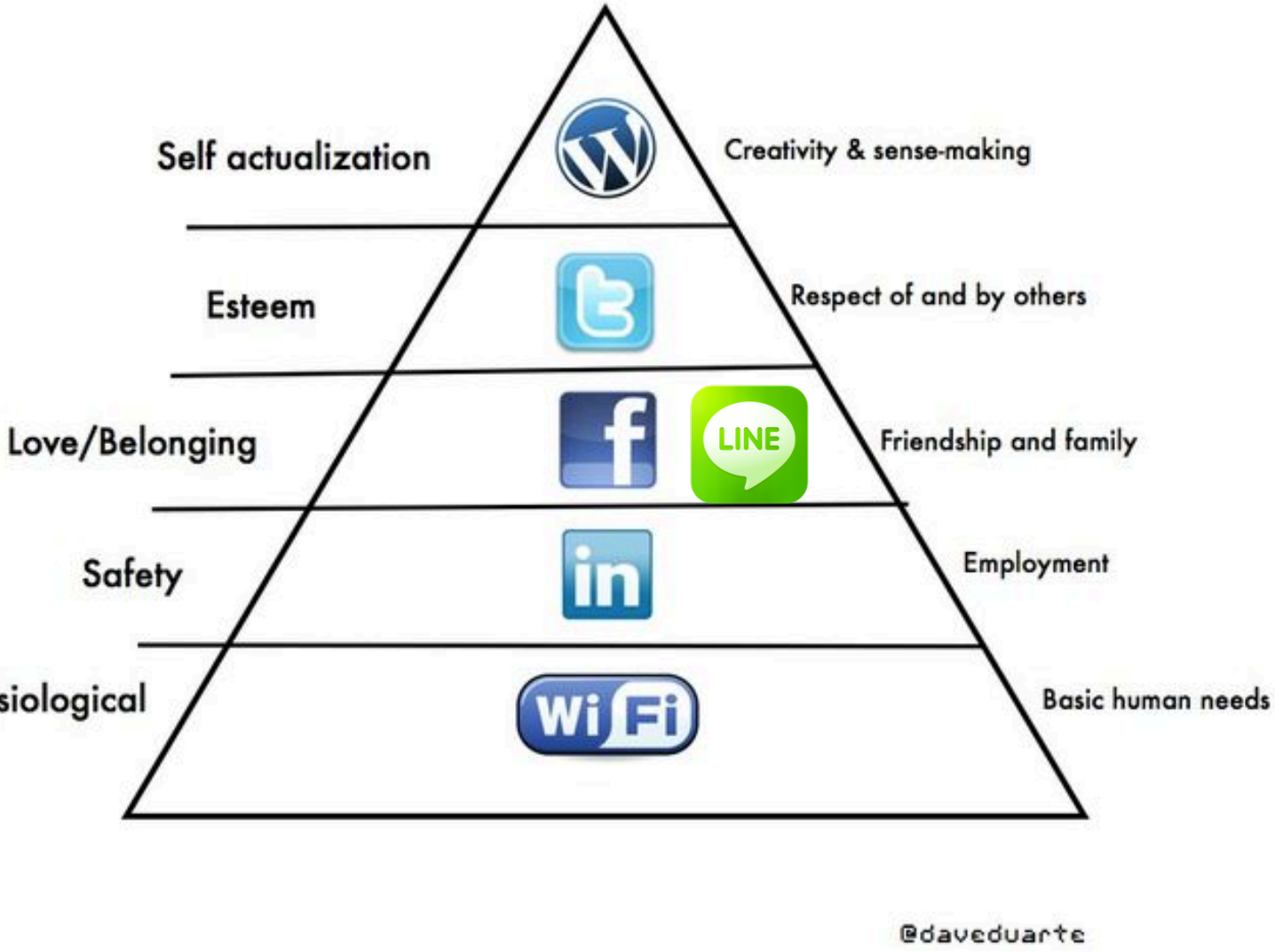
Source: Bing Liu (2011) , “Web Data Mining: Exploring Hyperlinks, Contents, and Usage Data,” Springer, 2nd Edition,

# Maslow's Hierarchy of Needs



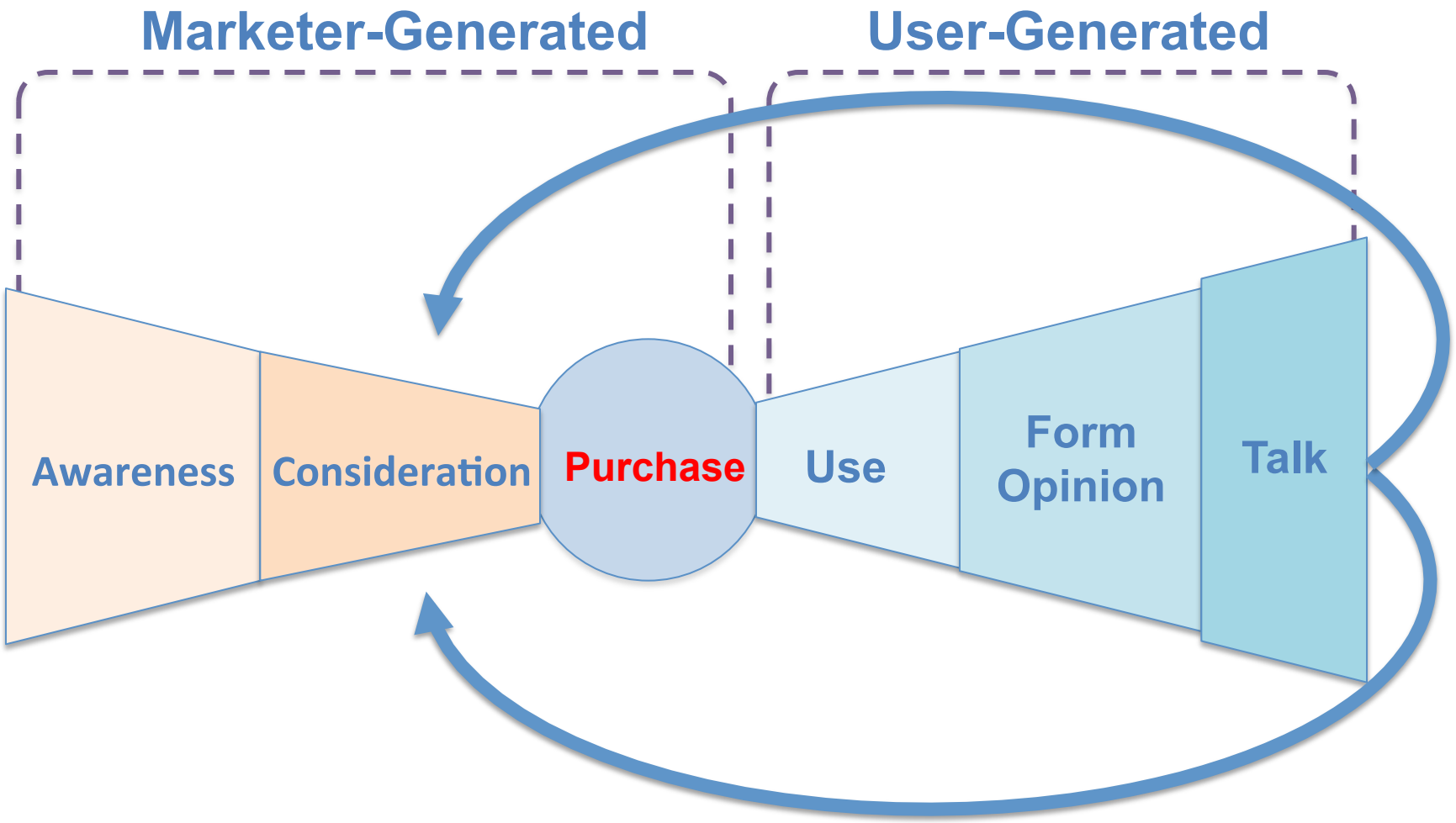

Source: Philip Kotler & Kevin Lane Keller, Marketing Management, 14th ed., Pearson, 2012

# Social Media Hierarchy of Needs



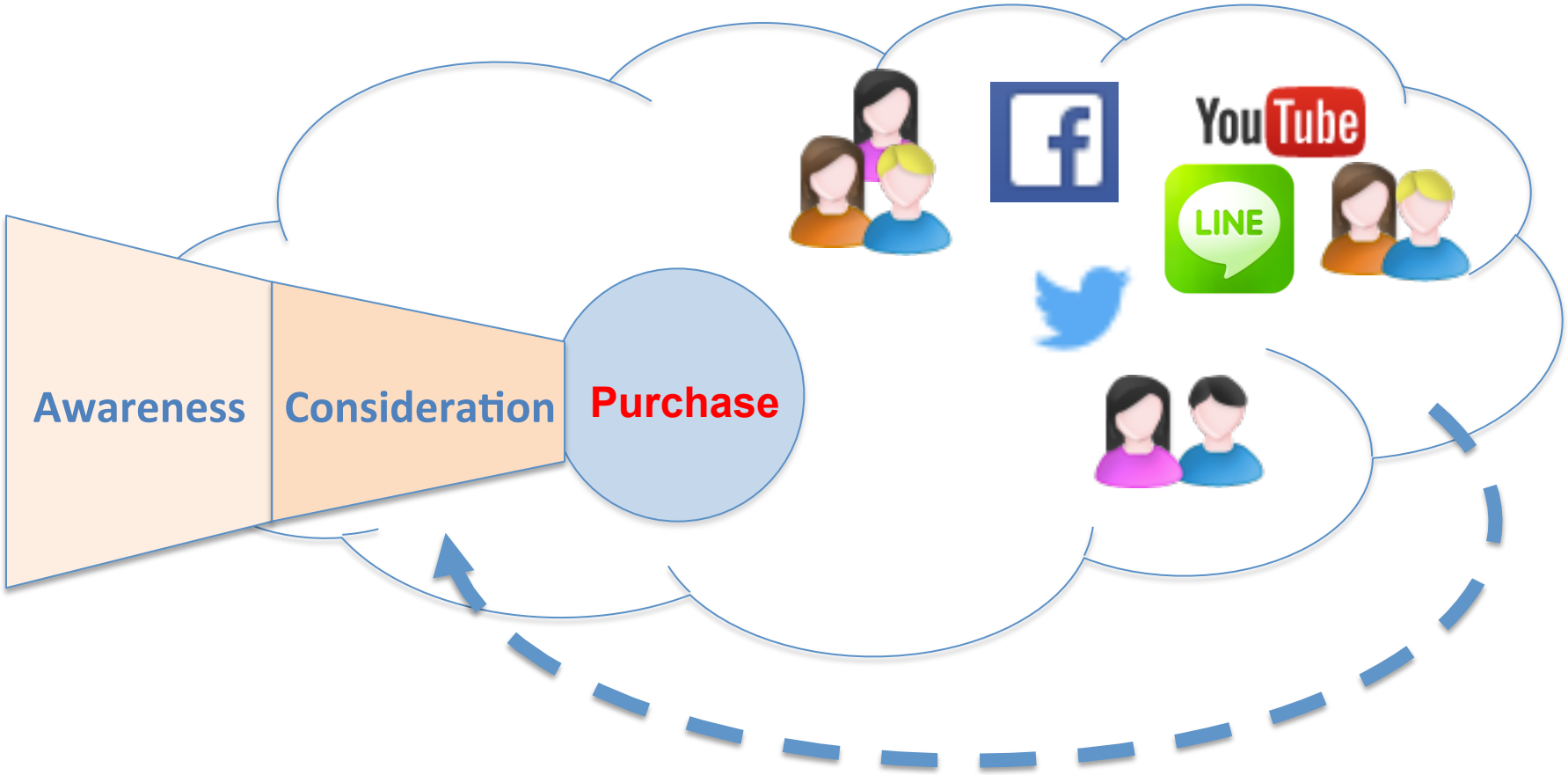

Source: http://www.pinterest.com/pin/18647785930903585/

# The Social Feedback Cycle
# Consumer Behavior on Social Media




Source: Evans et al. (2010), Social Media Marketing: The Next Generation of Business Engagement

# The New Customer Influence Path




Source: Evans et al. (2010), Social Media Marketing: The Next Generation of Business Engagement

# Example of Opinion: review segment on iPhone

"I bought an iPhone a few days ago.

It was such a nice phone.

The touch screen was really cool.

The voice quality was clear too.

However, my mother was mad with me as I did not tell her before I bought it.

She also thought the phone was too expensive, and wanted me to return it to the shop. … "

Source: Bing Liu (2011) , "Web Data Mining: Exploring Hyperlinks, Contents, and Usage Data," Springer, 2nd Edition,

# Example of Opinion: review segment on iPhone

"(1) I bought an iPhone a few days ago.

(2) It was such a **nice** phone.

(3) The touch screen was really **cool**.

**+Positive Opinion**

(4) The voice quality was **clear** too.

(5) However, my mother was mad with me as I did not tell her before I bought it.

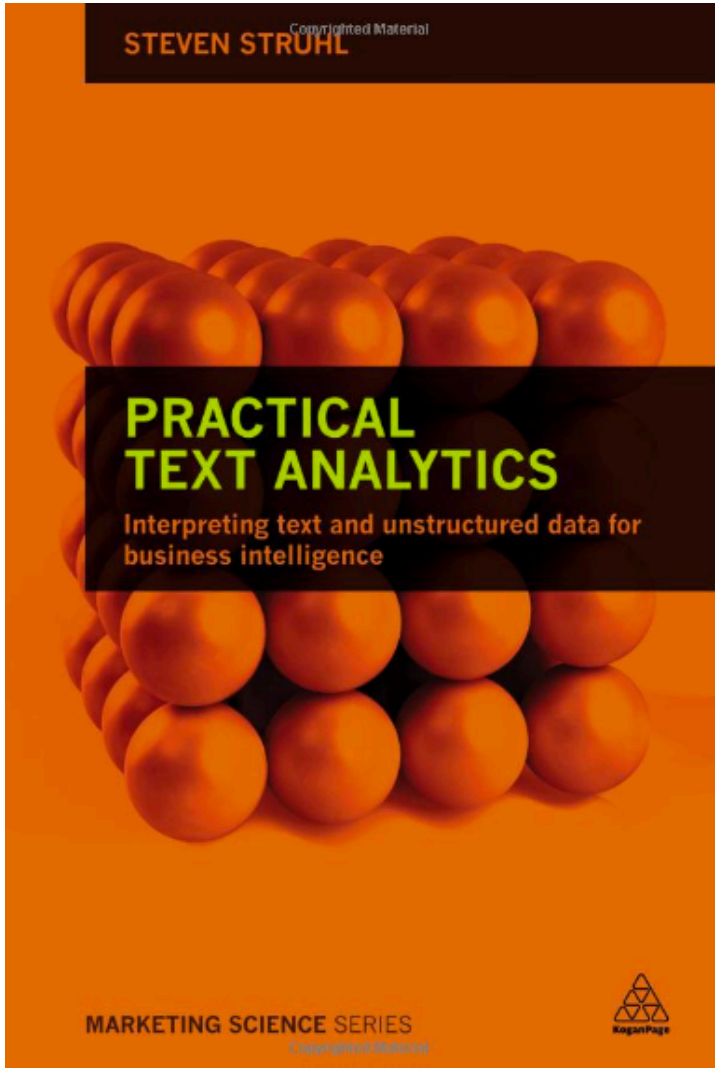
(6) She also thought the phone was too **expensive**, and wanted me to return it to the shop. … "

**-Negative Opinion**

Source: Bing Liu (2011) , "Web Data Mining: Exploring Hyperlinks, Contents, and Usage Data," Springer, 2nd Edition,

# Text Mining Technologies

# Steven Struhl (2015), Practical Text Analytics: Interpreting Text and Unstructured Data for Business Intelligence (Marketing Science), Kogan Page




http://www.amazon.com/Practical-Text-Analytics-Interpreting-Unstructured/dp/0749474017

# 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

Text mining

Text Data Mining

Intelligent Text Analysis

Knowledge-Discovery in Text (KDT)

Source: Vishal Gupta and Gurpreet S. Lehal (2009), "A survey of text mining techniques and applications," Journal of emerging technologies in web intelligence, vol. 1, no. 1, pp. 60-76.

# Text Mining:

## the process of extracting interesting and non-trivial information and knowledge from unstructured text.

Source: Vishal Gupta and Gurpreet S. Lehal (2009), "A survey of text mining techniques and applications," Journal of emerging technologies in web intelligence, vol. 1, no. 1, pp. 60-76.

# Text Mining:

discovery by computer of

new, previously

unknown information,

by automatically

extracting information

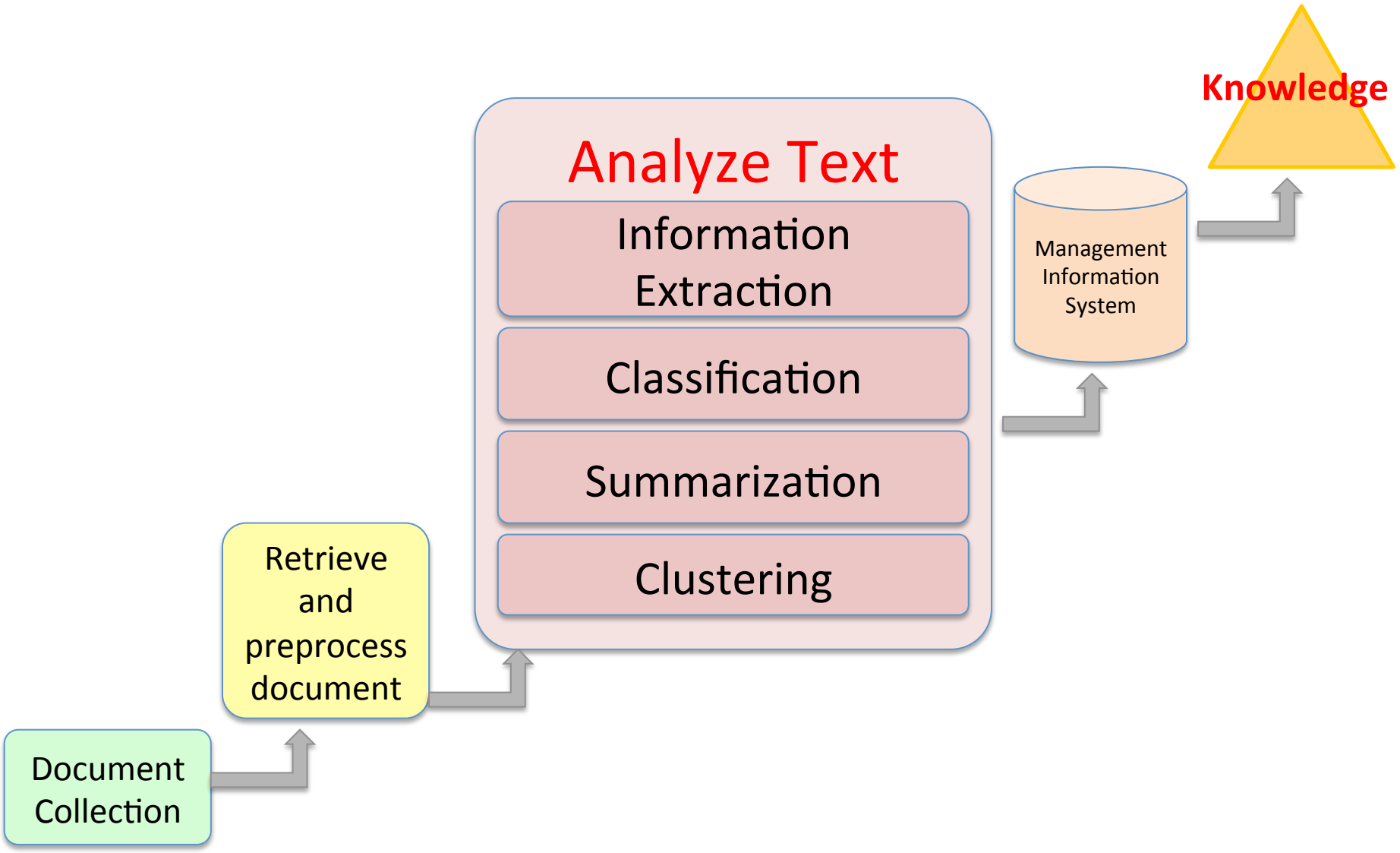
from different written resources.

Source: Vishal Gupta and Gurpreet S. Lehal (2009), "A survey of text mining techniques and applications," Journal of emerging technologies in web intelligence, vol. 1, no. 1, pp. 60-76.

