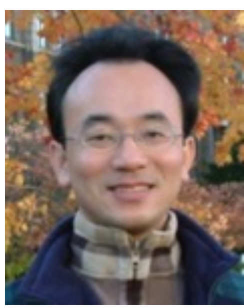
Research on Social Computing and Big Data Analytics (社群運算與大數據分析研究)

Time: 2016/11/17 (Thu) (15:30-17:30)
Place: 東吳大學資管研究所 <城中校區 教室：4303>
Host: 鄭麗珍 教授 (Prof. Li-chen Cheng)



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淡江大學 資訊管理學系

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2016-11-17

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淡江大學資管系專任助理教授

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)

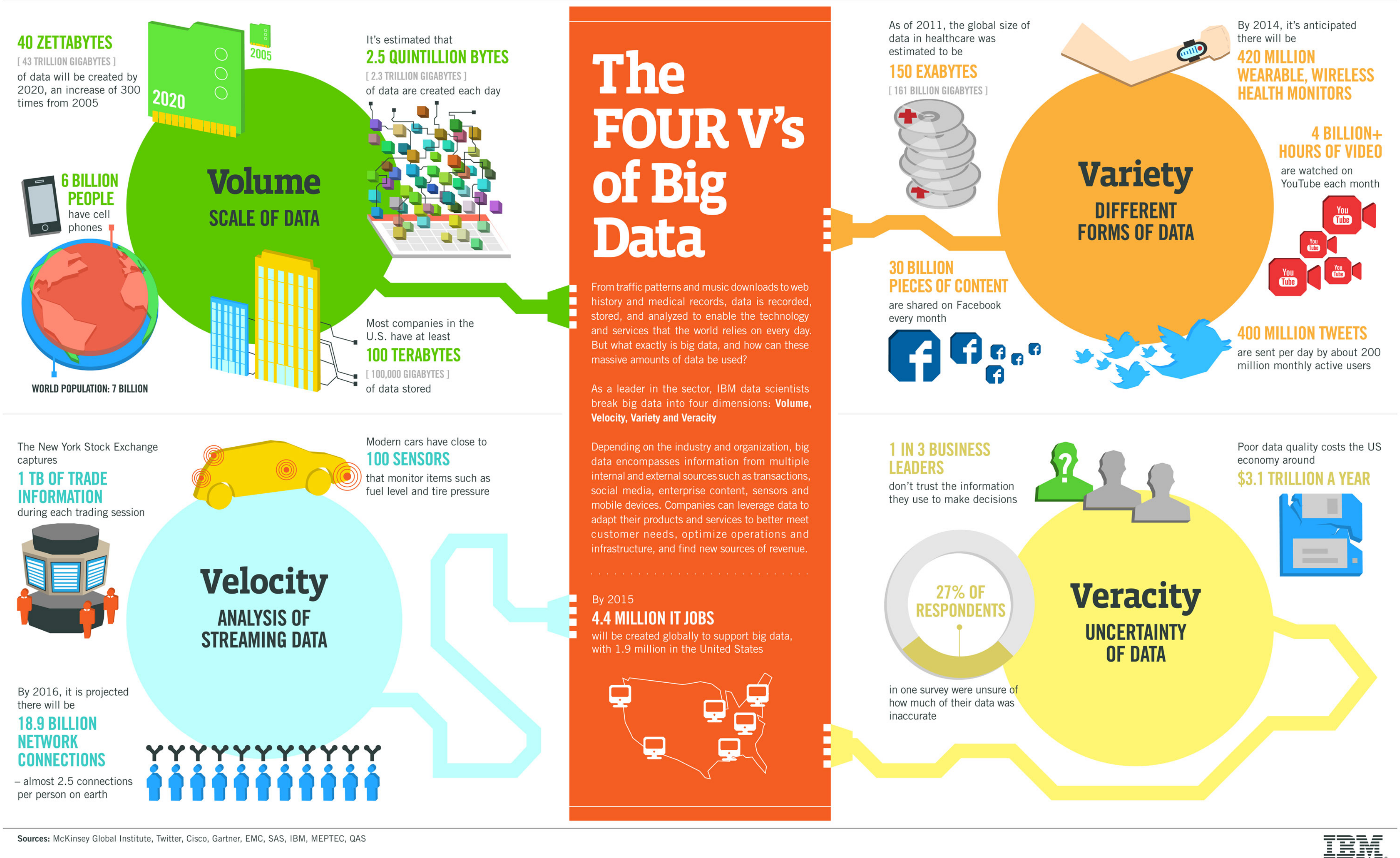
Outline

- Big Data Sentiment Analysis
- Social Computing
- International Research Collaboration and Mobility