# Text Mining (TM)

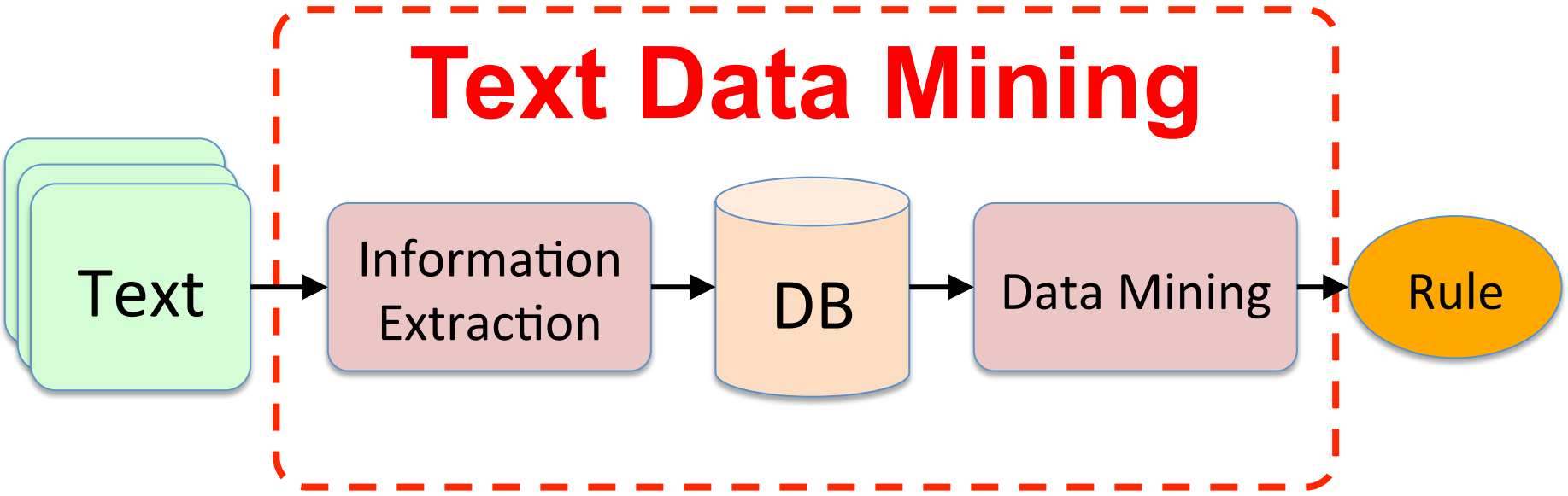
## Natural Language Processing (NLP)

# An example of Text Mining



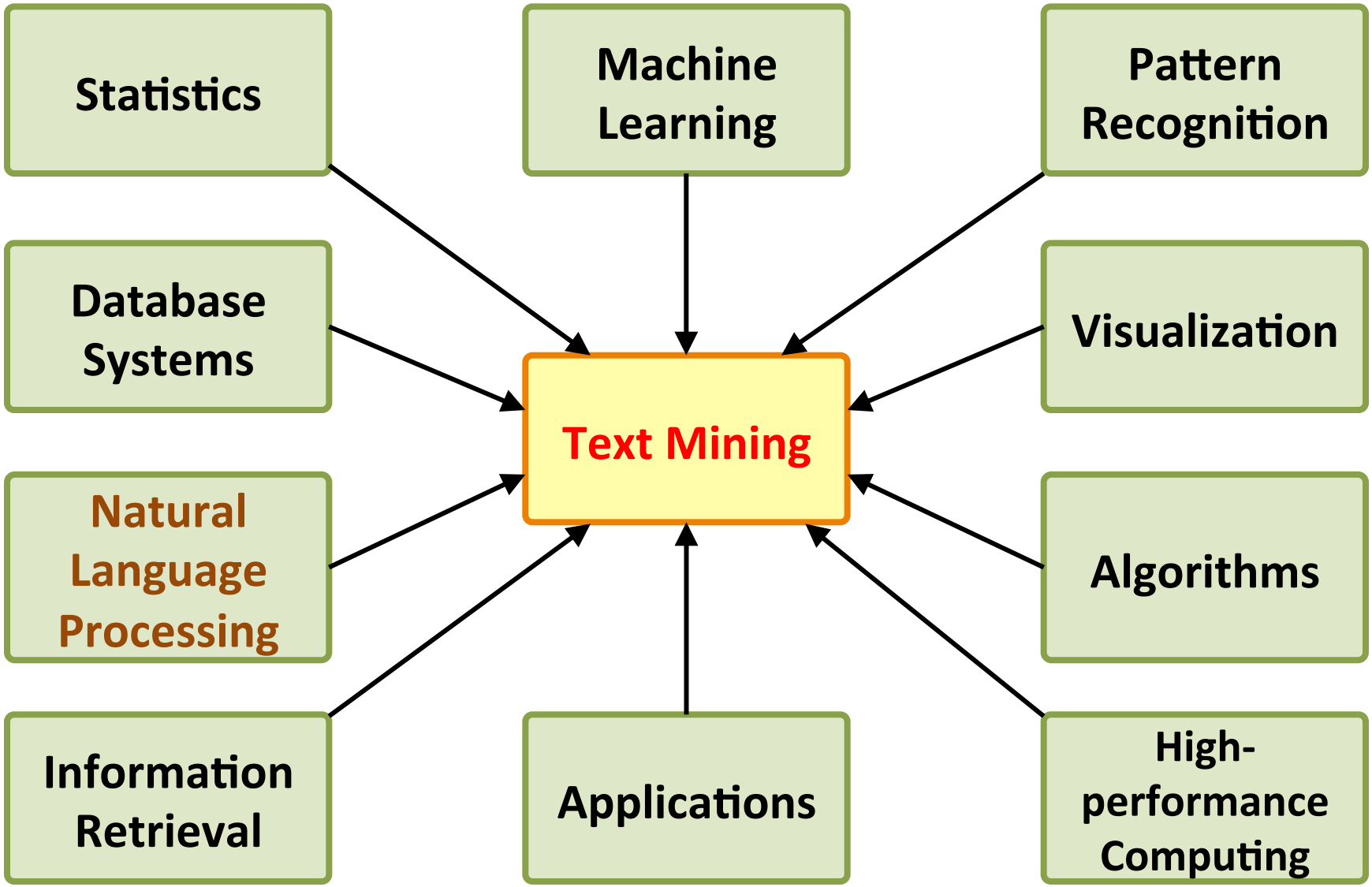

Source: Vishal Gupta and Gurpreet S. Lehal (2009), "A survey of text mining techniques and applications," Journal of emerging technologies in web intelligence, vol. 1, no. 1, pp. 60-76.

# Overview of Information Extraction based Text Mining Framework




Source: Vishal Gupta and Gurpreet S. Lehal (2009), "A survey of text mining techniques and applications," Journal of emerging technologies in web intelligence, vol. 1, no. 1, pp. 60-76.

# Text Mining Technologies



# 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

# Data Mining:

## Core Analytics Process

## The KDD Process for Extracting Useful Knowledge from Volumes of Data

Source: Fayyad, U., Piatetsky-Shapiro, G., & Smyth, P. (1996). The KDD Process for Extracting Useful Knowledge from Volumes of Data. Communications of the ACM, 39(11), 27-34.

Fayyad, U., Piatetsky-Shapiro, G., & Smyth, P. (1996).

**The KDD Process for**

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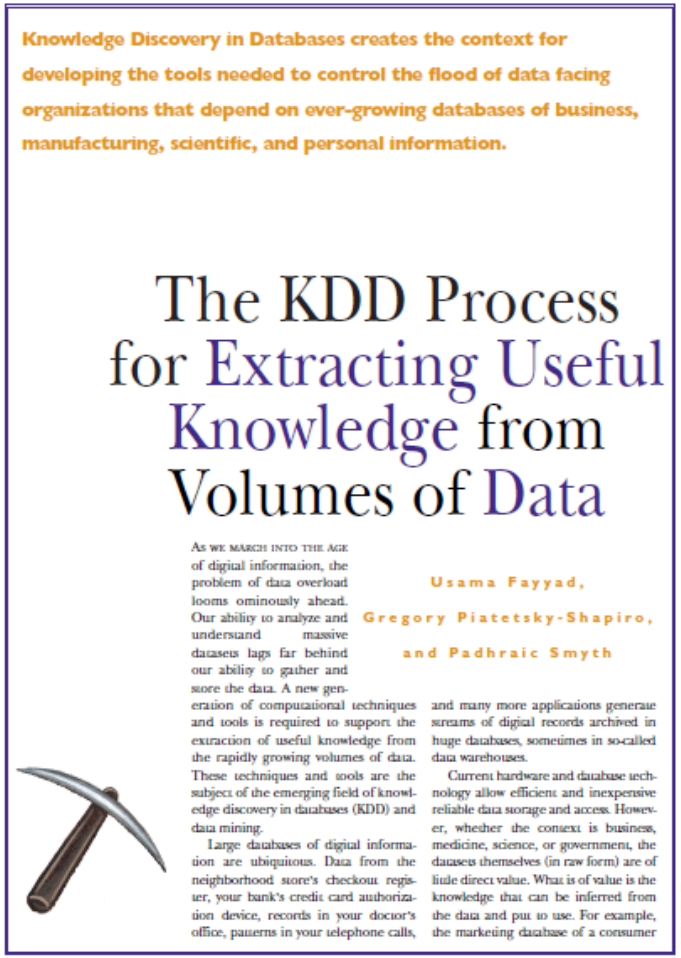
**from Volumes of Data.**

Communications of the ACM, 39(11), 27-34.



**Knowledge Discovery in Databases creates the context for developing the tools needed to control the flood of data facing organizations that depend on ever-growing databases of business, manufacturing, scientific, and personal information.**

# The KDD Process for Extracting Useful Knowledge from Volumes of Data

Usama Fayyad,
Gregory Piatetsky-Shapiro,
and Padhraic Smyth

As we march into the age of digital information, the problem of data overload looms ominously ahead. Our ability to analyze and understand massive datasets lags far behind our ability to gather and store the data. A new generation of computational techniques and tools is required to support the extraction of useful knowledge from the rapidly growing volumes of data. These techniques and tools are the subject of the emerging field of knowledge discovery in databases (KDD) and data mining.

Large databases of digital information are ubiquitous. Data from the neighborhood store's checkout register, your bank's credit card authorization device, records in your doctor's office, patterns in your telephone calls, and many more applications generate streams of digital records archived in huge databases, sometimes in so-called data warehouses.

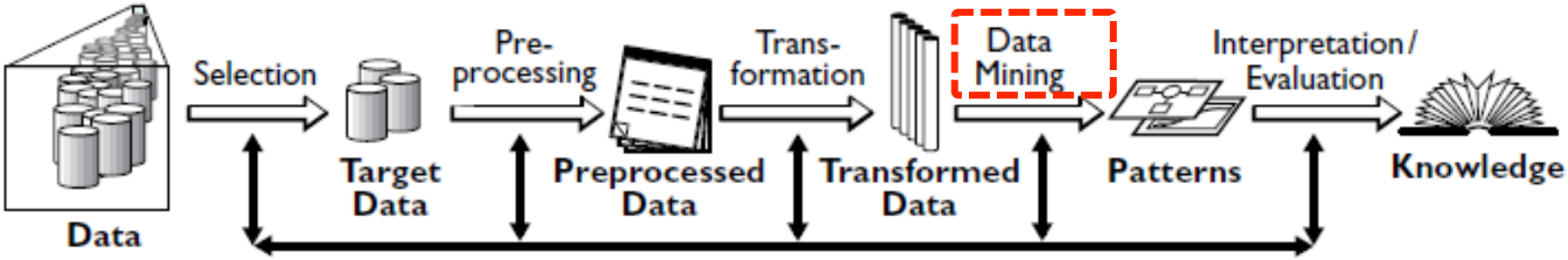
Current hardware and database technology allow efficient and inexpensive reliable data storage and access. However, whether the context is business, medicine, science, or government, the datasets themselves (in raw form) are of little direct value. What is of value is the knowledge that can be inferred from the data and put to use. For example, the marketing database of a consumer

TERRY WEEHER

# Data Mining

## Knowledge Discovery in Databases (KDD) Process

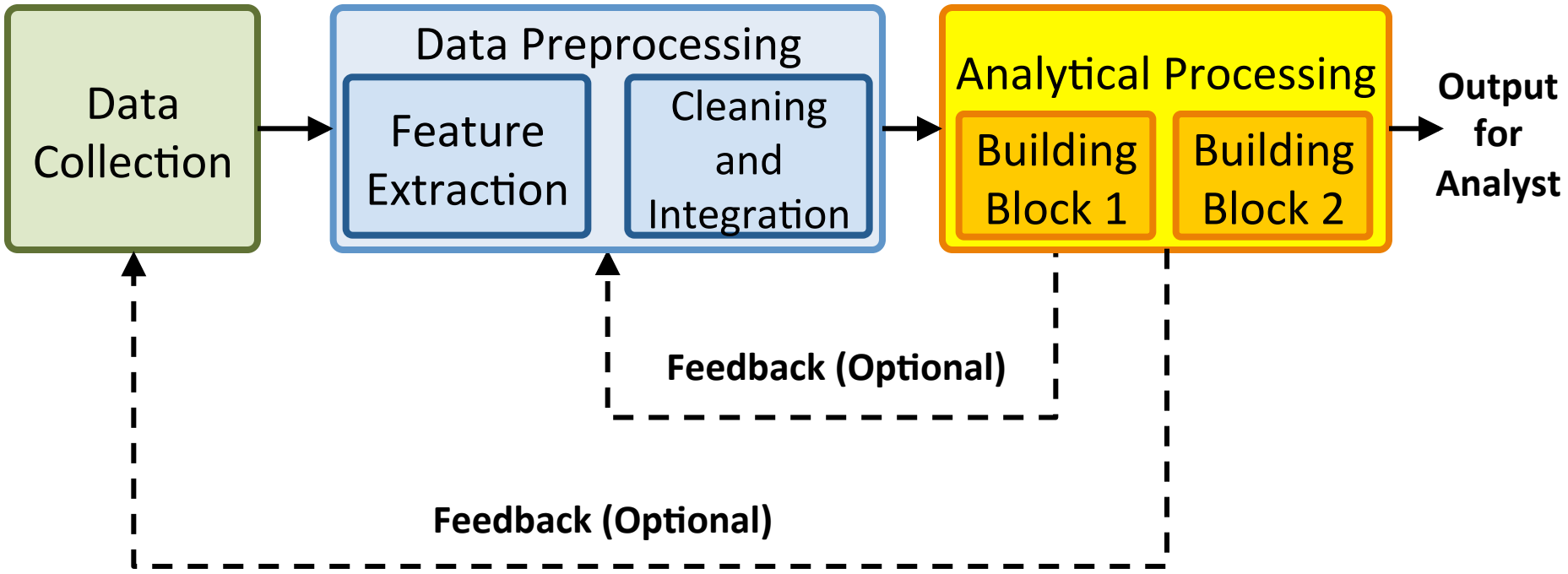
(Fayyad et al., 1996)




Source: Fayyad, U., Piatetsky-Shapiro, G., & Smyth, P. (1996). The KDD Process for Extracting Useful Knowledge from Volumes of Data. Communications of the ACM, 39(11), 27-34.

# Data Mining Processing Pipeline

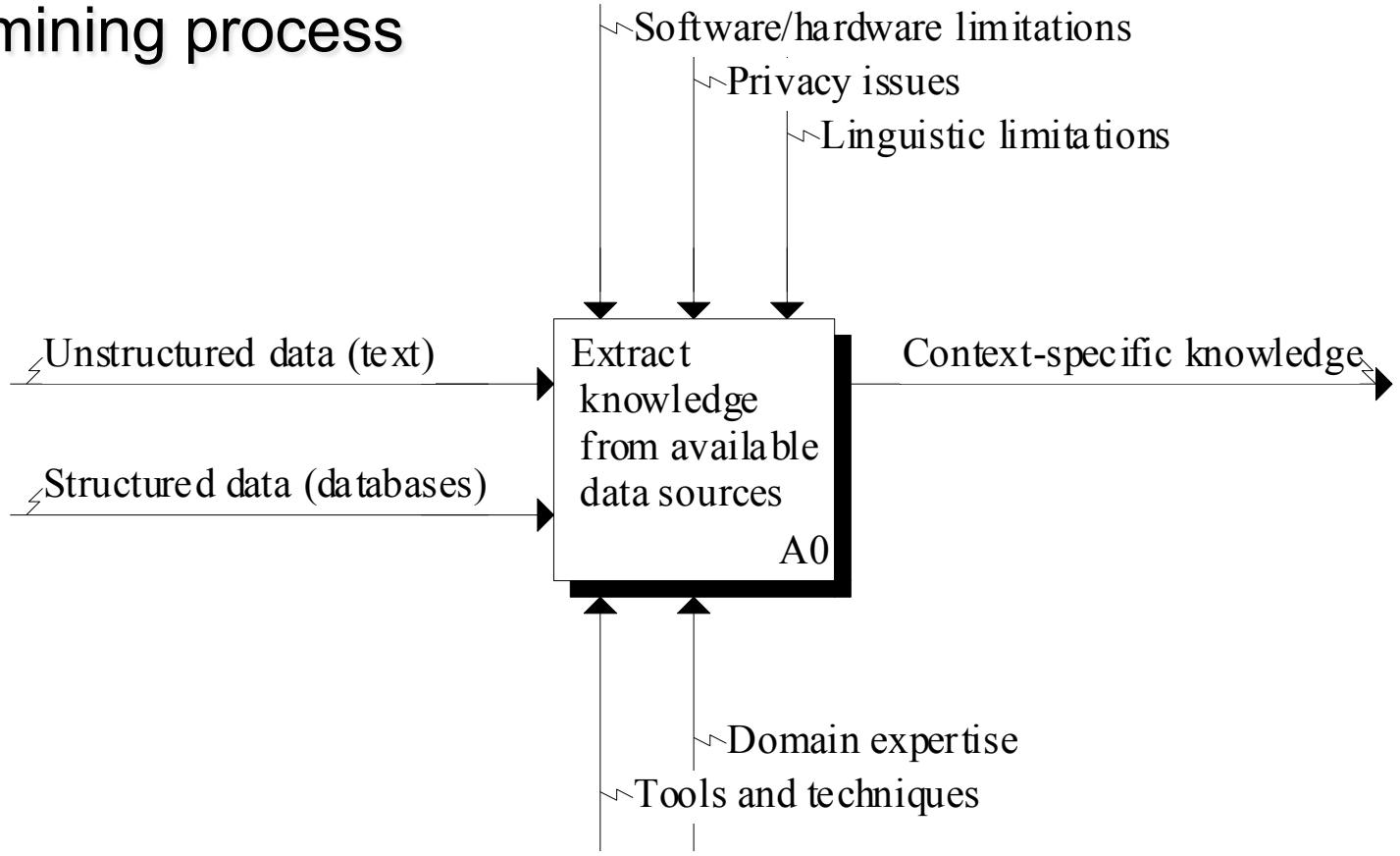
(Charu Aggarwal, 2015)




Source: Charu Aggarwal (2015), Data Mining: The Textbook Hardcover, Springer

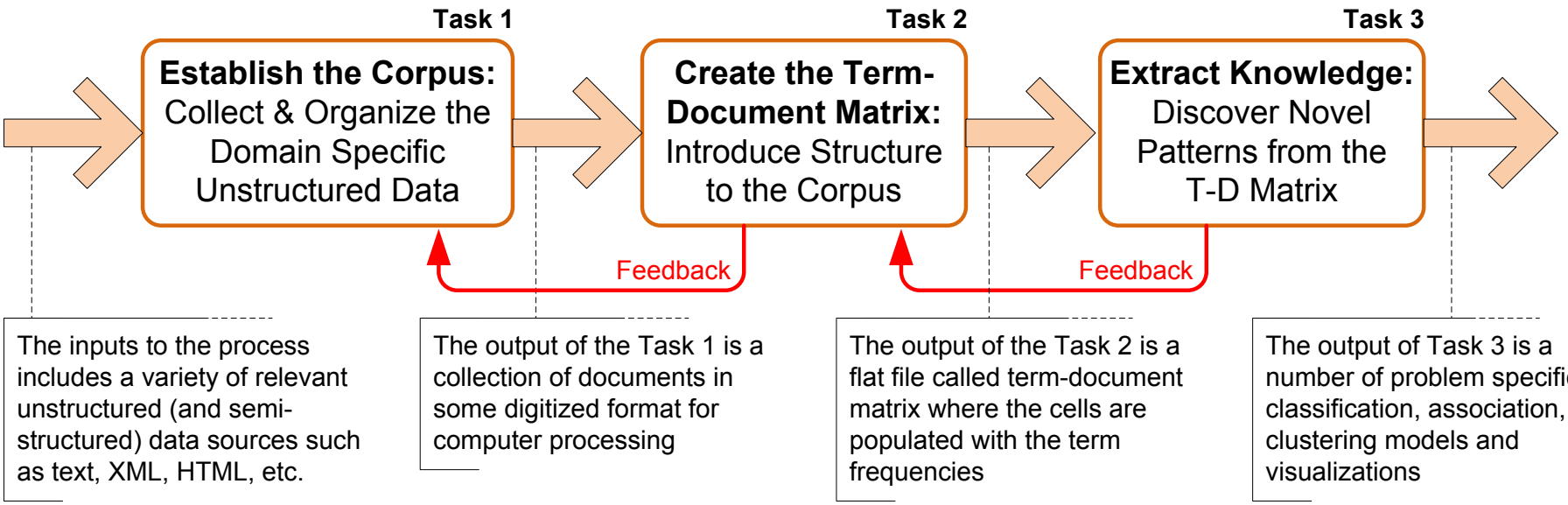
# Text Mining Process

Context diagram for the text mining process




Source: Turban et al. (2011), Decision Support and Business Intelligence Systems

# Text Mining Process




The three-step text mining process

Source: Turban et al. (2011), Decision Support and Business Intelligence Systems

# 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 | | | |
| ... | | | | | | | |

Source: Turban et al. (2011), Decision Support and Business Intelligence Systems

# 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

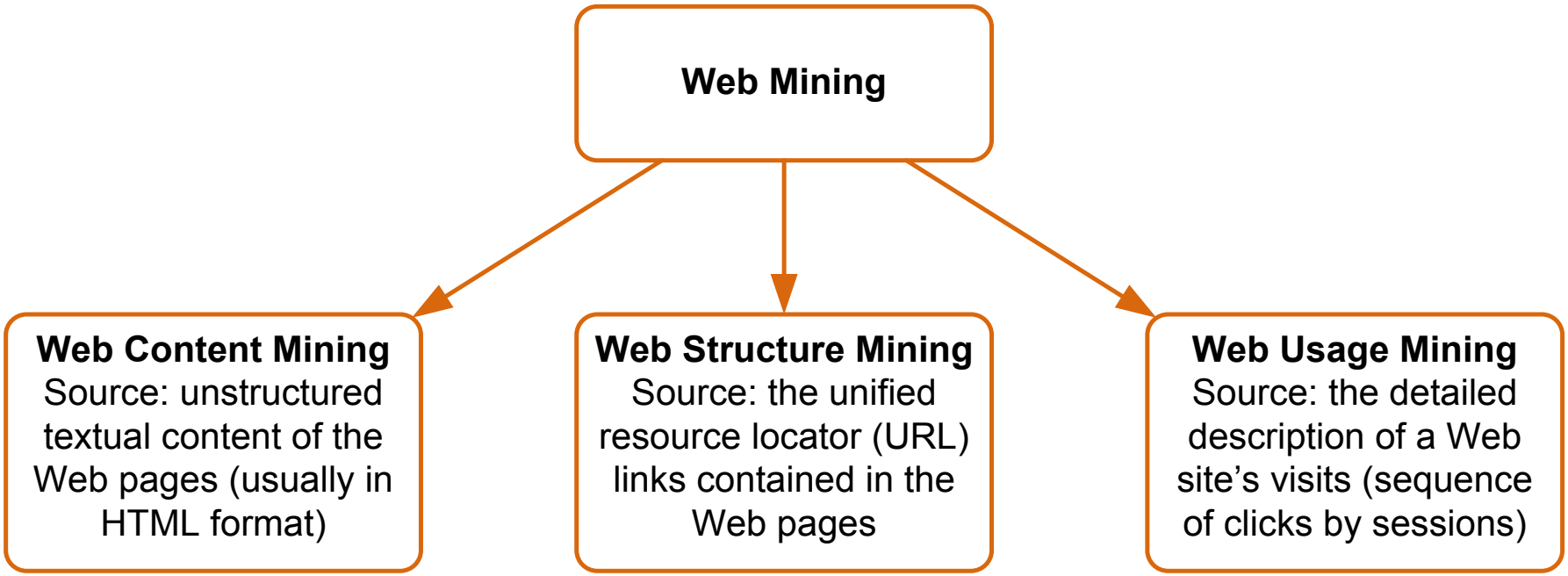
- Step 2: Create the Term–by–Document Matrix (TDM), cont.
  - TDM is a sparse matrix. How can we reduce the dimensionality of the TDM?
    - Manual - a domain expert goes through it
    - Eliminate terms with very few occurrences in very few documents (?)
    - Transform the matrix using singular value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

# Web Mining

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



# 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 communization 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)

# 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)

Source: Turban et al. (2011), Decision Support and Business Intelligence Systems

# CKIP 中研院中文斷詞系統

http://ckipsvr.iis.sinica.edu.tw/


歐巴馬(Nb) 是(SHI) 美國(Nc) 的(DE) 一(Neu) 位(Nf) 總統(Na)

# 中文文字處理:中文斷詞

即時 要聞 娛樂 運動 全球 社會 產經 股市 健康 生活 文教 評論 地方 兩岸

## 莎士比亞在淡江 遇見賽萬提斯

分享 分享 留言 列印 存新聞 A- A+

2016-04-26 02:27 聯合報 記者徐葳倫／淡水報導 讚 分享 20 傳送 G+1 0


淡江大學舉辦「當莎士比亞遇見賽萬提斯」系列活動，讓師生幫莎士比亞、賽萬提斯著色，畫出五彩繽紛的「文學大師」。 記者徐葳倫／攝影

4月23日是「世界閱讀日」，也是英國大文豪莎士比亞的生日與忌日，及「唐吉訶德」作

莎士比亞在淡江 遇見賽萬提斯
2016-04-26 02:27 聯合報 記者徐葳倫／淡水報導

分享4月23日是「世界閱讀日」，也是英國大文豪莎士比亞的生日與忌日，及「唐吉訶德」作者賽萬提斯逝世之日。英專起家的淡江大學舉辦「當莎士比亞遇見賽萬提斯」活動，規畫主題書展、彩繪活動，並添購新書，拉近學生與經典文學的距離。

首波登場的「主題書展」，展出2大文豪經典作品的原著、各種譯本以及DVD、電子書等數位化資料，校方也添購許多新書，吸引學生「搶鮮」閱讀經典名作。現場還規畫「彩繪大師」，讓學生發揮創意，畫出五彩繽紛的莎士比亞和賽萬提斯人像。
英語系四年級學生陳彥伶說，讀英語系接觸莎士比亞作品，但過去沒有舉辦書展時，這些作品都放在圖書館8樓，現在搬到1樓大廳陳列，不僅有很多莎士比亞、賽萬提斯的經典新書，還可藉由電子書、電影理解兩位作家，是以前沒有過的體驗。

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http://udn.com/news/story/7323/1653437-%E8%8E%8E%E5%A3%AB%E6%AF%94%E4%BA%9E%E5%9C%A8%E6%B7%A1%E6%B1%9F-%E9%81%87%E8%A6%8B%E8%B3%BD%E8%90%AC%E6%8F%90%E6%96%AF

# CKIP 中研院中文斷詞系統

http://ckipsvr.iis.sinica.edu.tw/

中文斷詞系統

相關系統： 斷詞系統 | 剖析系統 | 詞首詞尾 | 平衡語料庫 | 廣義知網 | 句結構樹庫 | 錯字偵測

- 簡介
- 未知詞擷取做法
- 詞類標記列表
- 線上展示
- 線上服務申請
- 線上資源
- 公告
- 聯絡我們

自 2014/01/06 起，本斷詞系統已經處理過 28270134 篇文章

送出 清除

莎士比亞在淡江 遇見賽萬提斯
2016-04-26 02:27 聯合報 記者徐葳倫 / 淡水報導

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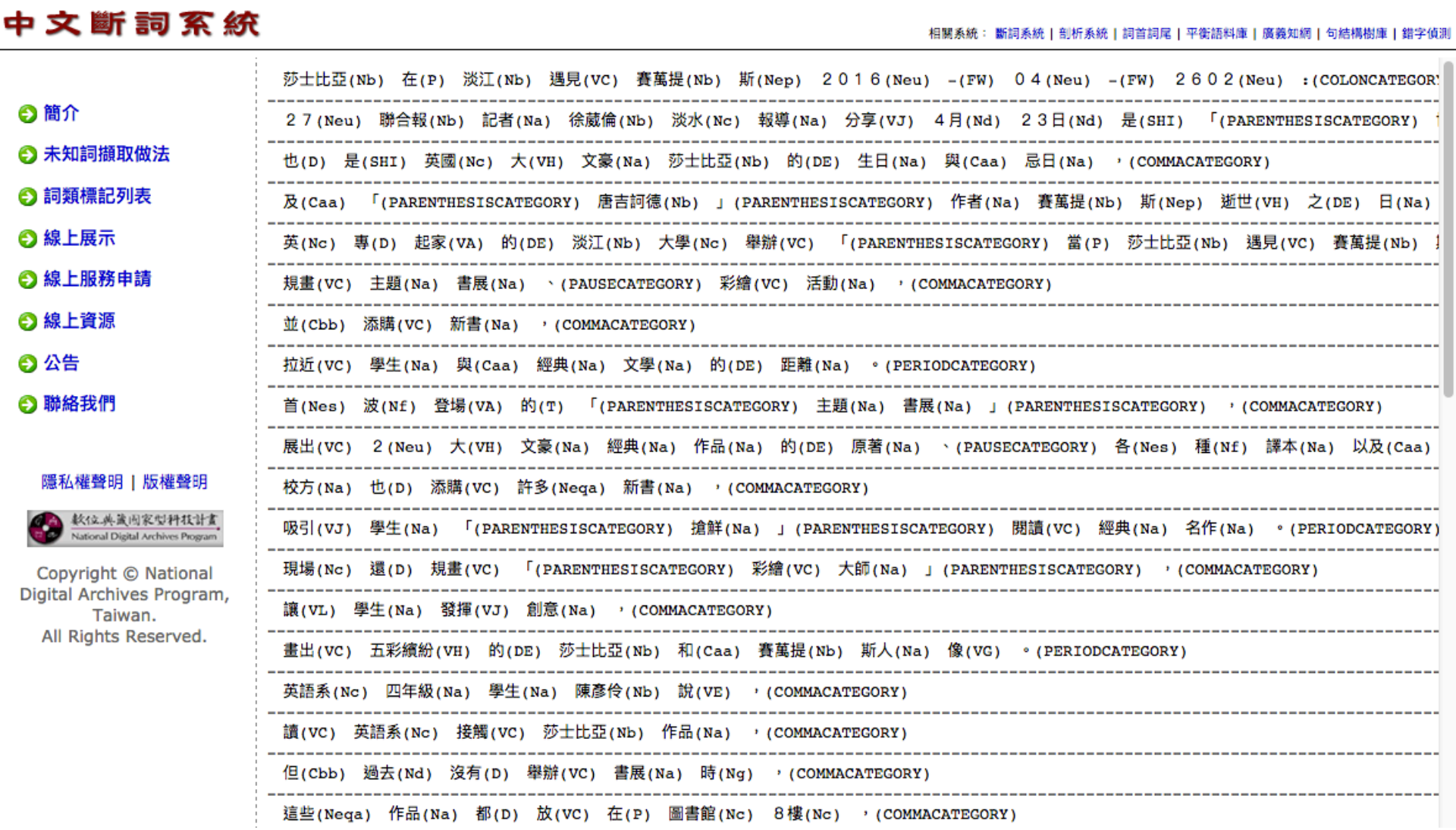

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莎士比亞(Nb) 在(P) 淡江(Nb) 遇見(VC) 賽萬提(Nb) 斯(Nep) 2016(Neu) -(FW) 04(Neu) -(FW) 2602(Neu) :(COLONCATEGORY)
27(Neu) 聯合報(Nb) 記者(Na) 徐葳倫(Nb) 淡水(Nc) 報導(Na) 分享(VJ) 4月(Nd) 23日(Nd) 是(SHI) 「(PARENTHESISCATEGORY) 世界(Nc) 閱讀日(Na) 」(PARENTHESISCATEGORY) ，(COMMACATEGORY)
也(D) 是(SHI) 英國(Nc) 大(VH) 文豪(Na) 莎士比亞(Nb) 的(DE) 生日(Na) 與(Caa) 忌日(Na) ，(COMMACATEGORY)
及(Caa) 「(PARENTHESISCATEGORY) 唐吉訶德(Nb) 」(PARENTHESISCATEGORY) 作者(Na) 賽萬提(Nb) 斯(Nep) 逝世(VH) 之(DE) 日(Na) 。(PERIODCATEGORY)
英(Nc) 專(D) 起家(VA) 的(DE) 淡江(Nb) 大學(Nc) 舉辦(VC) 「(PARENTHESISCATEGORY) 當(P) 莎士比亞(Nb) 遇見(VC) 賽萬提(Nb) 斯(Nep) 」(PARENTHESISCATEGORY) 活動(Na) ，(COMMACATEGORY)
規畫(VC) 主題(Na) 書展(Na) 、(PAUSECATEGORY) 彩繪(VC) 活動(Na) ，(COMMACATEGORY)
並(Cbb) 添購(VC) 新書(Na) ，(COMMACATEGORY)
拉近(VC) 學生(Na) 與(Caa) 經典(Na) 文學(Na) 的(DE) 距離(Na) 。(PERIODCATEGORY)

http://nlp.stanford.edu/software/index.shtml

# The Stanford Natural Language Processing Group

home · people · teaching · research · publications · software · events · local

The Stanford NLP Group makes parts of our Natural Language Processing software available to everyone. These are statistical NLP toolkits for various major computational linguistics problems. They can be incorporated into applications with human language technology needs.

All the software we distribute here is written in Java. All recent distributions require Oracle Java 6+ or OpenJDK 7+. Distribution packages include components for command-line invocation, jar files, a Java API, and source code. A number of helpful people have extended our work with bindings or translations for other languages. As a result, much of this software can also easily be used from Python (or Jython), Ruby, Perl, Javascript, and F# or other .NET languages.

## Supported software distributions

This code is being developed, and we try to answer questions and fix bugs on a best-effort basis.

All these software distributions are open source, **licensed under the GNU General Public License** (v2 or later). Note that this is the *full* GPL, which allows many free uses, but *does not allow* its incorporation into any type of distributed proprietary software, even in part or in translation. **Commercial licensing** is also available; please contact us if you are interested.

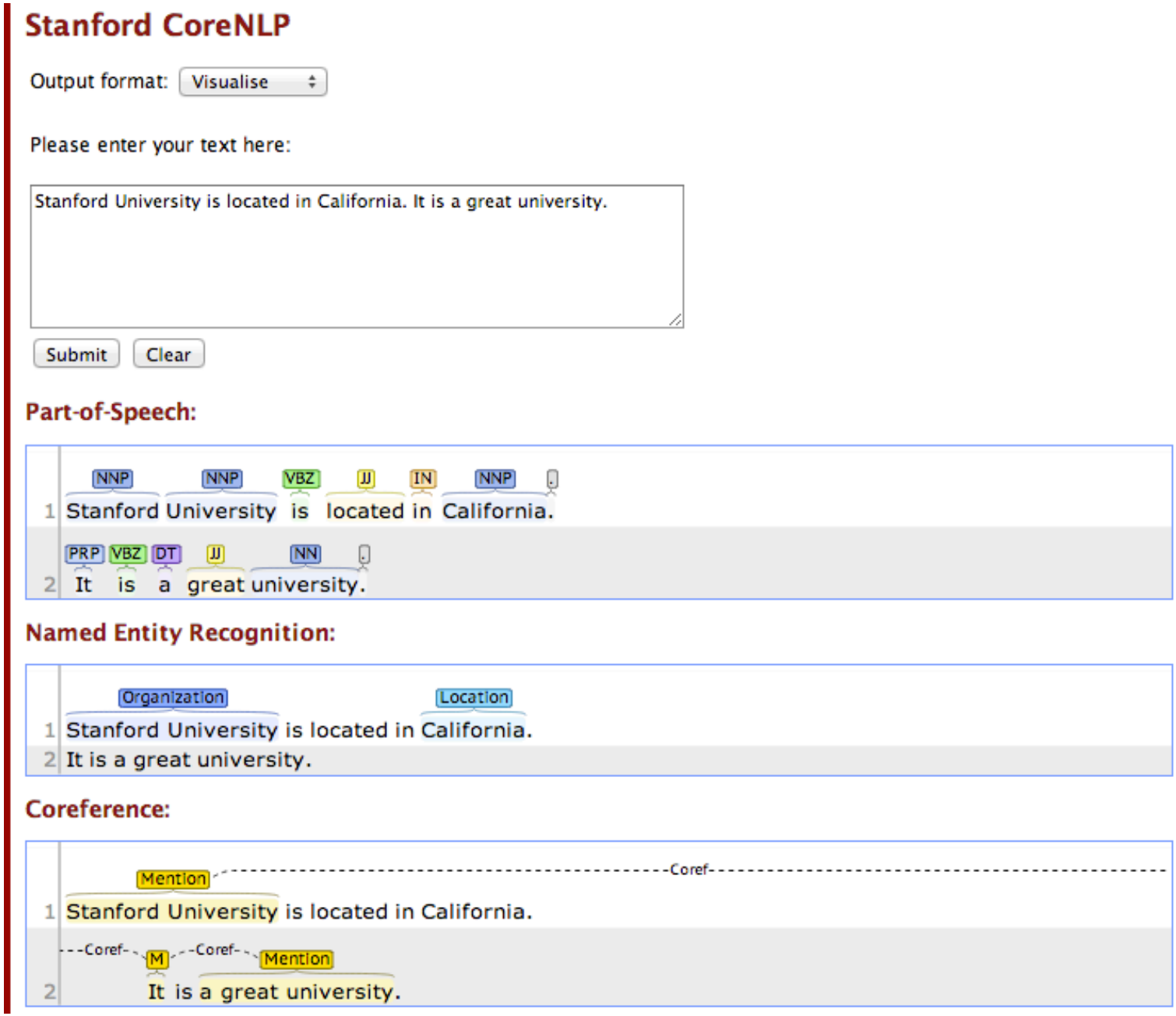
Stanford CoreNLP
: An integrated suite of natural language processing tools for English and (mainland) Chinese in Java, including tokenization, part-of-speech tagging, named entity recognition, parsing, and coreference. See also: Stanford Deterministic Coreference Resolution, and the online CoreNLP demo, and the CoreNLP FAQ.

Stanford Parser
: Implementations of probabilistic natural language parsers in Java: highly optimized PCFG and dependency parsers, a lexicalized PCFG parser, and a deep learning reranker. See also: Online parser demo, the Stanford Dependencies page, and Parser FAQ.

Stanford POS Tagger
: A maximum-entropy (CMM) part-of-speech (POS) tagger for English,

# Stanford NLP Software

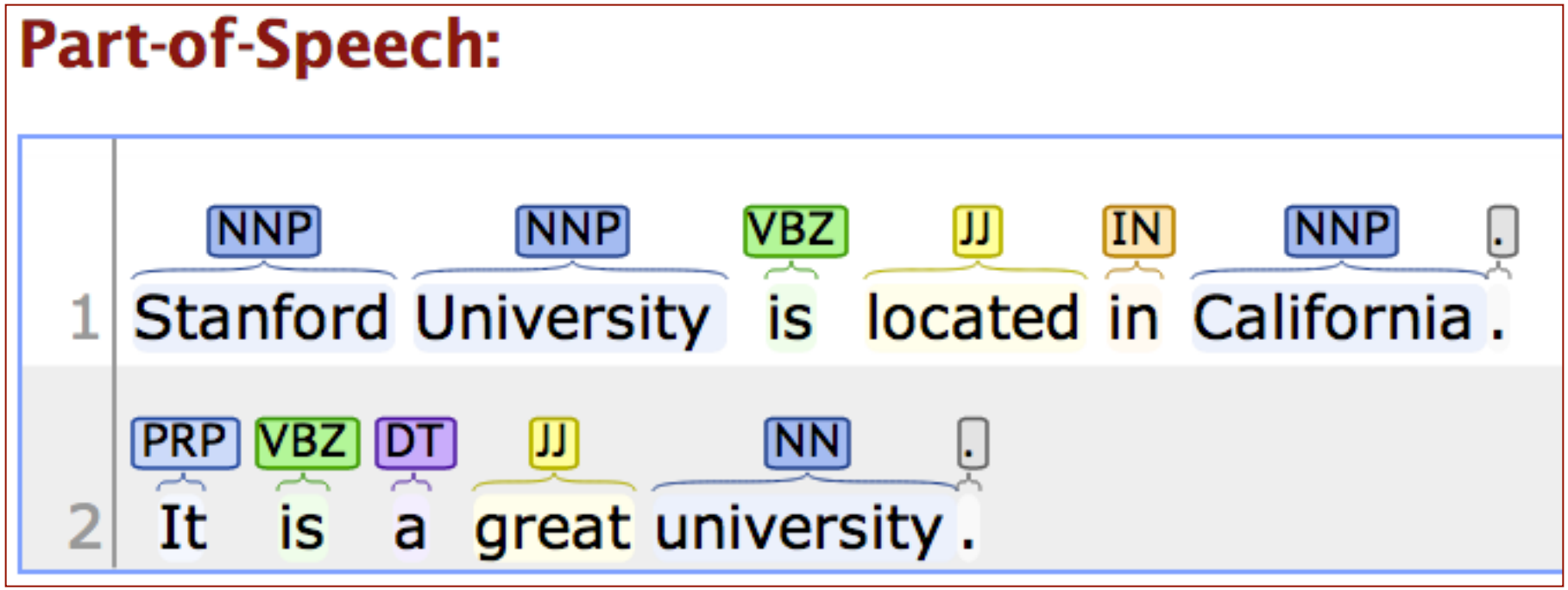
# Stanford CoreNLP http://nlp.stanford.edu:8080/corenlp/process



# Stanford CoreNLP

http://nlp.stanford.edu:8080/corenlp/process

Stanford University is located in California.
It is a great university.



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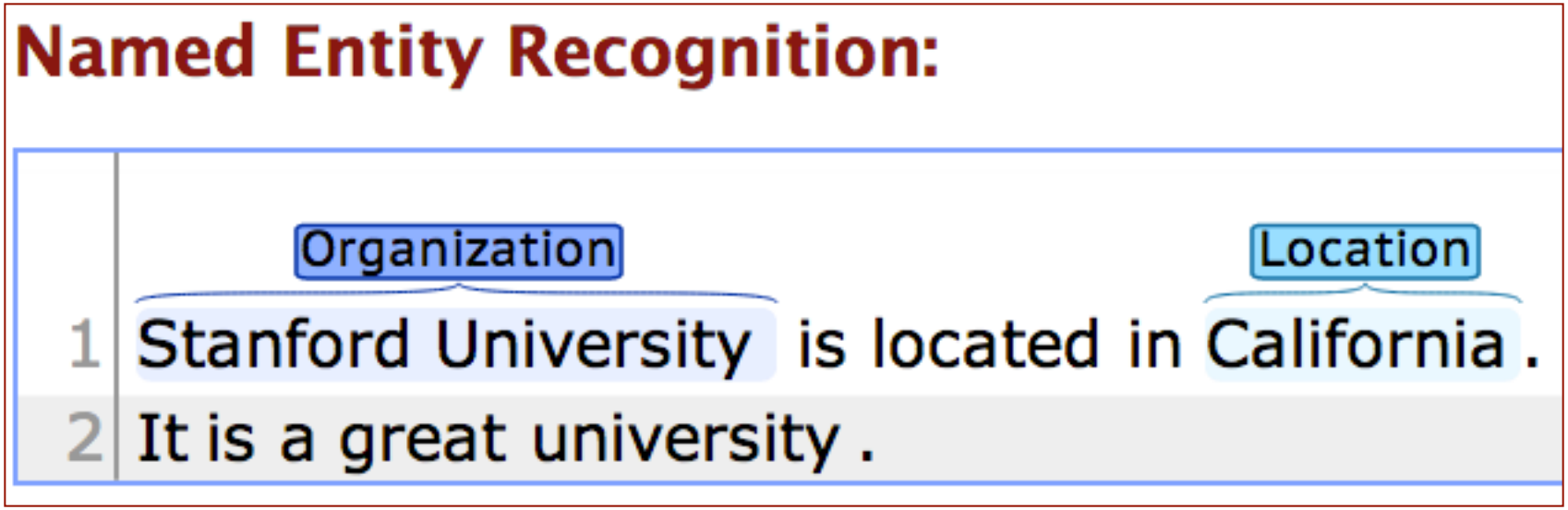

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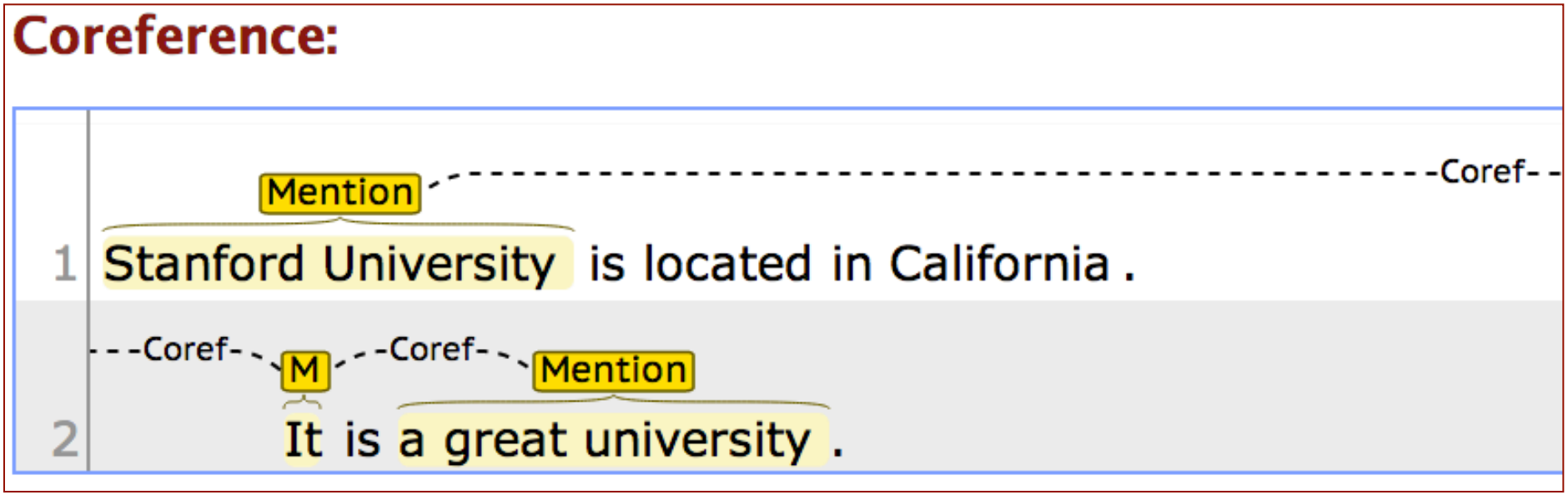