Big Data Sentiment Analysis

Big Data Analytics

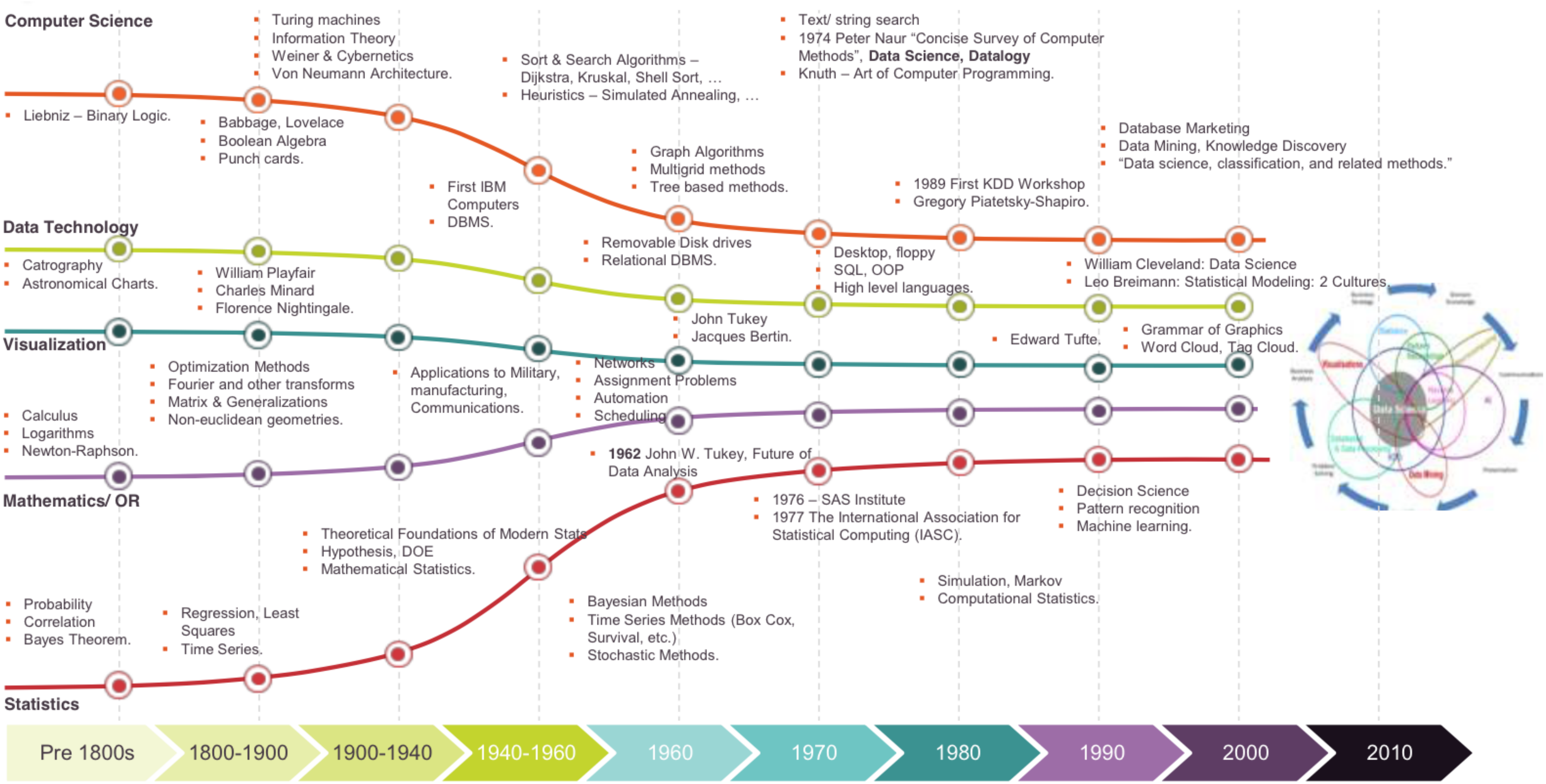
Big Data 4 V



Source: https://www-01.ibm.com/software/data/bigdata/

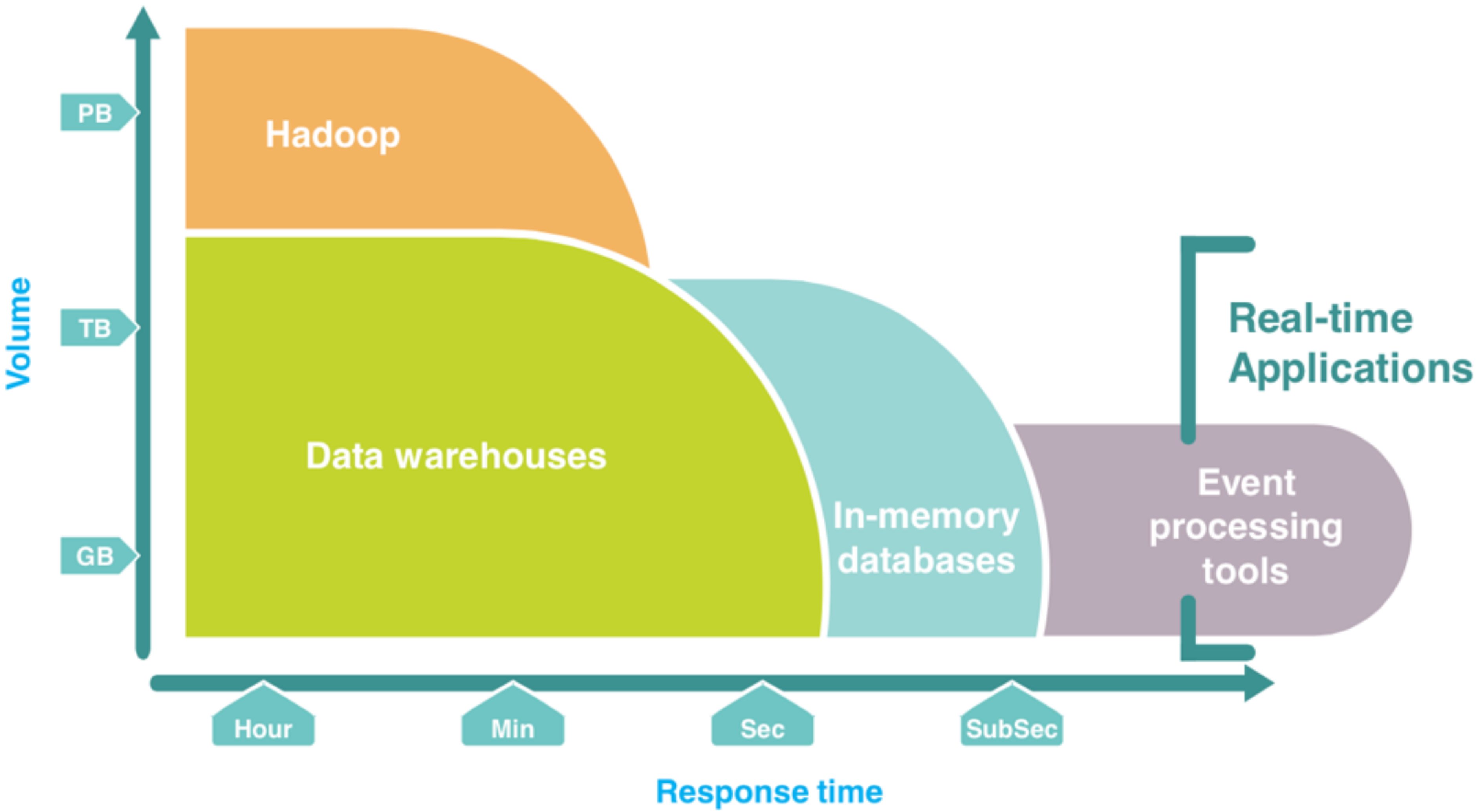
Value