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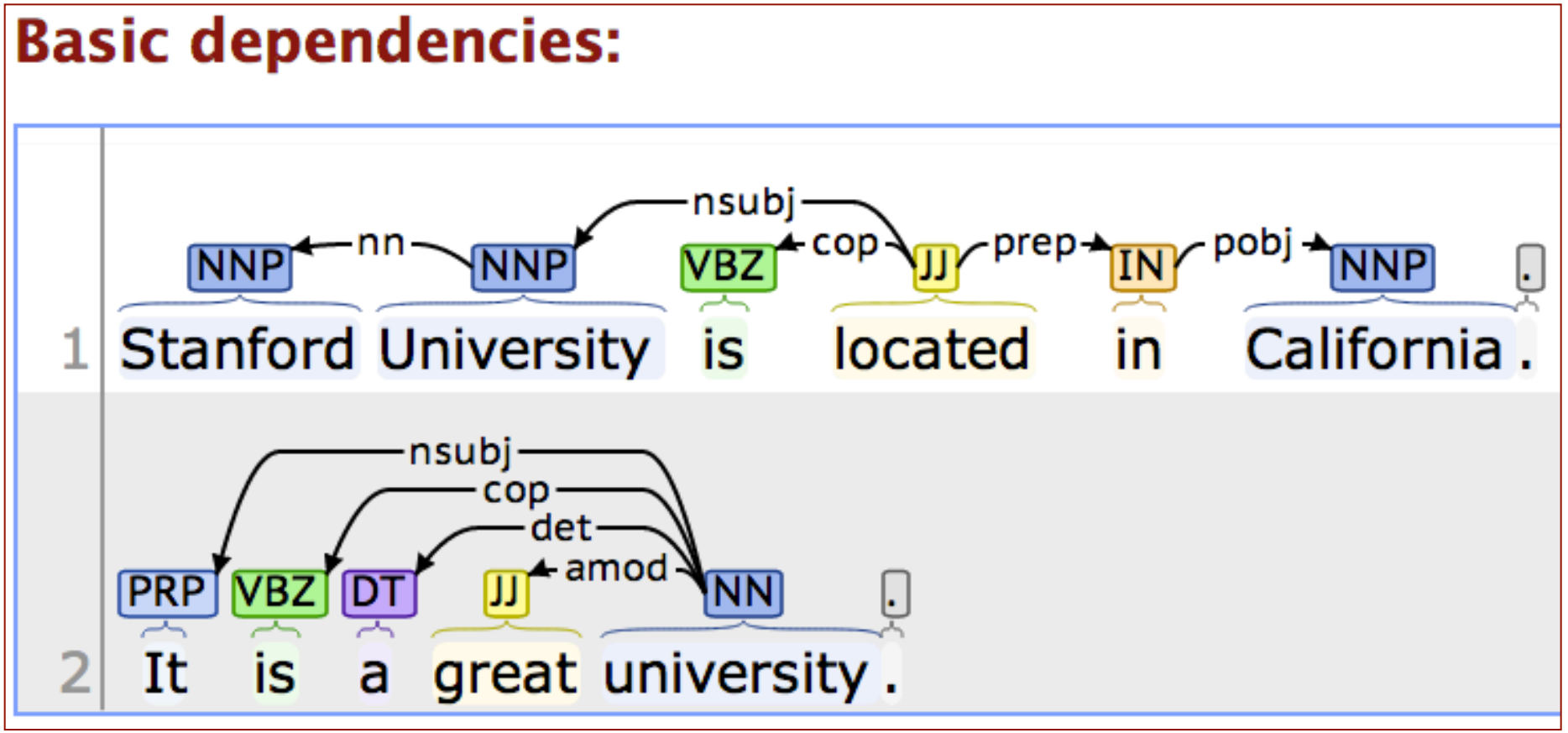
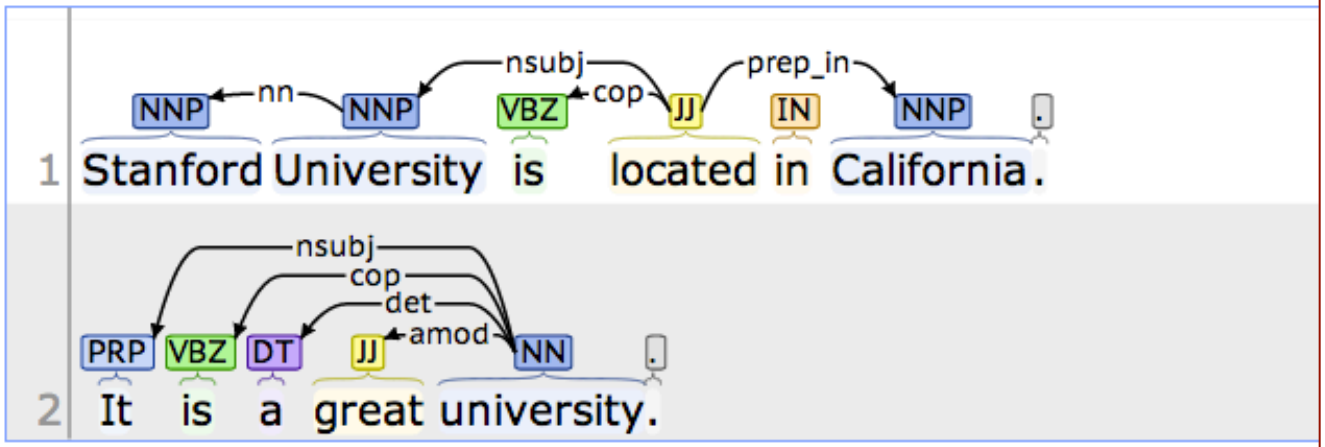


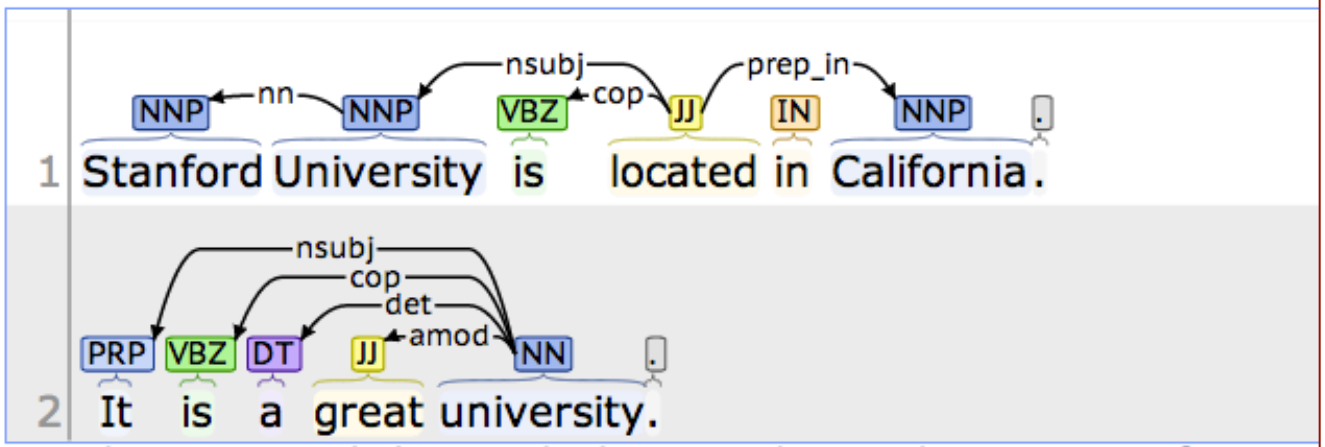
# Stanford CoreNLP

http://nlp.stanford.edu:8080/corenlp/process

**Collapsed dependencies:**




**Collapsed CC-processed dependencies:**




Visualisation provided using the brat visualisation/annotation software.

## Stanford CoreNLP

http://nlp.stanford.edu:8080/corenlp/process

Output format: Pretty print

Please enter your text here:

Stanford University is located in California. It is a great university.

Submit Clear

### Stanford CoreNLP XML Output

**Document**

**Document Info**

**Sentences**

***Sentence #1***

*Tokens*

| Id | Word | Lemma | Char begin | Char end | POS | NER | Normalized NER | Speaker |
|---|---|---|---|---|---|---|---|---|
| 1 | Stanford | Stanford | 0 | 8 | NNP | ORGANIZATION | | PER0 |
| 2 | University | University | 9 | 19 | NNP | ORGANIZATION | | PER0 |
| 3 | is | be | 20 | 22 | VBZ | O | | PER0 |
| 4 | located | located | 23 | 30 | JJ | O | | PER0 |
| 5 | in | in | 31 | 33 | IN | O | | PER0 |
| 6 | California | California | 34 | 44 | NNP | LOCATION | | PER0 |
| 7 | . | . | 44 | 45 | . | O | | PER0 |

*Parse tree*

(ROOT (S (NP (NNP Stanford) (NNP University)) (VP (VBZ is) (ADJP (JJ located) (PP (IN in) (NP (NNP California))))) (. .)))

# Stanford CoreNLP

http://nlp.stanford.edu:8080/corenlp/process

Stanford University is located in California.
It is a great university.

***Sentence #1***

*Tokens*

| Id | Word | Lemma | Char begin | Char end | POS | NER | Normalized NER | Speaker |
|---|---|---|---|---|---|---|---|---|
| 1 | Stanford | Stanford | 0 | 8 | NNP | ORGANIZATION | | PER0 |
| 2 | University | University | 9 | 19 | NNP | ORGANIZATION | | PER0 |
| 3 | is | be | 20 | 22 | VBZ | O | | PER0 |
| 4 | located | located | 23 | 30 | JJ | O | | PER0 |
| 5 | in | in | 31 | 33 | IN | O | | PER0 |
| 6 | California | California | 34 | 44 | NNP | LOCATION | | PER0 |
| 7 | . | . | 44 | 45 | . | O | | PER0 |

*Parse tree*

(ROOT (S (NP (NNP Stanford) (NNP University)) (VP (VBZ is) (ADJP (JJ located) (PP (IN in) (NP (NNP California))))) (. .)))

# Stanford CoreNLP

http://nlp.stanford.edu:8080/corenlp/process

Stanford University is located in California.
It is a great university.

***Sentence #2***

*Tokens*

| Id | Word | Lemma | Char begin | Char end | POS | NER | Normalized NER | Speaker |
|---|---|---|---|---|---|---|---|---|
| 1 | It | it | 46 | 48 | PRP | O | | PER0 |
| 2 | is | be | 49 | 51 | VBZ | O | | PER0 |
| 3 | a | a | 52 | 53 | DT | O | | PER0 |
| 4 | great | great | 54 | 59 | JJ | O | | PER0 |
| 5 | university | university | 60 | 70 | NN | O | | PER0 |
| 6 | . | . | 70 | 71 | . | O | | PER0 |

*Parse tree*

(ROOT (S (NP (PRP It)) (VP (VBZ is) (NP (DT a) (JJ great) (NN university))) (. .)))

# Stanford CoreNLP

http://nlp.stanford.edu:8080/corenlp/process

Stanford University is located in California.
It is a great university.

**Coreference resolution graph**

1.

| Sentence | Head | Text | Context |
|---|---|---|---|
| 1 | 2 (gov) | Stanford University | |
| 2 | 1 | It | |
| 2 | 5 | a great university | |

Tokens

| Id | Word | Lemma | Char begin | Char end | POS | NER | Normalized NER | Speaker |
|---|---|---|---|---|---|---|---|---|
| 1 | Stanford | Stanford | 0 | 8 | NNP | ORGANIZATION | | PER0 |
| 2 | University | University | 9 | 19 | NNP | ORGANIZATION | | PER0 |
| 3 | is | be | 20 | 22 | VBZ | O | PER0 | |
| 4 | located | located | 23 | 30 | JJ | O | PER0 | |
| 5 | in | in | 31 | 33 | IN | O | PER0 | |
| 6 | California | California | 34 | 44 | NNP | LOCATION | PER0 | |
| 7 | . | . | 44 | 45 | . | O | PER0 | |

Parse tree
(ROOT (S (NP (NNP Stanford) (NNP University)) (VP (VBZ is) (ADJP (JJ located) (PP (IN in) (NP (NNP California))))) (. .)))

Uncollapsed dependencies

root ( ROOT-0 , located-4 )
nn ( University-2 , Stanford-1 )
nsubj ( located-4 , University-2 )
cop ( located-4 , is-3 )
prep ( located-4 , in-5 )
pobj ( in-5 , California-6 )
Collapsed dependencies

root ( ROOT-0 , located-4 )
nn ( University-2 , Stanford-1 )
nsubj ( located-4 , University-2 )
cop ( located-4 , is-3 )
prep_in ( located-4 , California-6 )
Collapsed dependencies with CC processed

root ( ROOT-0 , located-4 )
nn ( University-2 , Stanford-1 )
nsubj ( located-4 , University-2 )
cop ( located-4 , is-3 )
prep_in ( located-4 , California-6 )

# Stanford CoreNLP

http://nlp.stanford.edu:8080/corenlp/process

Stanford University is located in California.
It is a great university.

## Stanford CoreNLP

http://nlp.stanford.edu:8080/corenlp/process

Output format: XML

Please enter your text here:

Stanford University is located in California. It is a great university.