History of Data Science



Source: http://www.kdnuggets.com/2015/02/history-data-science-infographic.html

Big Data Technologies are Enabling a New Approach



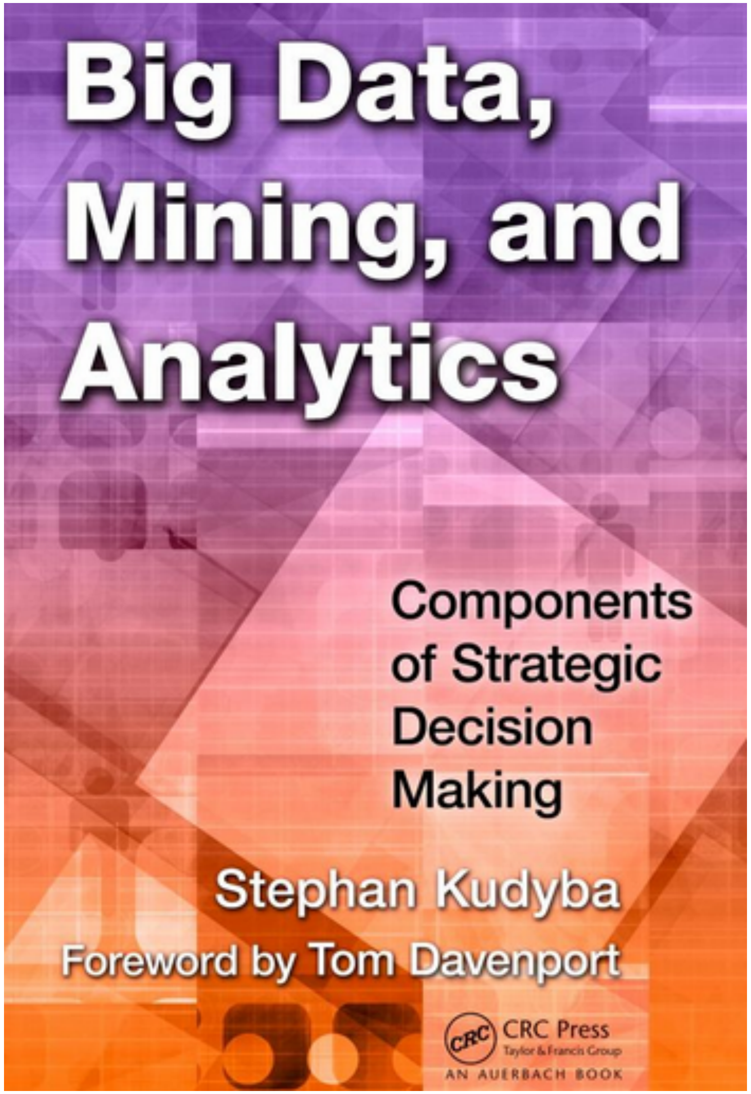