Submit Clear

```
<?xml version="1.0" encoding="UTF-8"?>
<?xml-stylesheet href="CoreNLP-to-HTML.xsl" type="text/xsl"?>
<root>
  <document>
    <sentences>
      <sentence id="1">
        <tokens>
          <token id="1">
            <word>Stanford</word>
            <lemma>Stanford</lemma>
            <CharacterOffsetBegin>0</CharacterOffsetBegin>
            <CharacterOffsetEnd>8</CharacterOffsetEnd>
            <POS>NNP</POS>
            <NER>ORGANIZATION</NER>
            <Speaker>PER0</Speaker>
          </token>
          <token id="2">
            <word>University</word>
            <lemma>University</lemma>
            <CharacterOffsetBegin>9</CharacterOffsetBegin>
            <CharacterOffsetEnd>19</CharacterOffsetEnd>
            <POS>NNP</POS>
            <NER>ORGANIZATION</NER>
            <Speaker>PER0</Speaker>
          </token>
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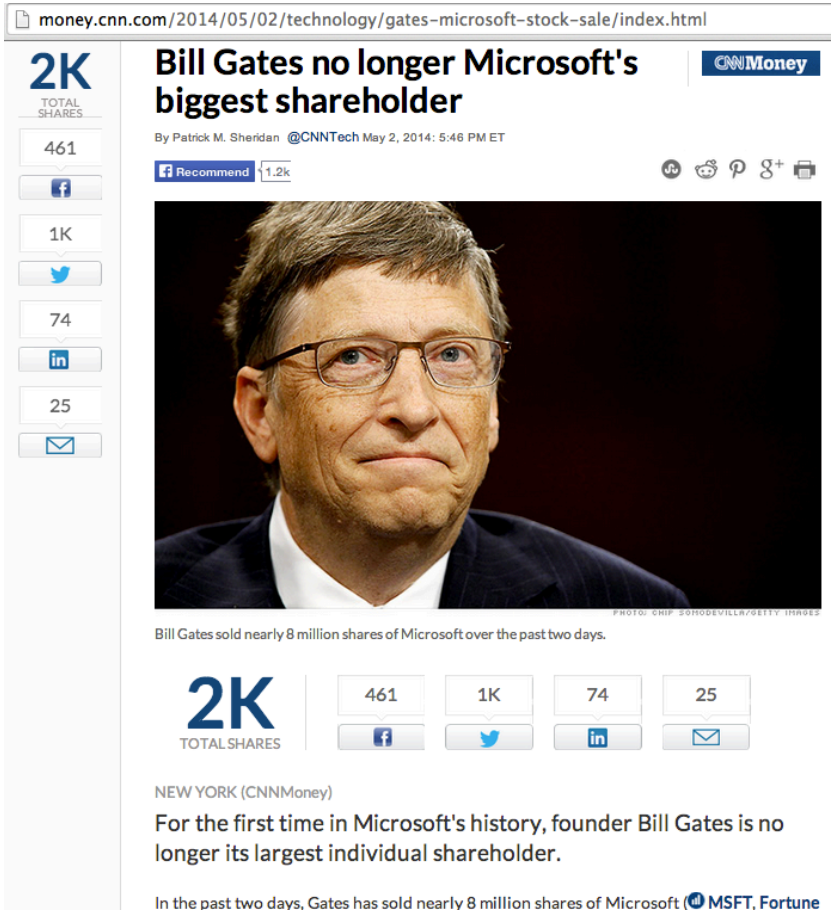
# NER for News Article

http://money.cnn.com/2014/05/02/technology/gates-microsoft-stock-sale/index.html




Bill Gates no longer Microsoft's biggest shareholder
By Patrick M. Sheridan @CNNTech May 2, 2014: 5:46 PM ET

Bill Gates sold nearly 8 million shares of Microsoft over the past two days.

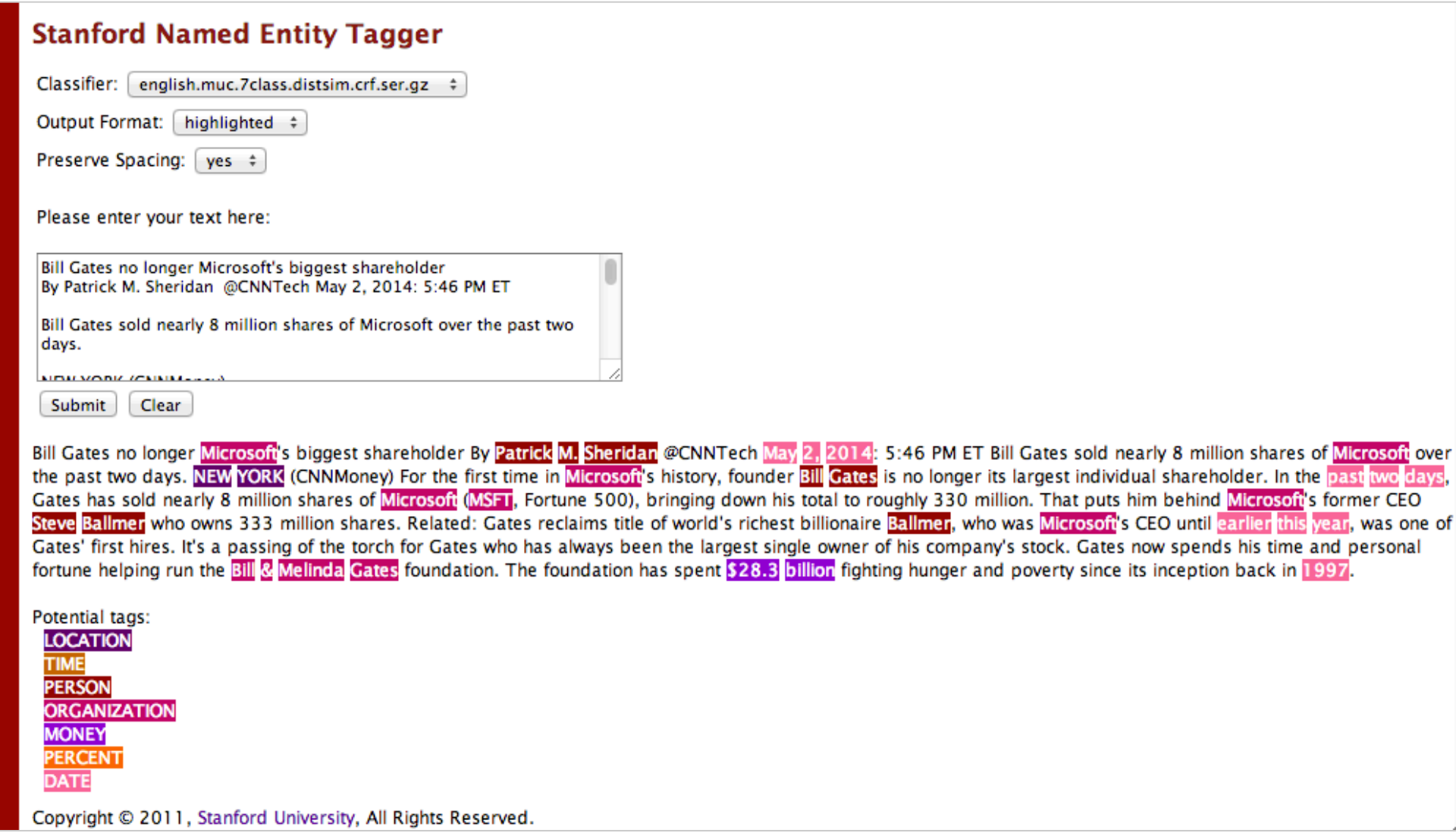
NEW YORK (CNNMoney)

For the first time in Microsoft's history, founder Bill Gates is no longer its largest individual shareholder.
In the past two days, Gates has sold nearly 8 million shares of Microsoft (MSFT, Fortune 500), bringing down his total to roughly 330 million.

That puts him behind Microsoft's former CEO Steve Ballmer who owns 333 million shares.
Related: Gates reclaims title of world's richest billionaire
Ballmer, who was Microsoft's CEO until earlier this year, was one of Gates' first hires.
It's a passing of the torch for Gates who has always been the largest single owner of his company's stock. Gates now spends his time and personal fortune helping run the Bill & Melinda Gates foundation.
The foundation has spent $28.3 billion fighting hunger and poverty since its inception back in 1997.

# Stanford Named Entity Tagger (NER)

http://nlp.stanford.edu:8080/ner/process



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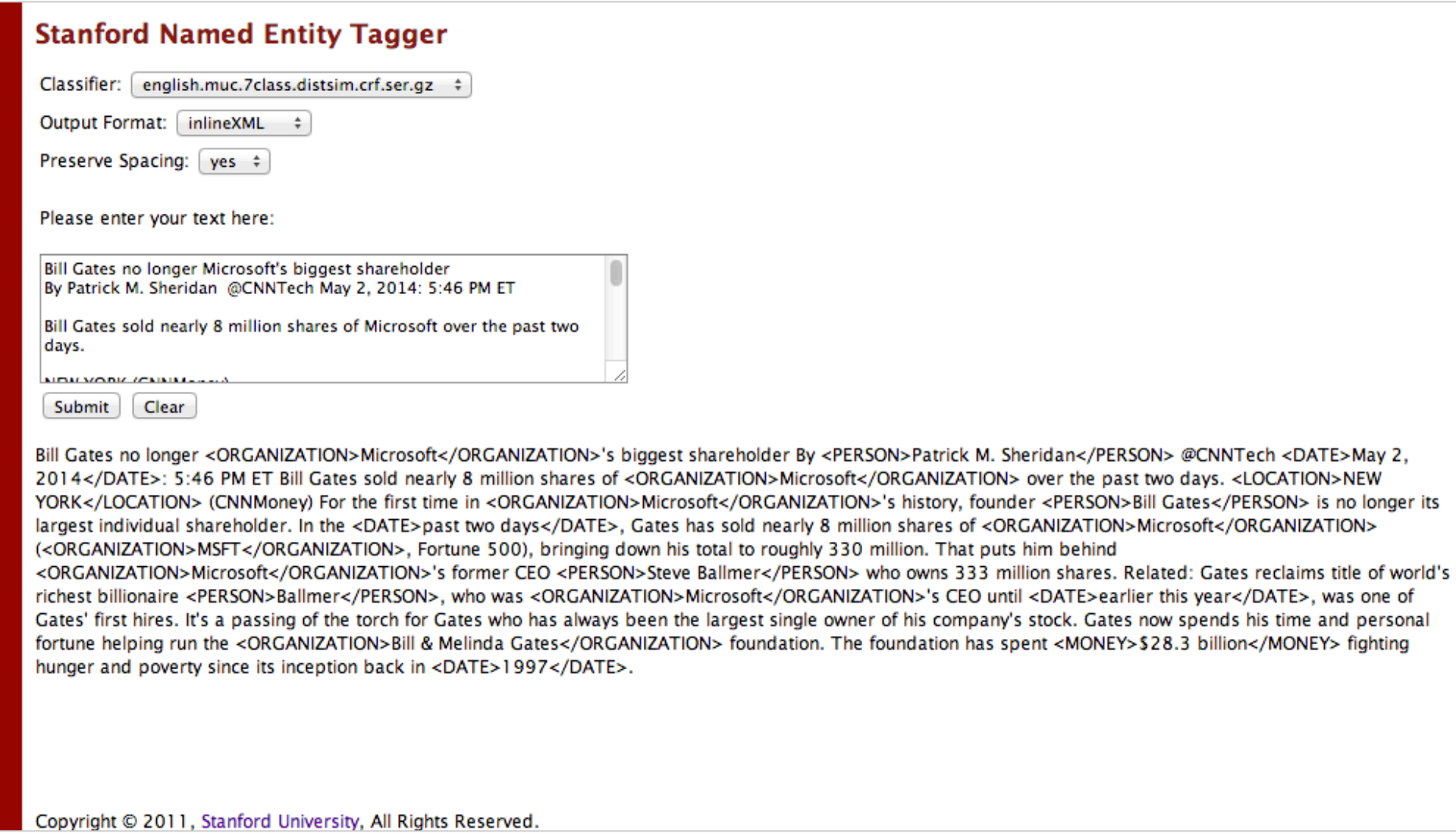
http://nlp.stanford.edu:8080/ner/process



# Stanford Named Entity Tagger (NER)

http://nlp.stanford.edu:8080/ner/process

## Stanford Named Entity Tagger

Classifier: english.muc.7class.distsim.crf.ser.gz

Output Format: xml

Preserve Spacing: yes

Please enter your text here:

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NEW YORK (CNNMoney)

Submit Clear

<wi num="0" entity="O">Bill</wi> <wi num="1" entity="O">Gates</wi> <wi num="2" entity="O">no</wi> <wi num="3" entity="O">longer</wi> <wi num="4" entity="ORGANIZATION">Microsoft</wi><wi num="5" entity="O">'s</wi> <wi num="6" entity="O">biggest</wi> <wi num="7" entity="O">shareholder</wi> <wi num="8" entity="O">By</wi> <wi num="9" entity="PERSON">Patrick</wi> <wi num="10" entity="PERSON">M.</wi> <wi num="11" entity="PERSON">Sheridan</wi> <wi num="12" entity="O">@CNNTech</wi> <wi num="13" entity="DATE">May</wi> <wi num="14" entity="DATE">2</wi><wi num="15" entity="DATE">,</wi> <wi num="16" entity="DATE">2014</wi><wi num="17" entity="O">:</wi> <wi num="18" entity="O">5:46</wi> <wi num="19" entity="O">PM</wi> <wi num="20" entity="O">ET</wi> <wi num="21" entity="O">Bill</wi> <wi num="22" entity="O">Gates</wi> <wi num="23" entity="O">sold</wi> <wi num="24" entity="O">nearly</wi> <wi num="25" entity="O">8</wi> <wi num="26" entity="O">million</wi> <wi num="27" entity="O">shares</wi> <wi num="28" entity="O">of</wi> <wi num="29" entity="ORGANIZATION">Microsoft</wi> <wi num="30" entity="O">over</wi> <wi num="31" entity="O">the</wi> <wi num="32" entity="O">past</wi> <wi num="33" entity="O">two</wi> <wi num="34" entity="O">days</wi><wi num="35" entity="O">.</wi> <wi num="0" entity="LOCATION">NEW</wi> <wi num="1" entity="LOCATION">YORK</wi> <wi num="2" entity="O">-LRB-</wi><wi num="3" entity="O">CNNMoney</wi><wi num="4" entity="O">-RRB-</wi> <wi num="5" entity="O">For</wi> <wi num="6" entity="O">the</wi> <wi num="7" entity="O">first</wi> <wi num="8" entity="O">time</wi> <wi num="9" entity="O">in</wi> <wi num="10" entity="ORGANIZATION">Microsoft</wi><wi num="11" entity="O">'s</wi> <wi num="12" entity="O">history</wi><wi num="13" entity="O">,</wi> <wi num="14" entity="O">founder</wi> <wi num="15" entity="PERSON">Bill</wi> <wi num="16" entity="PERSON">Gates</wi> <wi num="17" entity="O">is</wi> <wi num="18" entity="O">no</wi> <wi num="19" entity="O">longer</wi> <wi num="20" entity="O">its</wi> <wi num="21" entity="O">largest</wi> <wi num="22" entity="O">individual</wi> <wi num="23" entity="O">shareholder</wi><wi num="24" entity="O">.</wi> <wi num="0" entity="O">In</wi> <wi num="1" entity="O">the</wi> <wi num="2" entity="DATE">past</wi> <wi num="3" entity="DATE">two</wi> <wi num="4" entity="DATE">days</wi><wi num="5" entity="O">,</wi> <wi num="6" entity="O">Gates</wi> <wi num="7" entity="O">has</wi> <wi num="8" entity="O">sold</wi>

# Stanford Named Entity Tagger (NER)

http://nlp.stanford.edu:8080/ner/process

## Stanford Named Entity Tagger

Classifier: english.muc.7class.distsim.crf.ser.gz

Output Format: slashTags

Preserve Spacing: yes

Please enter your text here:

Bill Gates no longer Microsoft's biggest shareholder
By Patrick M. Sheridan @CNNTech May 2, 2014: 5:46 PM ET

Bill Gates sold nearly 8 million shares of Microsoft over the past two days.

NEW YORK (CNNMoney)

Submit Clear

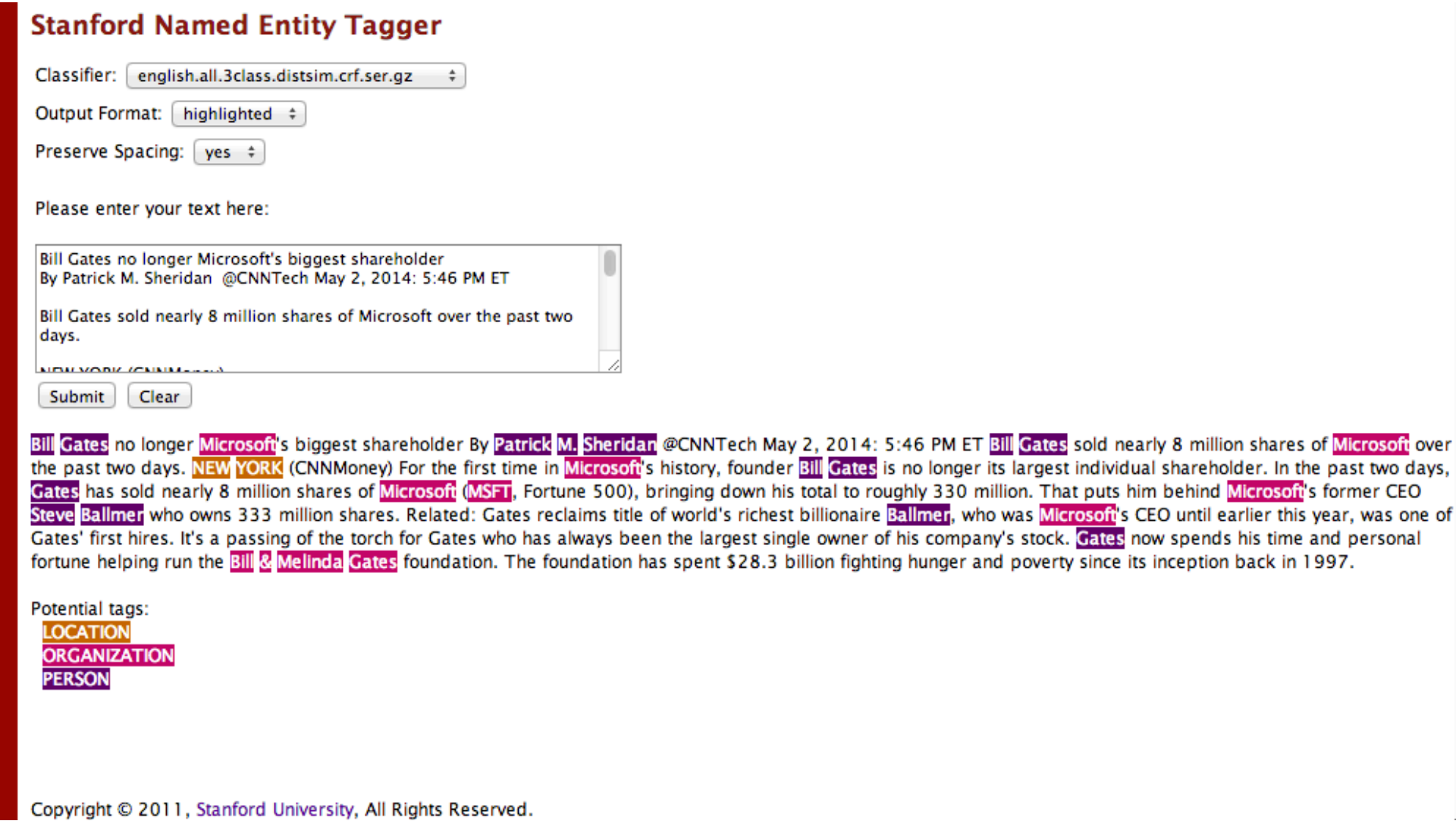
Bill/O Gates/O no/O longer/O Microsoft/ORGANIZATION's/O biggest/O shareholder/O By/O Patrick/PERSON M./PERSON Sheridan/PERSON @CNNTech/O May/DATE 2/DATE,/DATE 2014/DATE:/O 5:46/O PM/O ET/O Bill/O Gates/O sold/O nearly/O 8/O million/O shares/O of/O Microsoft/ORGANIZATION over/O the/O past/O two/O days/O./O NEW/LOCATION YORK/LOCATION -LRB-/OCNNMoney/O-RRB-/O For/O the/O first/O time/O in/O Microsoft/ORGANIZATION's/O history/O,/O founder/O Bill/PERSON Gates/PERSON is/O no/O longer/O its/O largest/O individual/O shareholder/O./O In/O the/O past/DATE two/DATE days/DATE,/O Gates/O has/O sold/O nearly/O 8/O million/O shares/O of/O Microsoft/ORGANIZATION -LRB-/OMSFT/ORGANIZATION,/O Fortune/O 500/O-RRB-/O,/O bringing/O down/O his/O total/O to/O roughly/O 330/O million/O./O That/O puts/O him/O behind/O Microsoft/ORGANIZATION's/O former/O CEO/O Steve/PERSON Ballmer/PERSON who/O owns/O 333/O million/O shares/O./O Related/O:/O Gates/O reclaims/O title/O of/O world/O's/O richest/O billionaire/O Ballmer/PERSON,/O who/O was/O Microsoft/ORGANIZATION's/O CEO/O until/O earlier/DATE this/DATE year/DATE,/O was/O one/O of/O Gates/O'/O first/O hires/O./O It/O's/O a/O passing/O of/O the/O torch/O for/O Gates/O who/O has/O always/O been/O the/O largest/O single/O owner/O of/O his/O company/O's/O stock/O./O Gates/O now/O spends/O his/O time/O and/O personal/O fortune/O helping/O run/O the/O Bill/ORGANIZATION &/ORGANIZATION Melinda/ORGANIZATION Gates/ORGANIZATION foundation/O./O The/O foundation/O has/O spent/O $/MONEY28.3/MONEY billion/MONEY fighting/O hunger/O and/O poverty/O since/O its/O inception/O back/O in/O 1997/DATE./O

# Stanford Named Entity Tagger (NER)

http://nlp.stanford.edu:8080/ner/process

# Stanford Named Entity Tagger (NER)

http://nlp.stanford.edu:8080/ner/process



## Classifier: english.muc.**7class**.distsim.crf.ser.gz

Bill Gates no longer Microsoft's biggest shareholder By Patrick M. Sheridan @CNNTech May 2, 2014: 5:46 PM ET Bill Gates sold nearly 8 million shares of Microsoft over the past two days. NEW YORK (CNNMoney) For the first time in Microsoft's history, founder Bill Gates is no longer its largest individual shareholder. In the past two days, Gates has sold nearly 8 million shares of Microsoft (MSFT, Fortune 500), bringing down his total to roughly 330 million. That puts him behind Microsoft's former CEO Steve Ballmer who owns 333 million shares. Related: Gates reclaims title of world's richest billionaire Ballmer, who was Microsoft's CEO until earlier this year, was one of Gates' first hires. It's a passing of the torch for Gates who has always been the largest single owner of his company's stock. Gates now spends his time and personal fortune helping run the Bill & Melinda Gates foundation. The foundation has spent $28.3 billion fighting hunger and poverty since its inception back in 1997.

Potential tags:
- LOCATION
- TIME
- PERSON
- ORGANIZATION
- MONEY
- PERCENT
- DATE

## Classifier: english.all.**3class**.distsim.crf.ser.gz

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Potential tags:
- LOCATION
- ORGANIZATION
- PERSON

# Stanford Named Entity Tagger (NER)

http://nlp.stanford.edu:8080/ner/process

## Stanford NER Output Format: inlineXML

Bill Gates no longer <ORGANIZATION>Microsoft</ORGANIZATION>'s biggest shareholder By <PERSON>Patrick M. Sheridan</PERSON> @CNNTech <DATE>May 2, 2014</DATE>: 5:46 PM ET Bill Gates sold nearly 8 million shares of <ORGANIZATION>Microsoft</ORGANIZATION> over the past two days. <LOCATION>NEW YORK</LOCATION> (CNNMoney) For the first time in <ORGANIZATION>Microsoft</ORGANIZATION>'s history, founder <PERSON>Bill Gates</PERSON> is no longer its largest individual shareholder. In the <DATE>past two days</DATE>, Gates has sold nearly 8 million shares of <ORGANIZATION>Microsoft</ ORGANIZATION> (<ORGANIZATION>MSFT</ORGANIZATION>, Fortune 500), bringing down his total to roughly 330 million. That puts him behind <ORGANIZATION>Microsoft</ORGANIZATION>'s former CEO <PERSON>Steve Ballmer</PERSON> who owns 333 million shares. Related: Gates reclaims title of world's richest billionaire <PERSON>Ballmer</PERSON>, who was <ORGANIZATION>Microsoft</ORGANIZATION>'s CEO until <DATE>earlier this year</ DATE>, was one of Gates' first hires. It's a passing of the torch for Gates who has always been the largest single owner of his company's stock. Gates now spends his time and personal fortune helping run the <ORGANIZATION>Bill & Melinda Gates</ ORGANIZATION> foundation. The foundation has spent <MONEY>$28.3 billion</ MONEY> fighting hunger and poverty since its inception back in <DATE>1997</DATE>.

# Stanford Named Entity Tagger (NER)

http://nlp.stanford.edu:8080/ner/process

## Stanford NER Output Format: slashTags

Bill/O Gates/O no/O longer/O Microsoft/ORGANIZATION's/O biggest/O shareholder/O By/O Patrick/PERSON M./PERSON Sheridan/PERSON @CNNTech/O May/DATE 2/DATE,/DATE 2014/DATE:/O 5:46/O PM/O ET/O Bill/O Gates/O sold/O nearly/O 8/O million/O shares/O of/O Microsoft/ORGANIZATION over/O the/O past/O two/O days/O./O NEW/LOCATION YORK/LOCATION -LRB-/OCNNMoney/O-RRB-/O For/O the/O first/O time/O in/O Microsoft/ORGANIZATION's/O history/O,/O founder/O Bill/PERSON Gates/PERSON is/O no/O longer/O its/O largest/O individual/O shareholder/O./O In/O the/O past/DATE two/DATE days/DATE,/O Gates/O has/O sold/O nearly/O 8/O million/O shares/O of/O Microsoft/ORGANIZATION -LRB-/OMSFT/ORGANIZATION,/O Fortune/O 500/O-RRB-/O,/O bringing/O down/O his/O total/O to/O roughly/O 330/O million/O./O That/O puts/O him/O behind/O Microsoft/ORGANIZATION's/O former/O CEO/O Steve/PERSON Ballmer/PERSON who/O owns/O 333/O million/O shares/O./O Related/O:/O Gates/O reclaims/O title/O of/O world/O's/O richest/O billionaire/O Ballmer/PERSON,/O who/O was/O Microsoft/ORGANIZATION's/O CEO/O until/O earlier/DATE this/DATE year/DATE,/O was/O one/O of/O Gates/O'/O first/O hires/O./O It/O's/O a/O passing/O of/O the/O torch/O for/O Gates/O who/O has/O always/O been/O the/O largest/O single/O owner/O of/O his/O company/O's/O stock/O./O Gates/O now/O spends/O his/O time/O and/O personal/O fortune/O helping/O run/O the/O Bill/ORGANIZATION &/ORGANIZATION Melinda/ORGANIZATION Gates/ORGANIZATION foundation/O./O The/O foundation/O has/O spent/O $/MONEY28.3/MONEY billion/MONEY fighting/O hunger/O and/O poverty/O since/O its/O inception/O back/O in/O 1997/DATE./O

# 自然語言處理與資訊檢索研究資源

http://mail.tku.edu.tw/myday/resources/

淡江大學資訊管理學系
(Department of Information Management, Tamkang University)
自然語言處理與資訊檢索研究資源
(Resources of Natural Language Processing and Information Retrieval)

1. 中央研究院CKIP中文斷詞系統
   授權單位:中央研究院詞庫小組
   授權金額:免費授權學術使用。
   授權日期:2011.03.31。
   CKIP: http://ckipsvr.iis.sinica.edu.tw/

2.「中央研究院中英雙語詞網」(The Academia Sinica Bilingual Wordnet)
「中央研究院中英雙語詞網」(The Academia Sinica Bilingual Wordnet),
授權「淡江大學資訊管理學系」(Department of Information Management, Tamkang University)學術使用。
   授權單位:中央研究院, 中華民國計算語言學學會
   授權金額:「中央研究院中英雙語詞網」(The Academia Sinica Bilingual Wordnet) 國內非營利機構(1-10人使用) 非會員:NT$61,000元,
   授權日期:2011.05.16。
   Sinica BOW: http://bow.ling.sinica.edu.tw/

# 自然語言處理與資訊檢索研究資源

http://mail.tku.edu.tw/myday/resources/

3. 開放式中研院專名問答系統 (OpenASQA)
   授權單位:中央研究院資訊科學研究所智慧型代理人系統實驗室
   授權金額:免費授權學術使用。
   授權日期:2011.05.05。
   ASQA: http://asqa.iis.sinica.edu.tw/

# 自然語言處理與資訊檢索研究資源

http://mail.tku.edu.tw/myday/resources/

4. 哈工大資訊檢索研究中心(HIT-CIR)語言技術平臺

語料資源

哈工大資訊檢索研究中心漢語依存樹庫 [HIT-CIR Chinese Dependency Treebank]

哈工大資訊檢索研究中心同義詞詞林擴展版 [HIT-CIR Tongyici Cilin (Extended)]

語言處理模組

斷句 (SplitSentence: Sentence Splitting)

詞法分析 (IRLAS: Lexical Analysis System)

基於SVMTool的詞性標注 (PosTag: Part-of-speech Tagging)

命名實體識別 (NER: Named Entity Recognition)

基於動態局部優化的依存句法分析 (Parser: Dependency Parsing)

基於圖的依存句法分析 (GParser: Graph-based DP)

全文詞義消歧 (WSD: Word Sense Disambiguation)

淺層語義標注模組 (SRL: hallow Semantics Labeling)

資料表示

語言技術置標語言 (LTML: Language Technology Markup Language)

視覺化工具

LTML視覺化XSL

授權單位:哈工大資訊檢索研究中心(HIT-CIR)

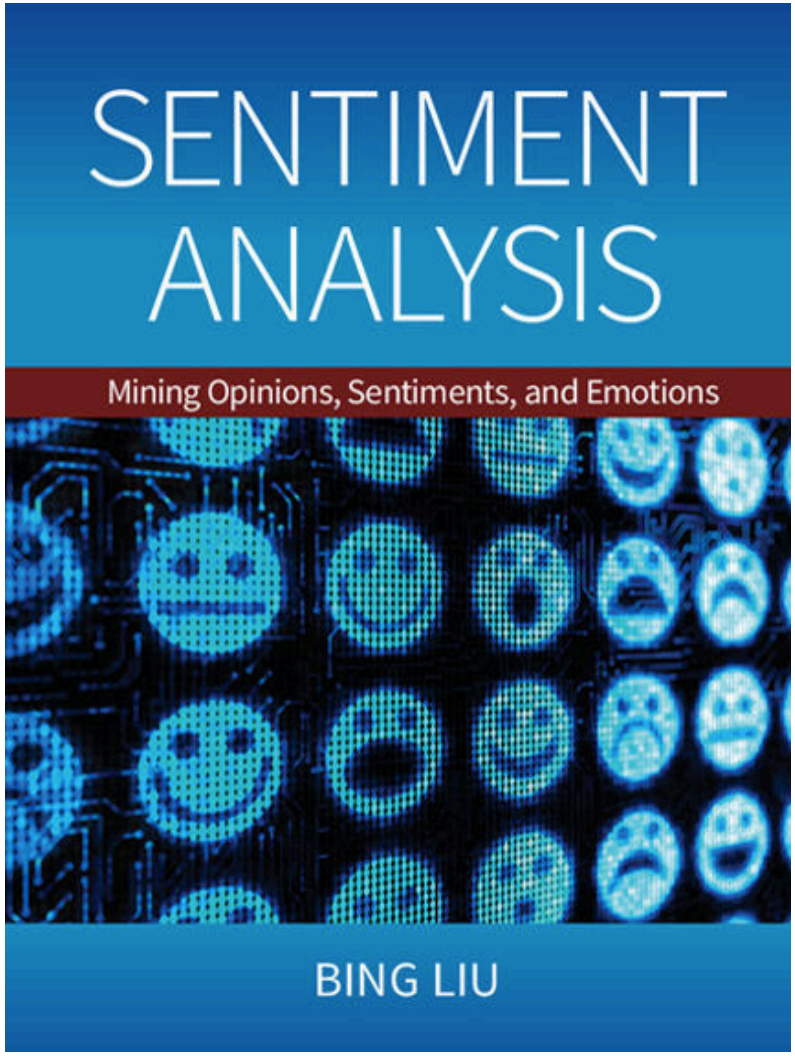
授權金額:免費授權學術使用。

授權日期:2011.05.03。

HIT IR: http://ir.hit.edu.cn/

# Architectures of Sentiment Analytics

# Bing Liu (2015), Sentiment Analysis: Mining Opinions, Sentiments, and Emotions, Cambridge University Press




http://www.amazon.com/Sentiment-Analysis-Opinions-Sentiments-Emotions/dp/1107017890

# Sentiment Analysis and Opinion Mining

- Computational study of
  opinions,
  sentiments,
  subjectivity,
  evaluations,
  attitudes,
  appraisal,
  affects,
  views,
  emotions,
  ets., expressed in text.
  - Reviews, blogs, discussions, news, comments, feedback, or any other documents

Source: Bing Liu (2011) , "Web Data Mining: Exploring Hyperlinks, Contents, and Usage Data," Springer, 2nd Edition,

# Research Area of Opinion Mining

- Many names and tasks with difference objective and models
  - Sentiment analysis
  - Opinion mining
  - Sentiment mining
  - Subjectivity analysis
  - Affect analysis
  - Emotion detection
  - Opinion spam detection

Source: Bing Liu (2011) , "Web Data Mining: Exploring Hyperlinks, Contents, and Usage Data," Springer, 2nd Edition,

# Example of Opinion: review segment on iPhone

"(1) I bought an iPhone a few days ago.

(2) It was such a **nice** phone.

(3) The touch screen was really **cool**.

**+Positive Opinion**

(4) The voice quality was **clear** too.

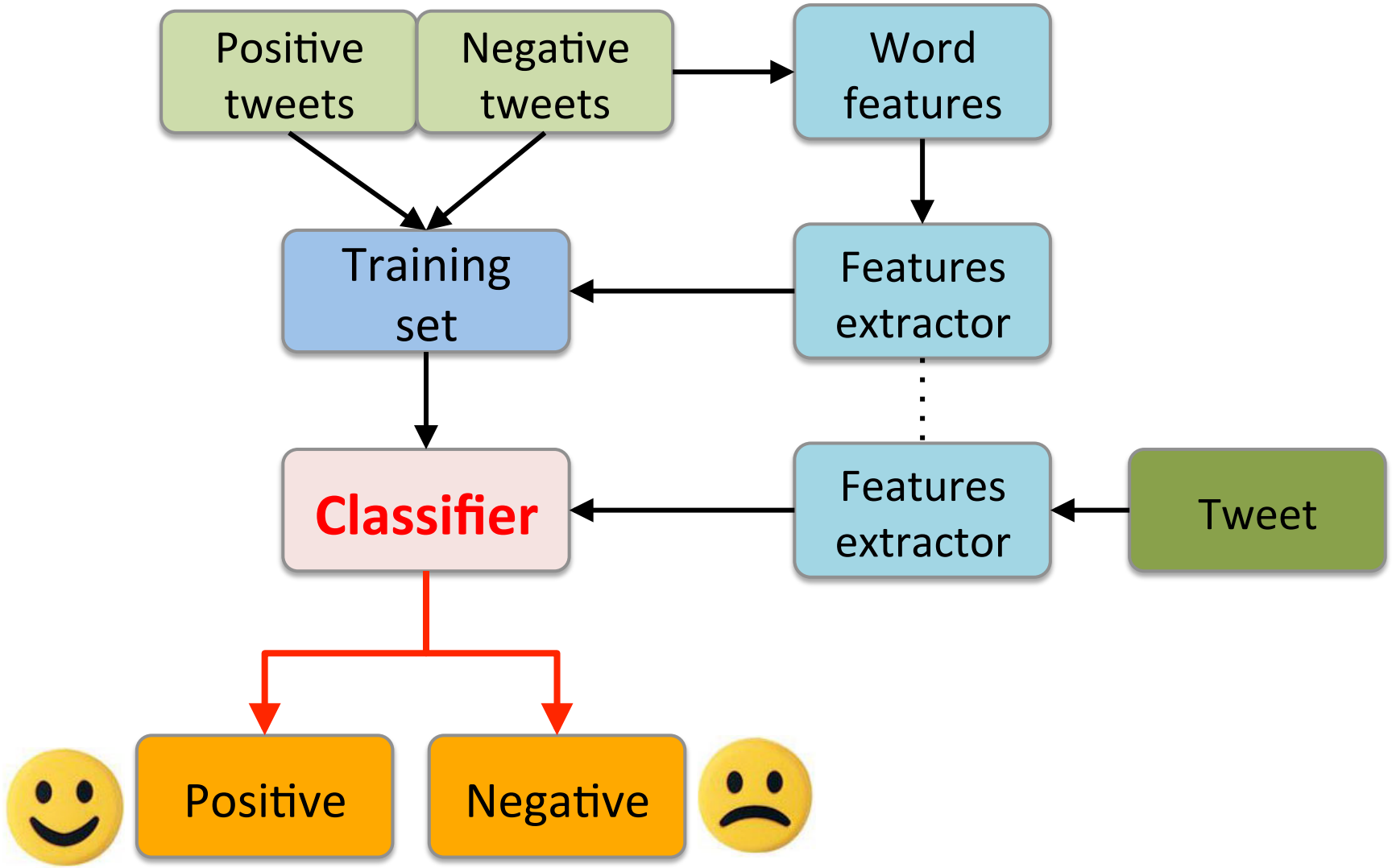
(5) However, my mother was mad with me as I did not tell her before I bought it.

(6) She also thought the phone was too **expensive**, and wanted me to return it to the shop. … "

**-Negative Opinion**

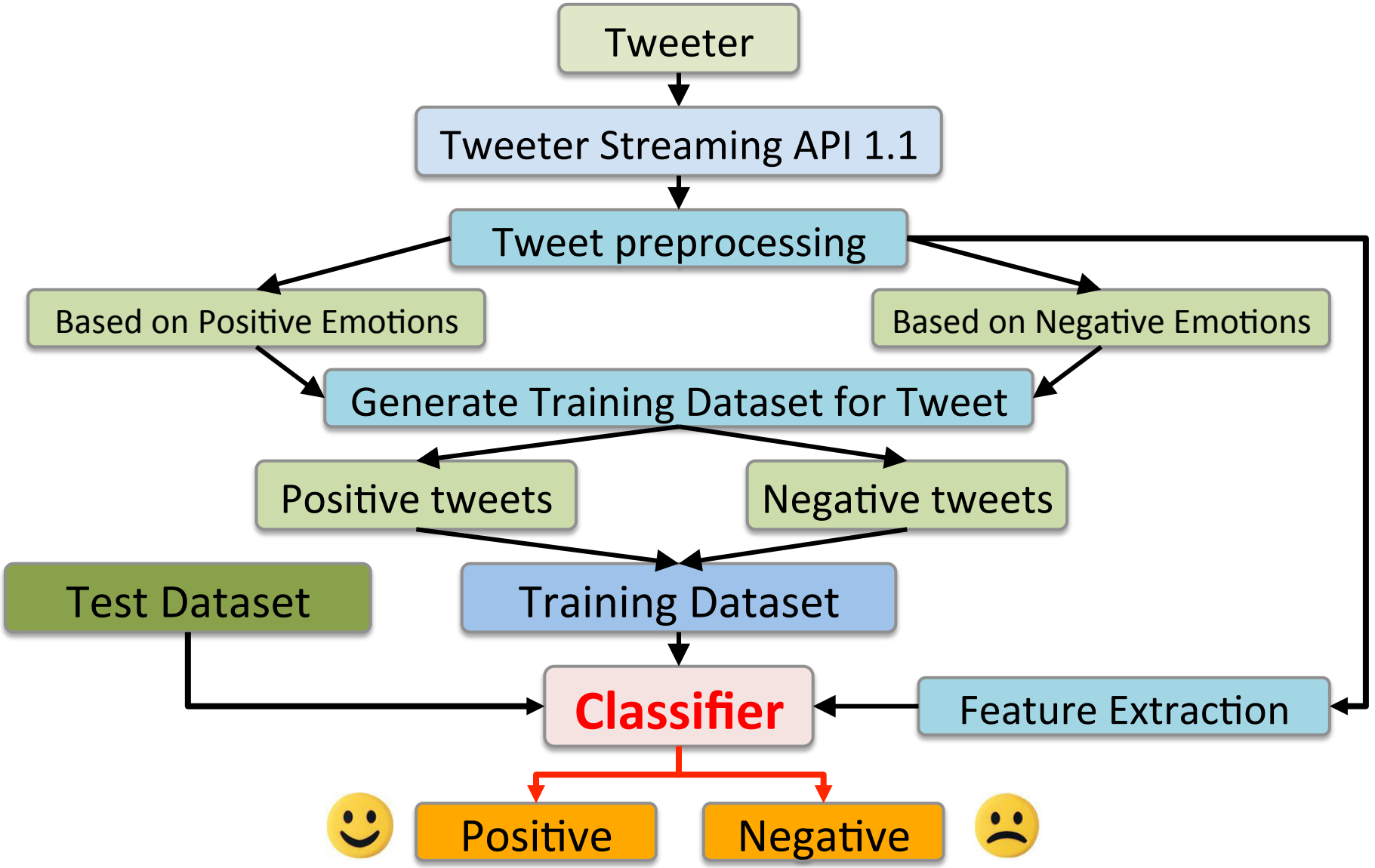
Source: Bing Liu (2011) , "Web Data Mining: Exploring Hyperlinks, Contents, and Usage Data," Springer, 2nd Edition,

# Sentiment Analysis Architecture



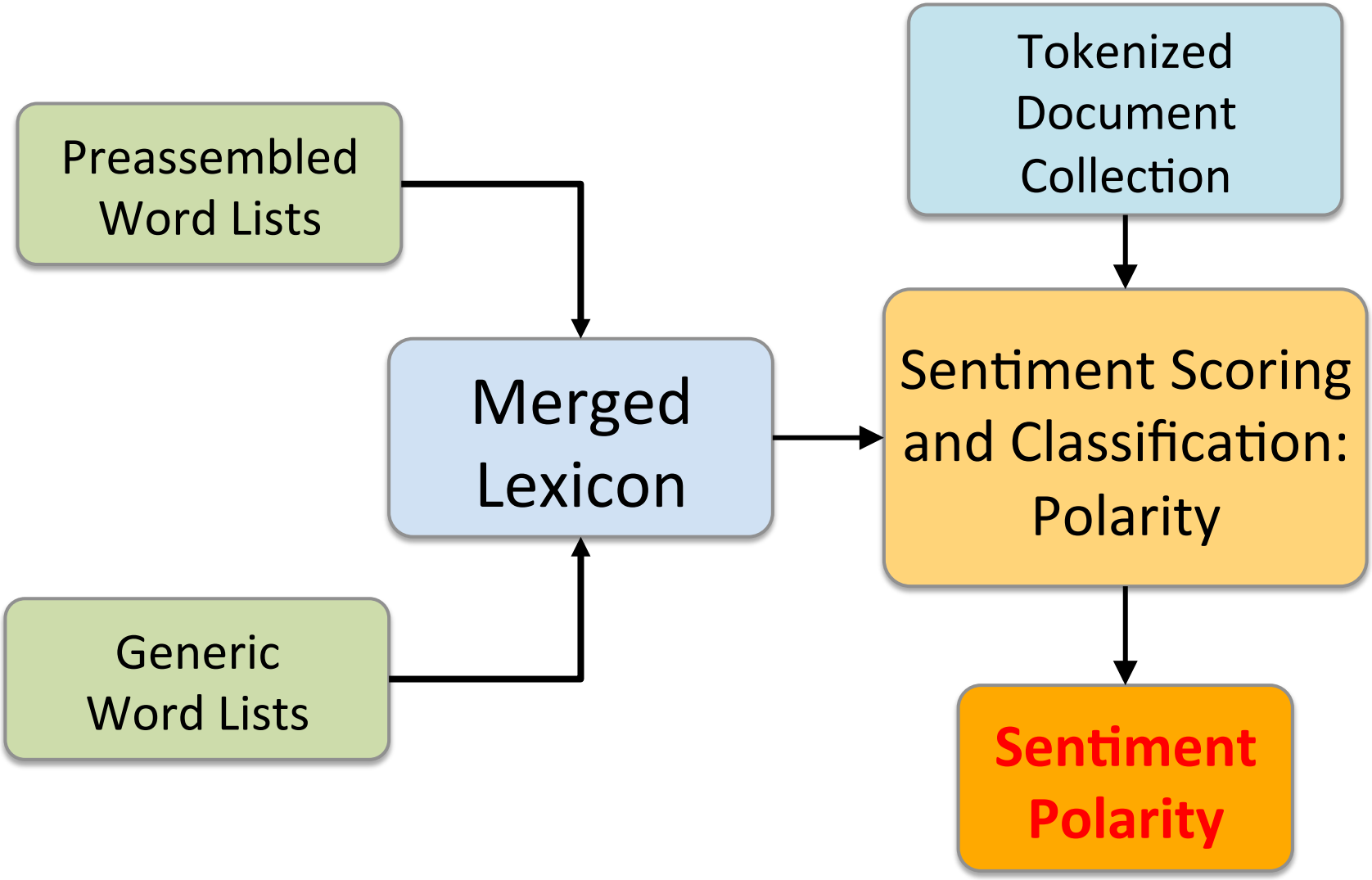

Vishal Kharde and Sheetal Sonawane (2016), "Sentiment Analysis of Twitter Data: A Survey of Techniques," International Journal of Computer Applications, Vol 139, No. 11, 2016. pp.5-15

# Sentiment Classification Based on Emoticons



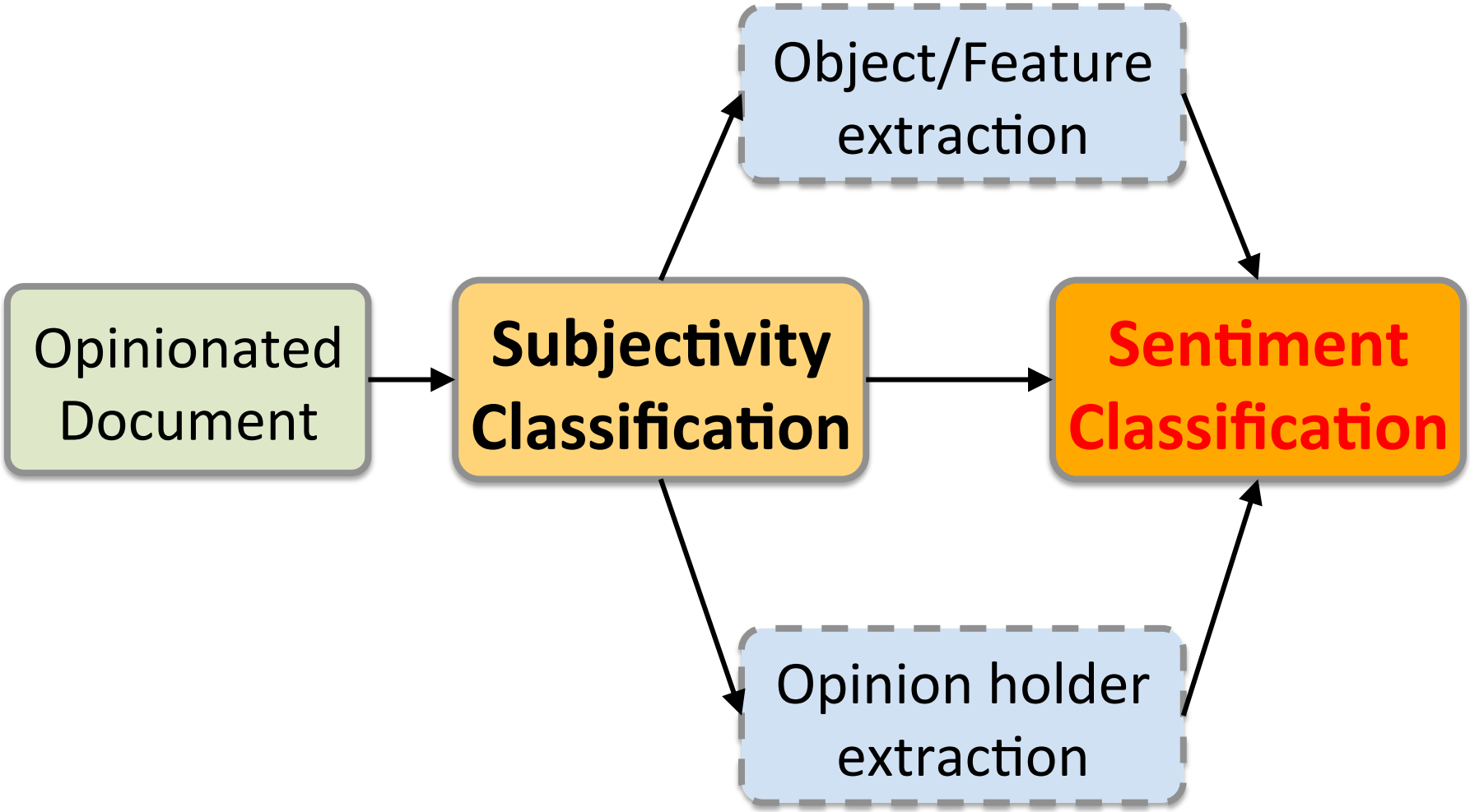

Vishal Kharde and Sheetal Sonawane (2016), "Sentiment Analysis of Twitter Data: A Survey of Techniques," International Journal of Computer Applications, Vol 139, No. 11, 2016. pp.5-15

# Lexicon-Based Model



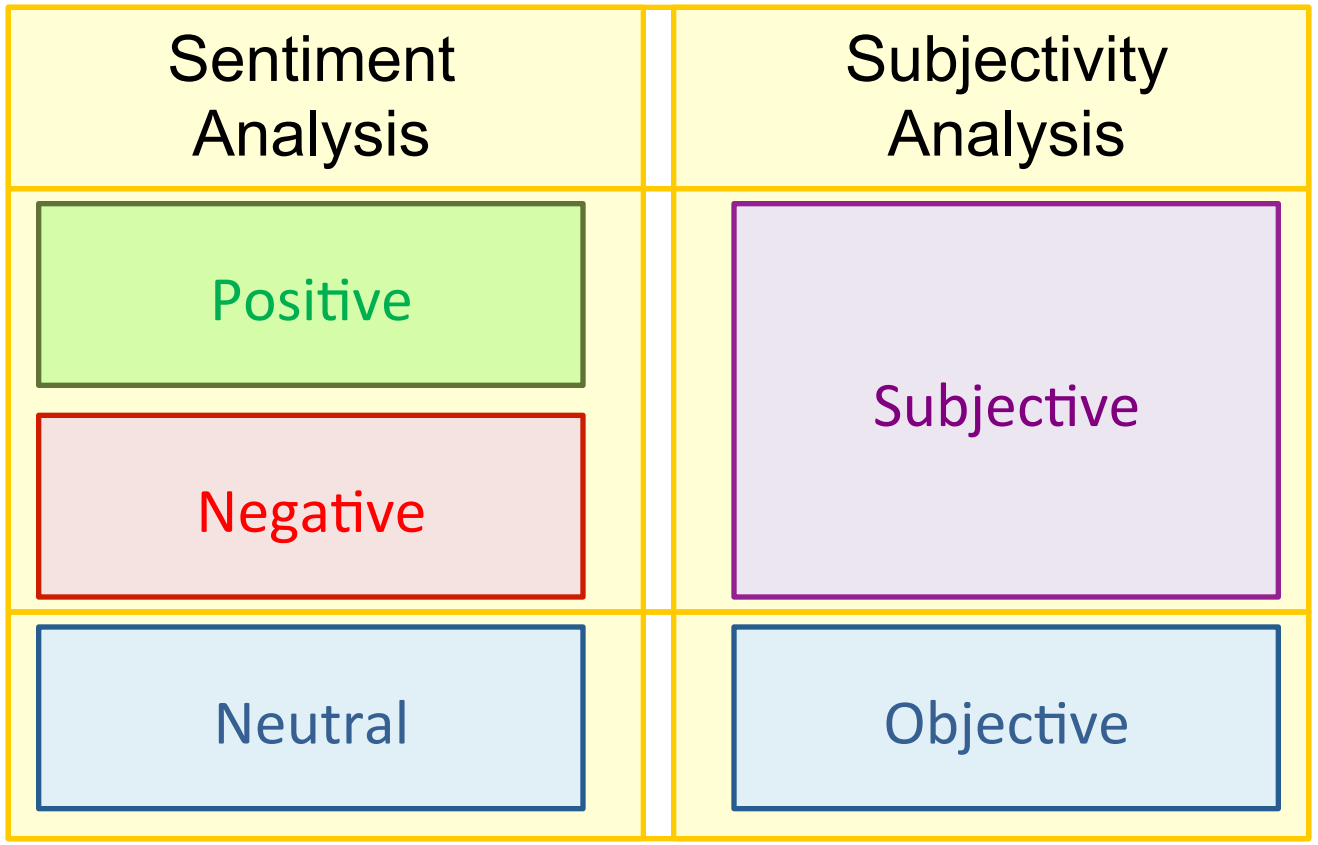

Vishal Kharde and Sheetal Sonawane (2016), "Sentiment Analysis of Twitter Data: A Survey of Techniques," International Journal of Computer Applications, Vol 139, No. 11, 2016. pp.5-15

# Sentiment Analysis Tasks

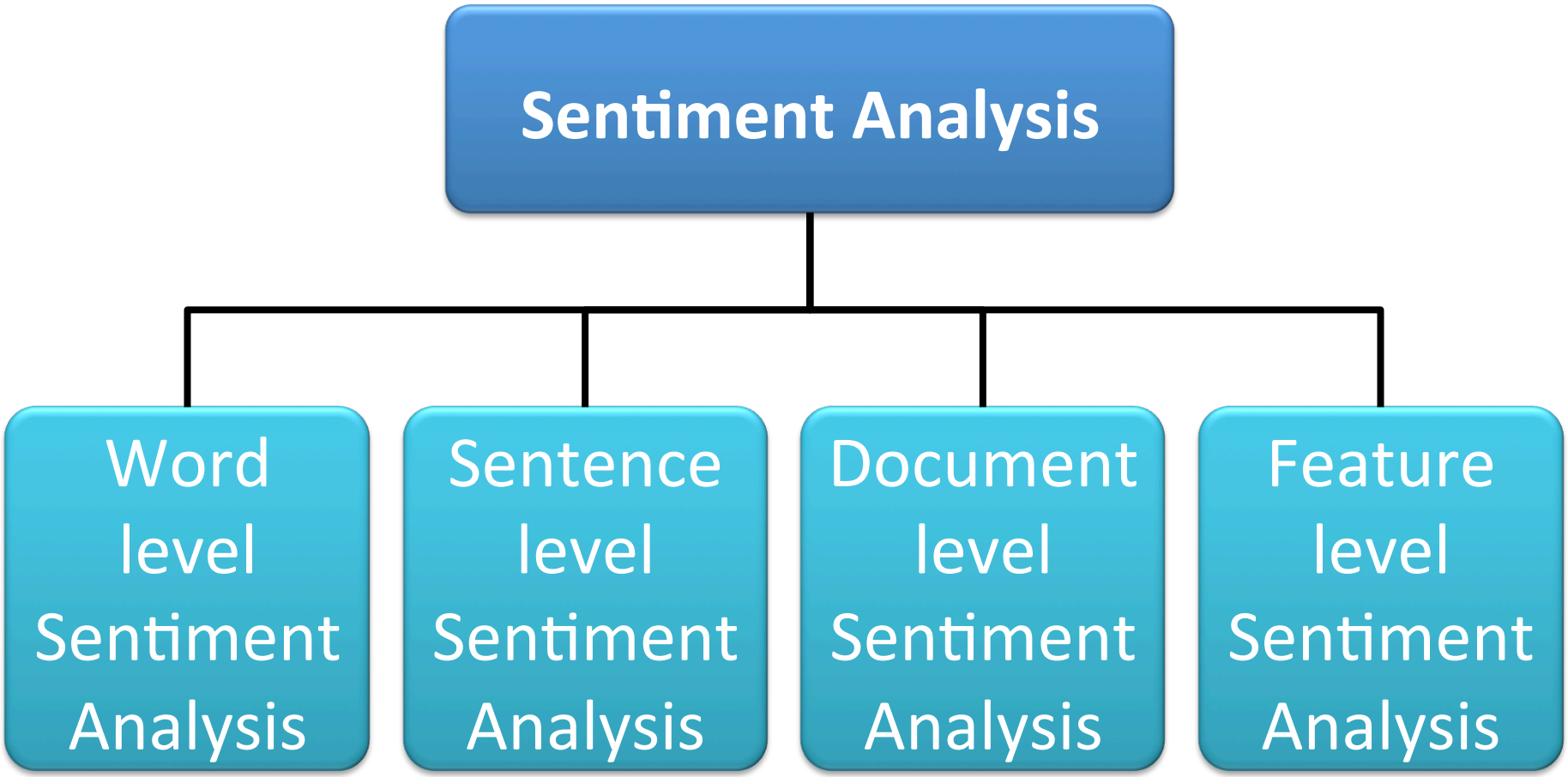



Vishal Kharde and Sheetal Sonawane (2016), "Sentiment Analysis of Twitter Data: A Survey of Techniques," International Journal of Computer Applications, Vol 139, No. 11, 2016. pp.5-15

# Sentiment Analysis vs. Subjectivity Analysis

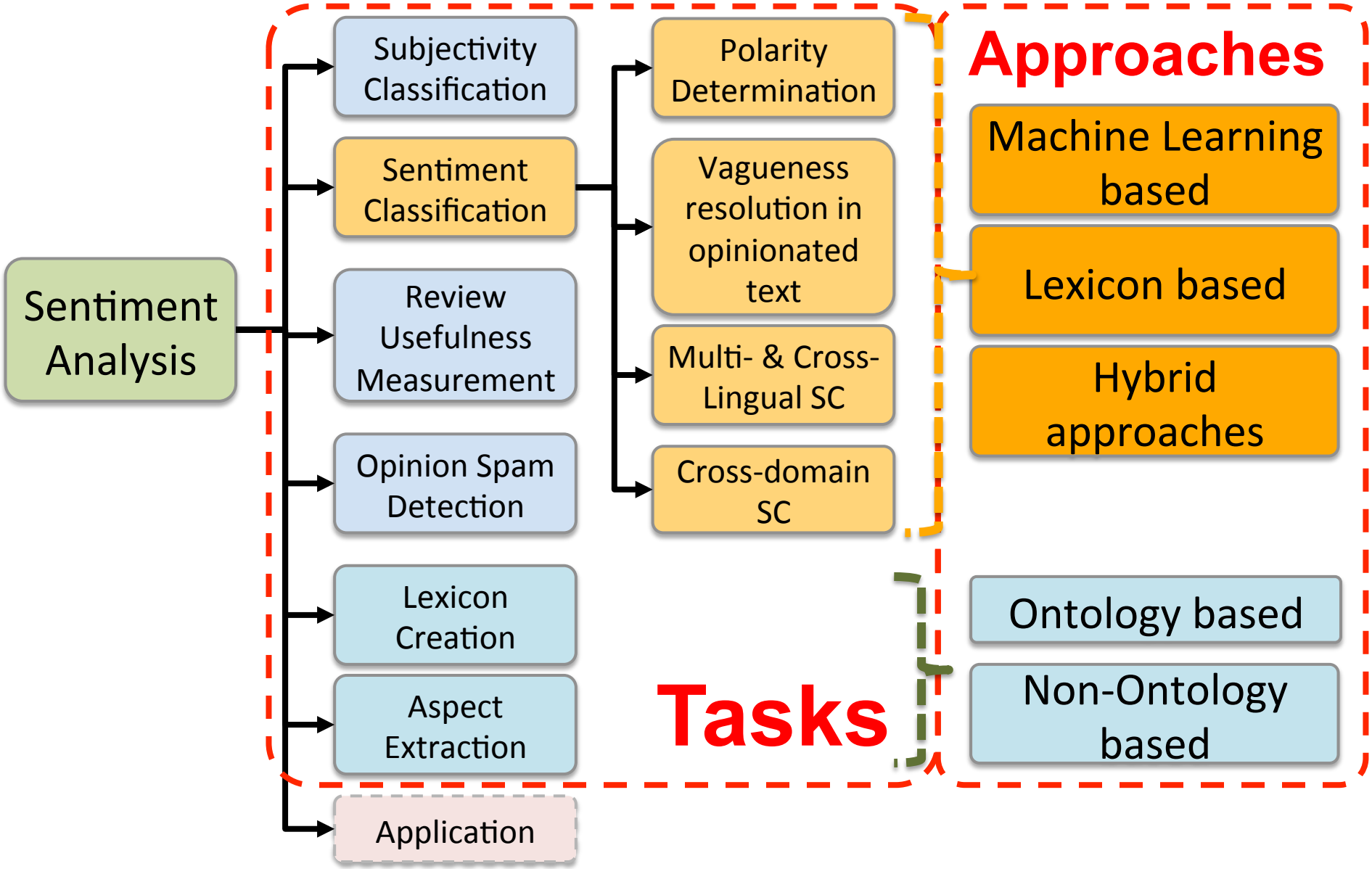


# Levels of Sentiment Analysis



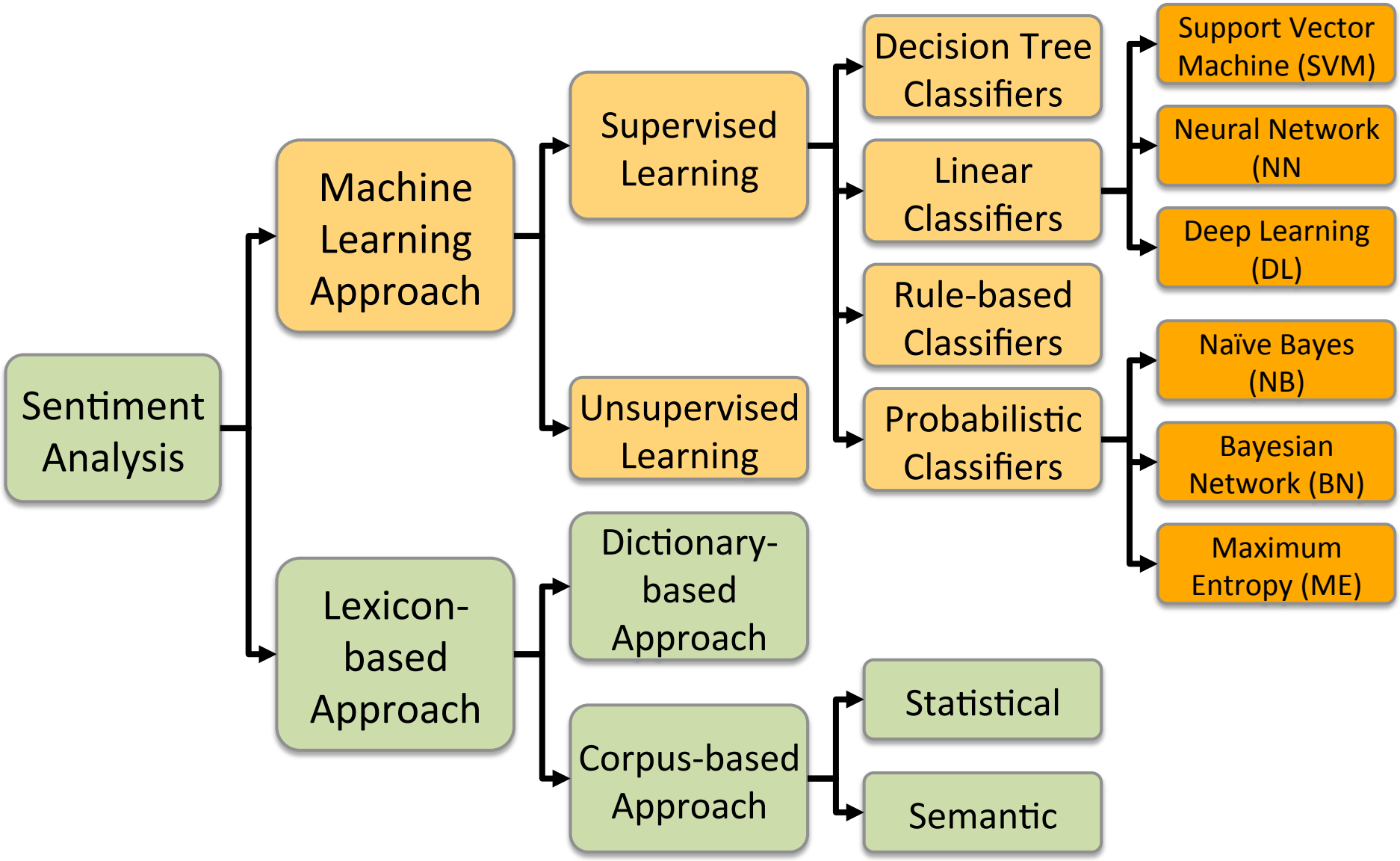

Vishal Kharde and Sheetal Sonawane (2016), "Sentiment Analysis of Twitter Data: A Survey of Techniques," International Journal of Computer Applications, Vol 139, No. 11, 2016. pp.5-15

# Sentiment Analysis




Source: Kumar Ravi and Vadlamani Ravi (2015), "A survey on opinion mining and sentiment analysis: tasks, approaches and applications." Knowledge-Based Systems, 89, pp.14-46.

# Sentiment Classification Techniques




Source: Jesus Serrano-Guerrero, Jose A. Olivas, Francisco P. Romero, and Enrique Herrera-Viedma (2015), "Sentiment analysis: A review and comparative analysis of web services," Information Sciences, 311, pp. 18-38.

# Example of SentiWordNet

| POS | ID | PosScore | NegScore | SynsetTerms | Gloss |
|---|---|---|---|---|---|
| a | 00217728 | 0.75 | 0 | beautiful#1 | delighting the senses or exciting intellectual or emotional admiration; "a beautiful child"; "beautiful country"; "a beautiful painting"; "a beautiful theory"; "a beautiful party“ |
| a | 00227507 | 0.75 | 0 | best#1 | (superlative of `good') having the most positive qualities; "the best film of the year"; "the best solution"; "the best time for planting"; "wore his best suit“ |
| r | 00042614 | 0 | 0.625 | unhappily#2 sadly#1 | in an unfortunate way; "sadly he died before he could see his grandchild“ |
| r | 00093270 | 0 | 0.875 | woefully#1 sadly#3 lamentably#1 deplorably#1 | in an unfortunate or deplorable manner; "he was sadly neglected"; "it was woefully inadequate“ |
| r | 00404501 | 0 | 0.25 | sadly#2 | with sadness; in a sad manner; "`She died last night,' he said sadly" |

# Evaluation of Text Mining and Sentiment Analysis

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

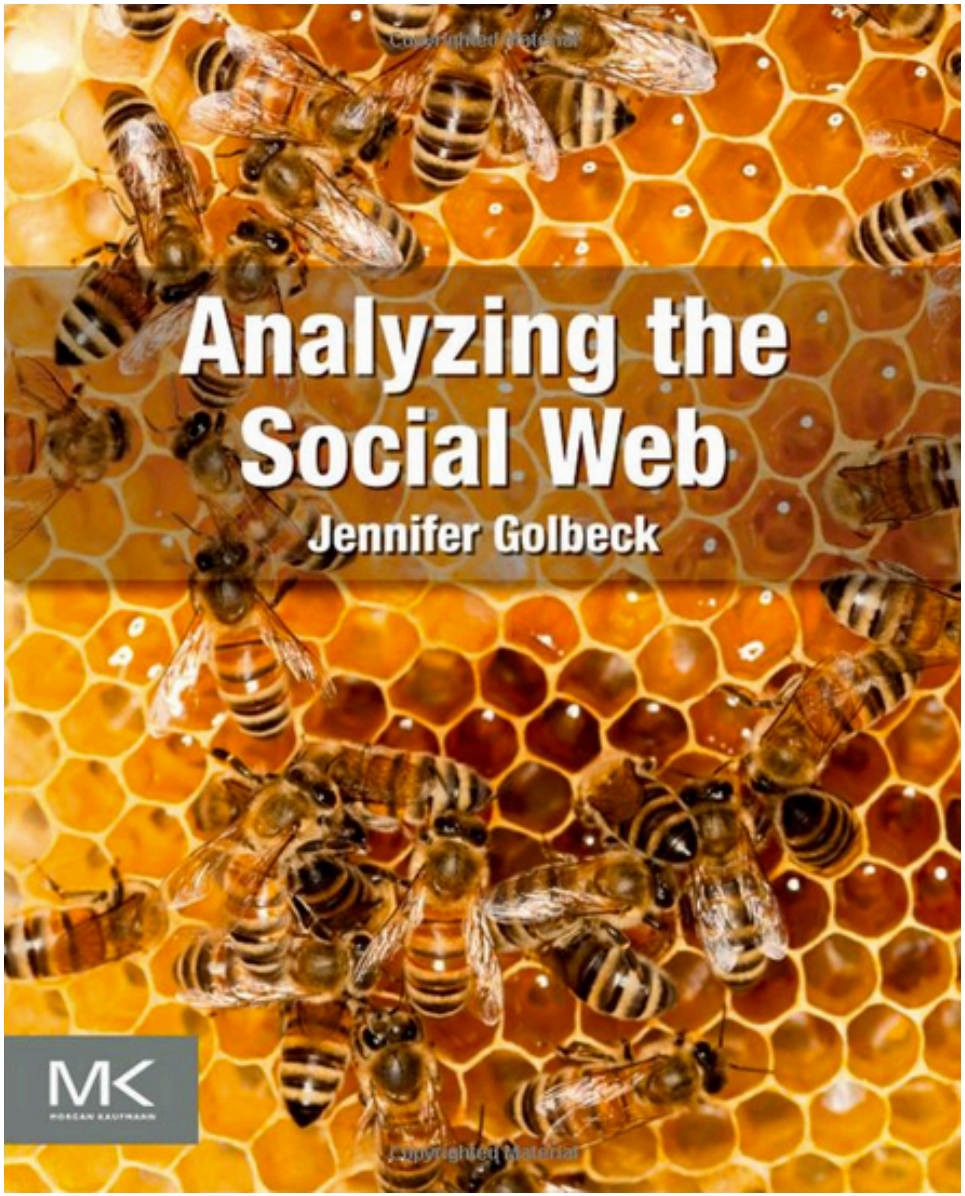
# Business Insights with Social Analytics

# Social Computing

- Social Network Analysis
- Link mining
- Community Detection
- Social Recommendation

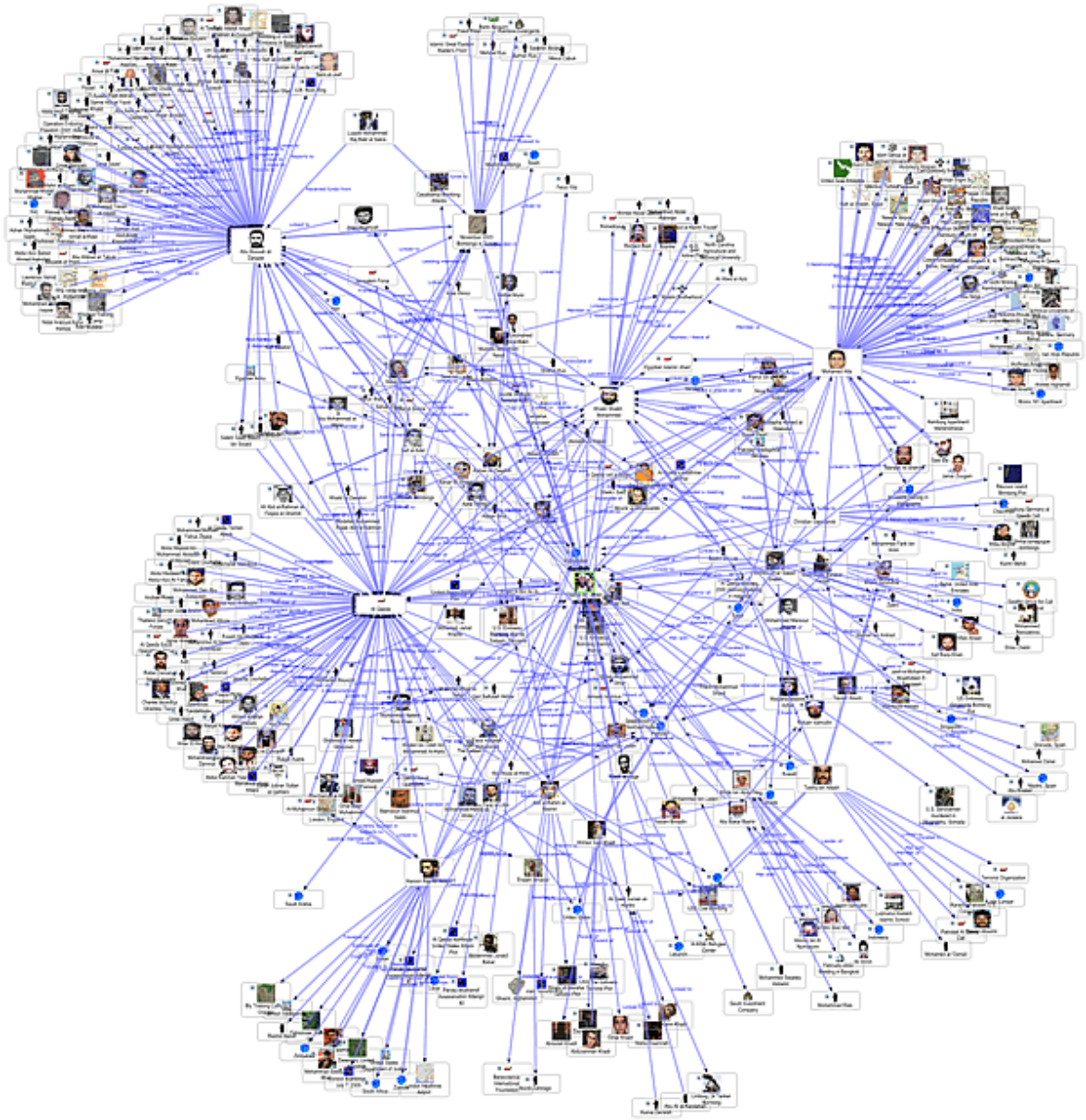
# Analyzing the Social Web:
# Social Network Analysis

# Jennifer Golbeck (2013), **Analyzing the Social Web**, Morgan Kaufmann




Source: http://www.amazon.com/Analyzing-Social-Web-Jennifer-Golbeck/dp/0124055311

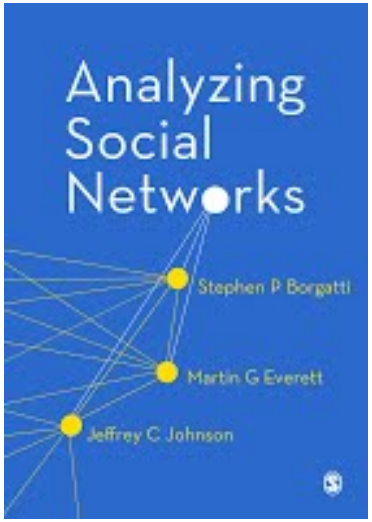
# Social Network Analysis



Source: http://www.fmsasg.com/SocialNetworkAnalysis/

# Social Network Analysis (SNA) Tools

- NetworkX
- igraph
- Gephi
- UCINet
- Pajek

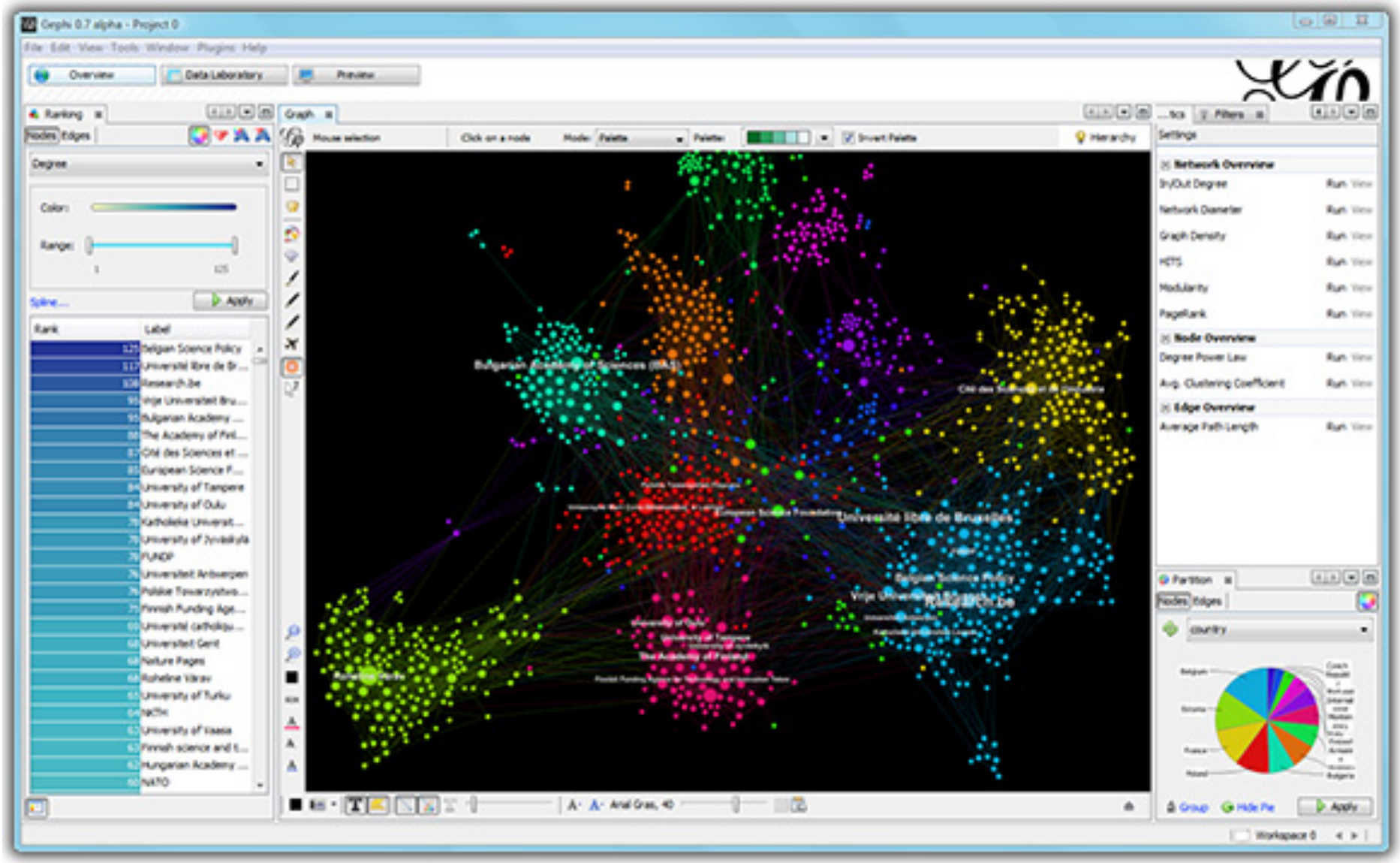




Gephi
makes graphs handy

# Gephi

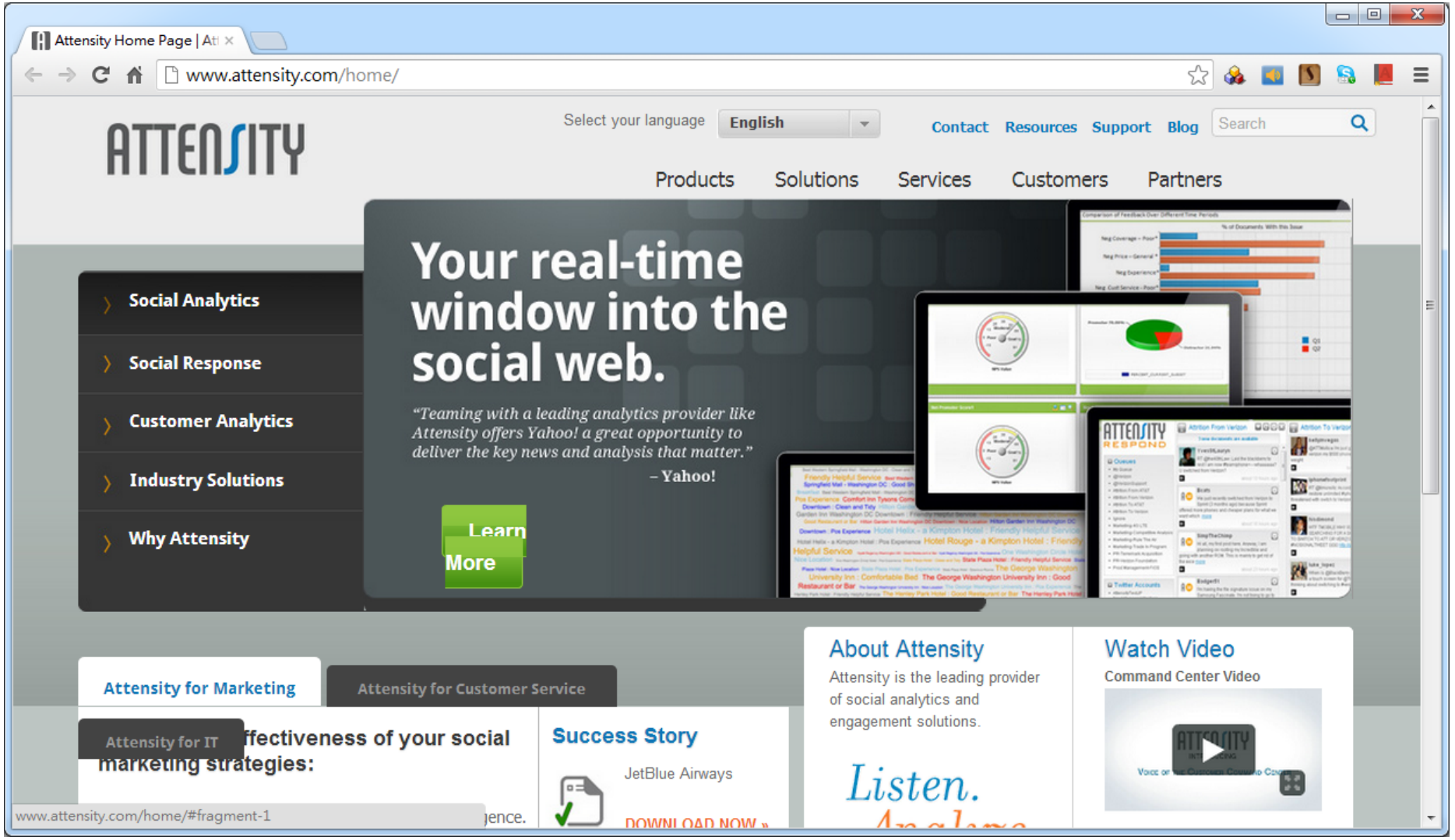
## The Open Graph Viz Platform




Source: https://gephi.org/

# Attensity: Track social sentiment across brands and competitors

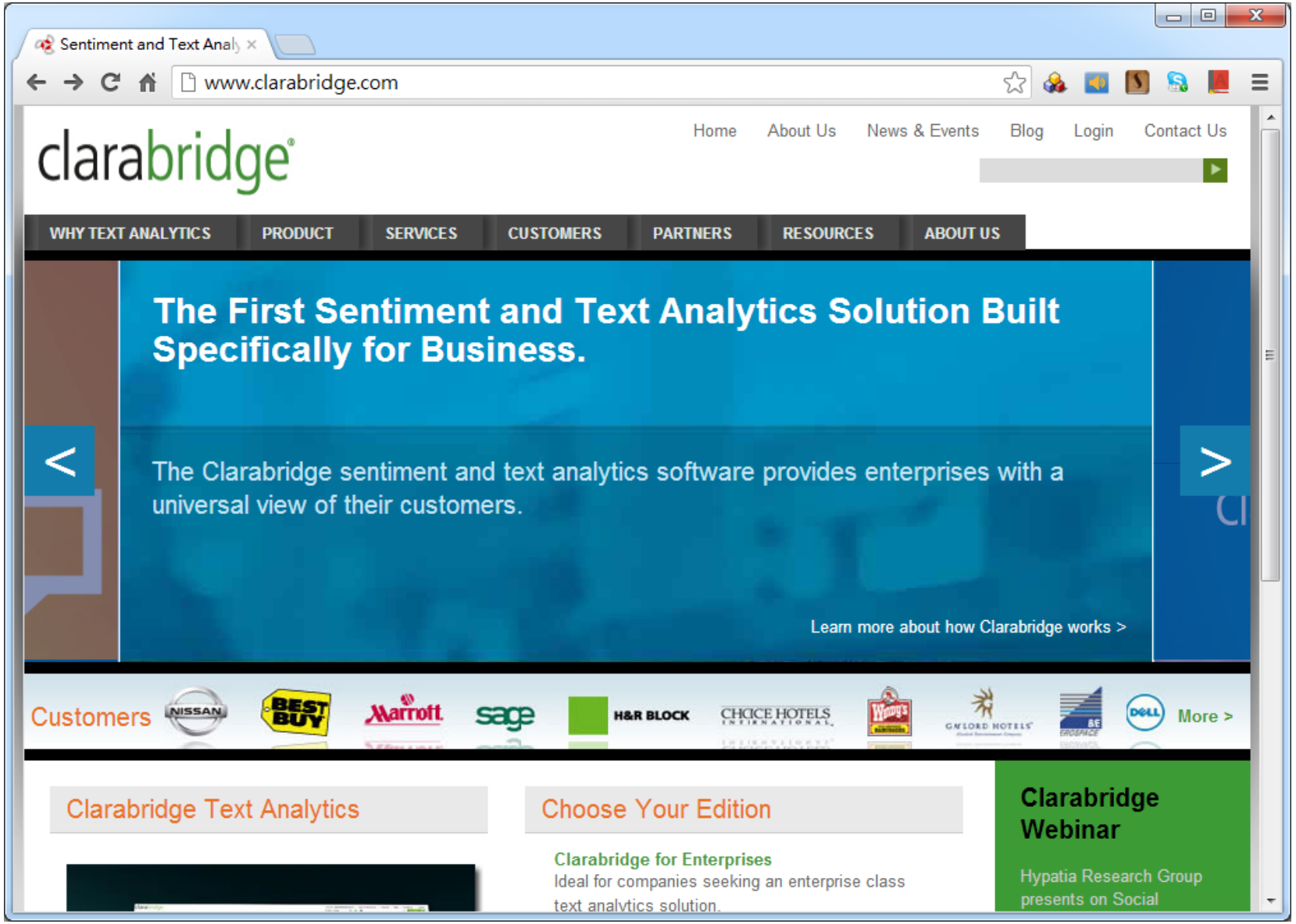
http://www.attensity.com/




http://www.youtube.com/watch?v=4goxmBEg2Iw#!

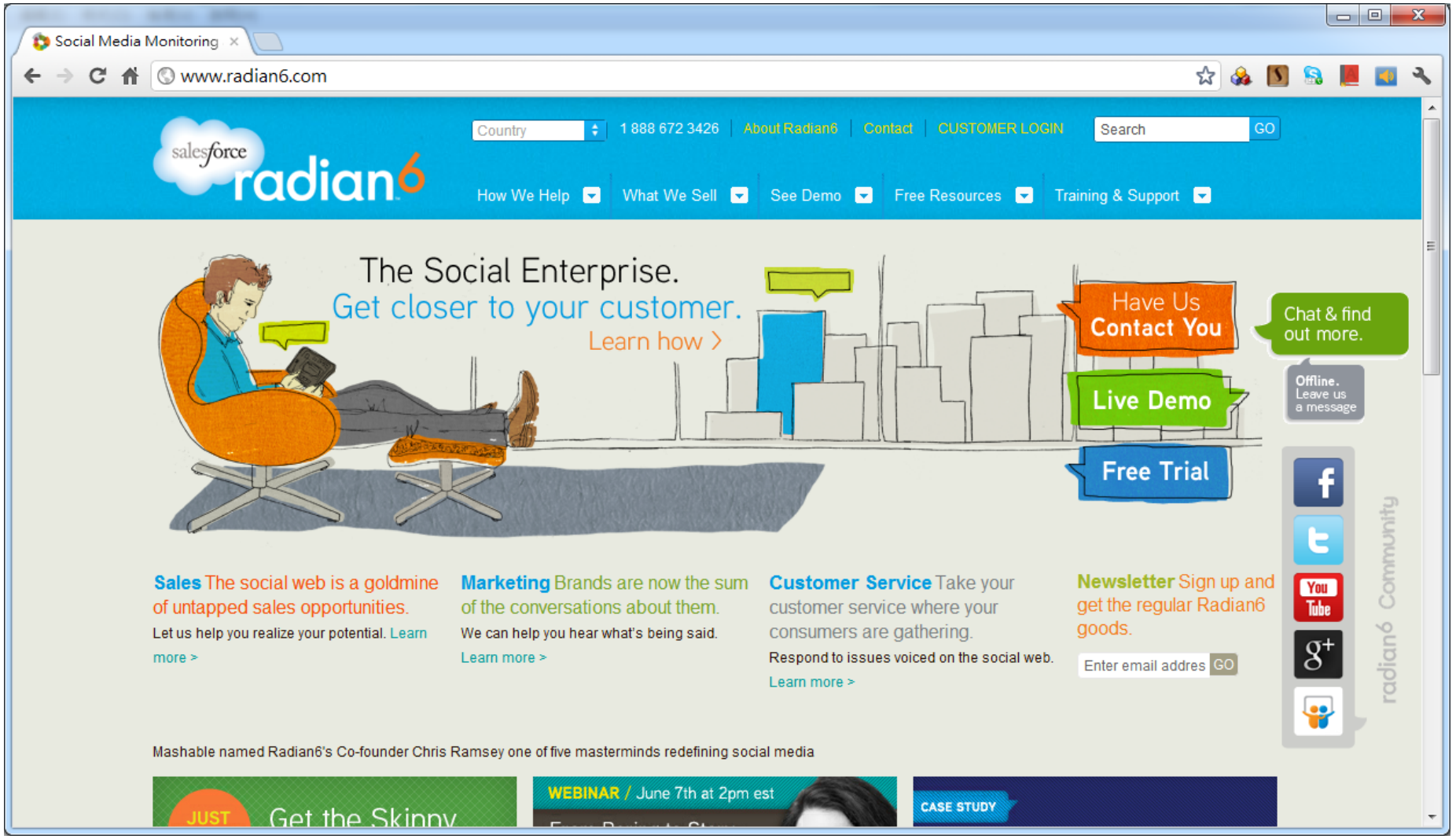
# Clarabridge: Sentiment and Text Analytics Software

http://www.clarabridge.com/



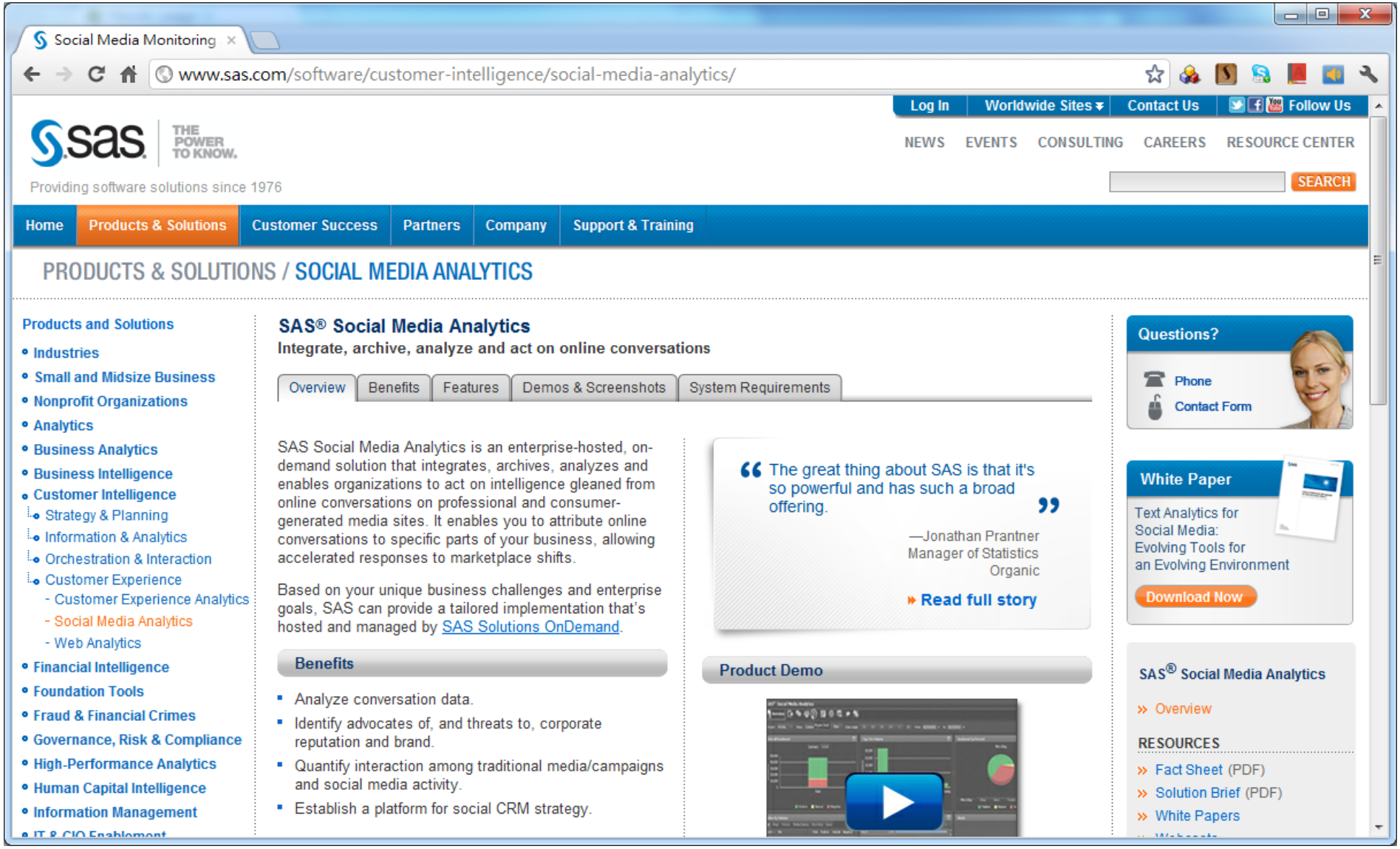

http://www.youtube.com/watch?v=IDHudt8M9P0

http://www.radian6.com/




http://www.youtube.com/watch?feature=player_embedded&v=8i6Exg3Urg0

http://www.sas.com/software/customer-intelligence/social-media-analytics/



# http://www.tweetfeel.com

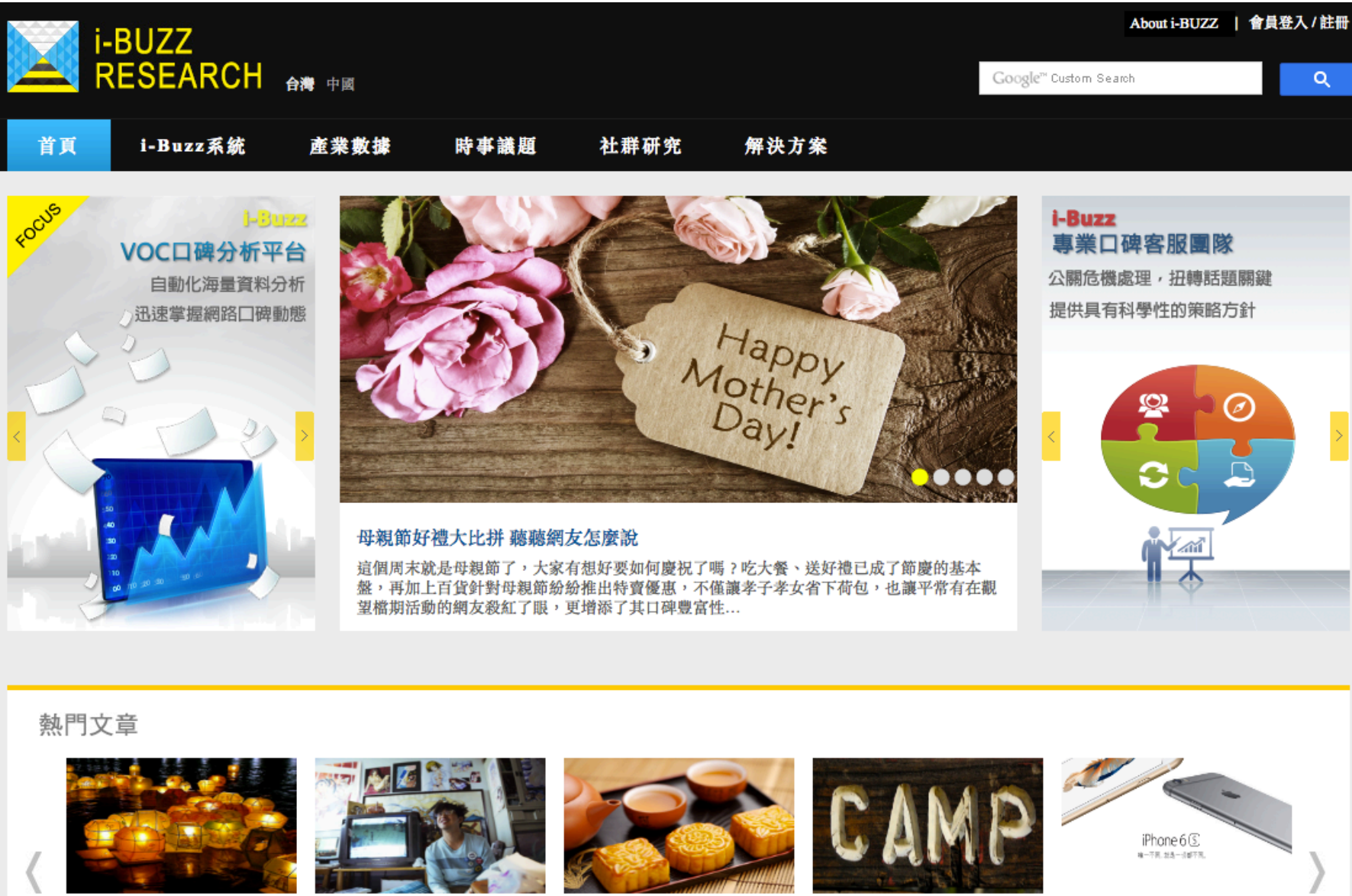
# eLand

http://www.eland.com.tw/

# OpView

http://www.opview.com.tw/

http://www.i-buzz.com.tw/



# Summary

- 文字探勘技術
  (Text Mining Technologies)

- 情感分析架構
  (Architectures of Sentiment Analytics)

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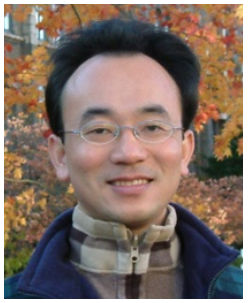
# Q & A

# 社群網路文字探勘與情感分析 (Text Mining and Sentiment Analytics on Social Media)

Time: 2016/05/10 (Tue) (12:00-14:00)
Place: 淡水校園覺生綜合大樓I501室

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2016-05-10