Source: http://www.doclens.com/119898/think-1-13-big-datas-impact-on-analytics/

Big Data Analytics and Data Mining

Stephan Kudyba (2014),

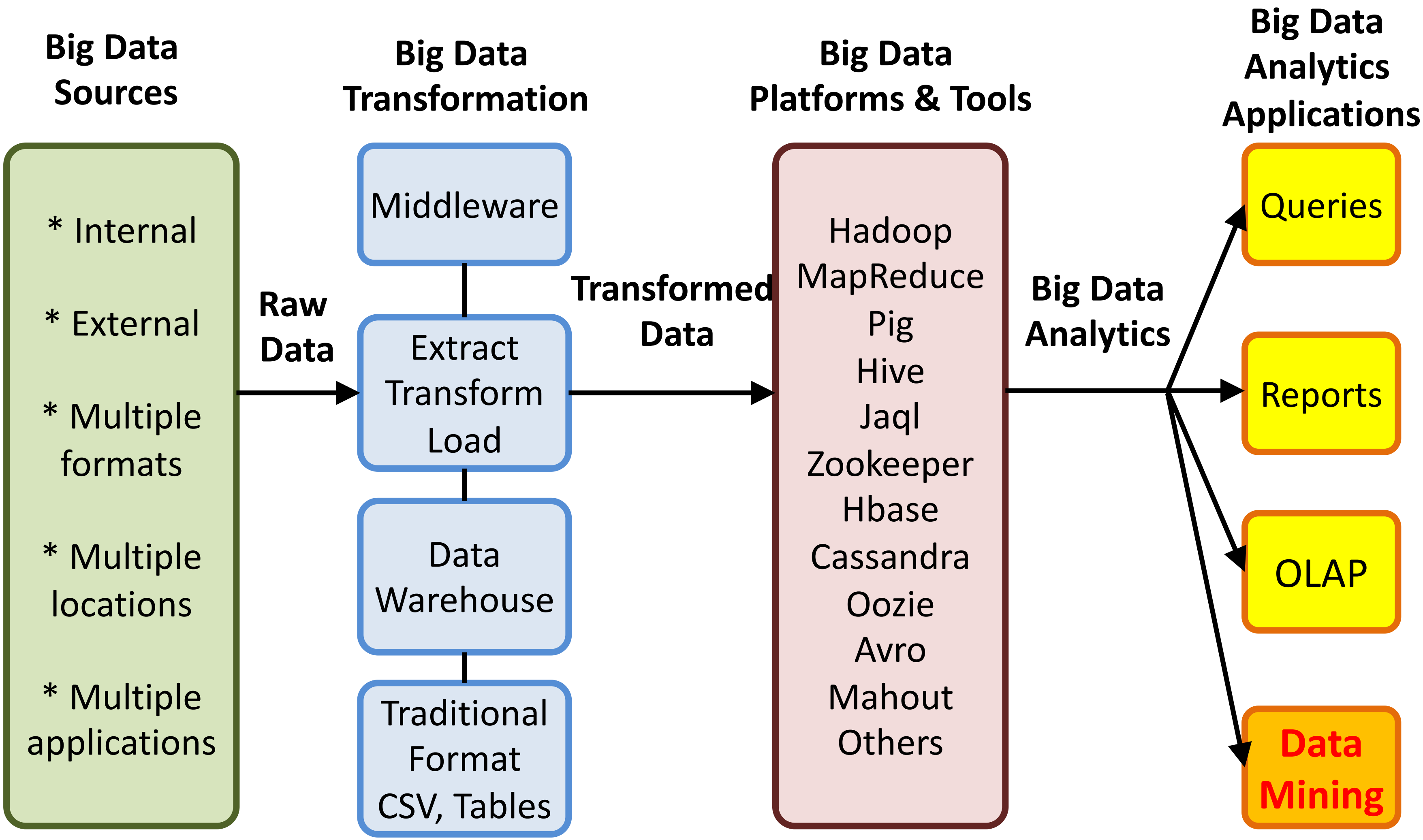
Big Data, Mining, and Analytics:

Components of Strategic Decision Making, Auerbach Publications



Source: http://www.amazon.com/gp/product/1466568704

Architecture of Big Data Analytics



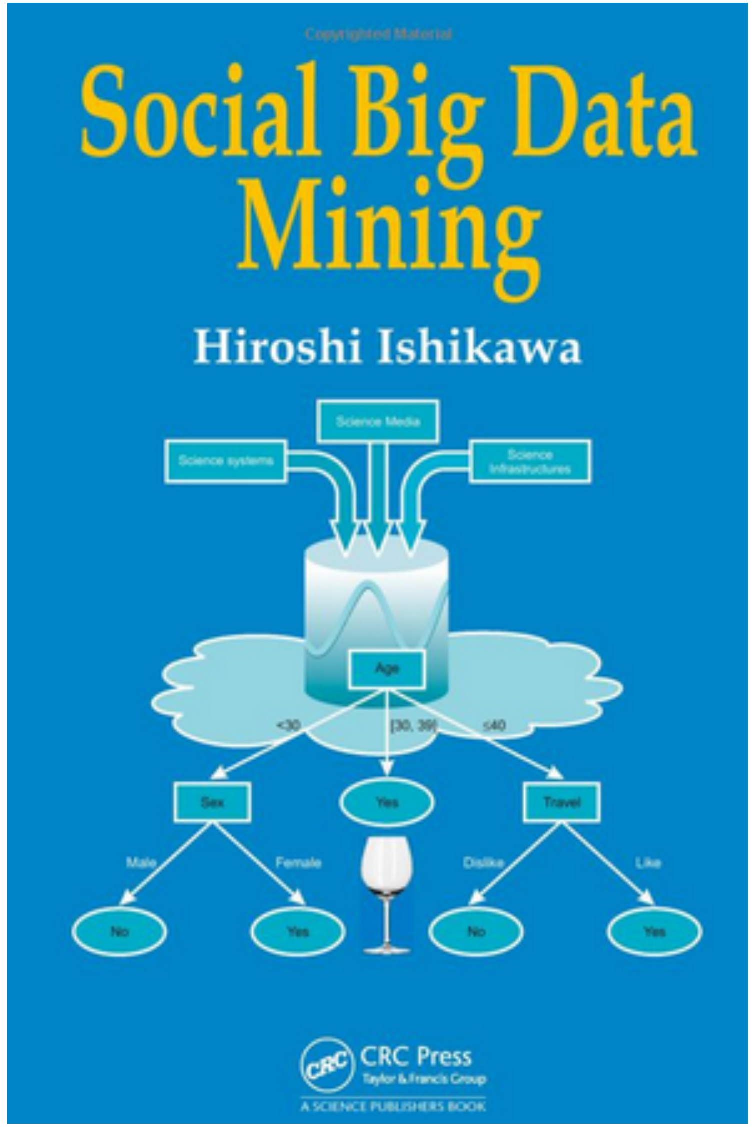
Source: Stephan Kudyba (2014), Big Data, Mining, and Analytics: Components of Strategic Decision Making, Auerbach Publications

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)



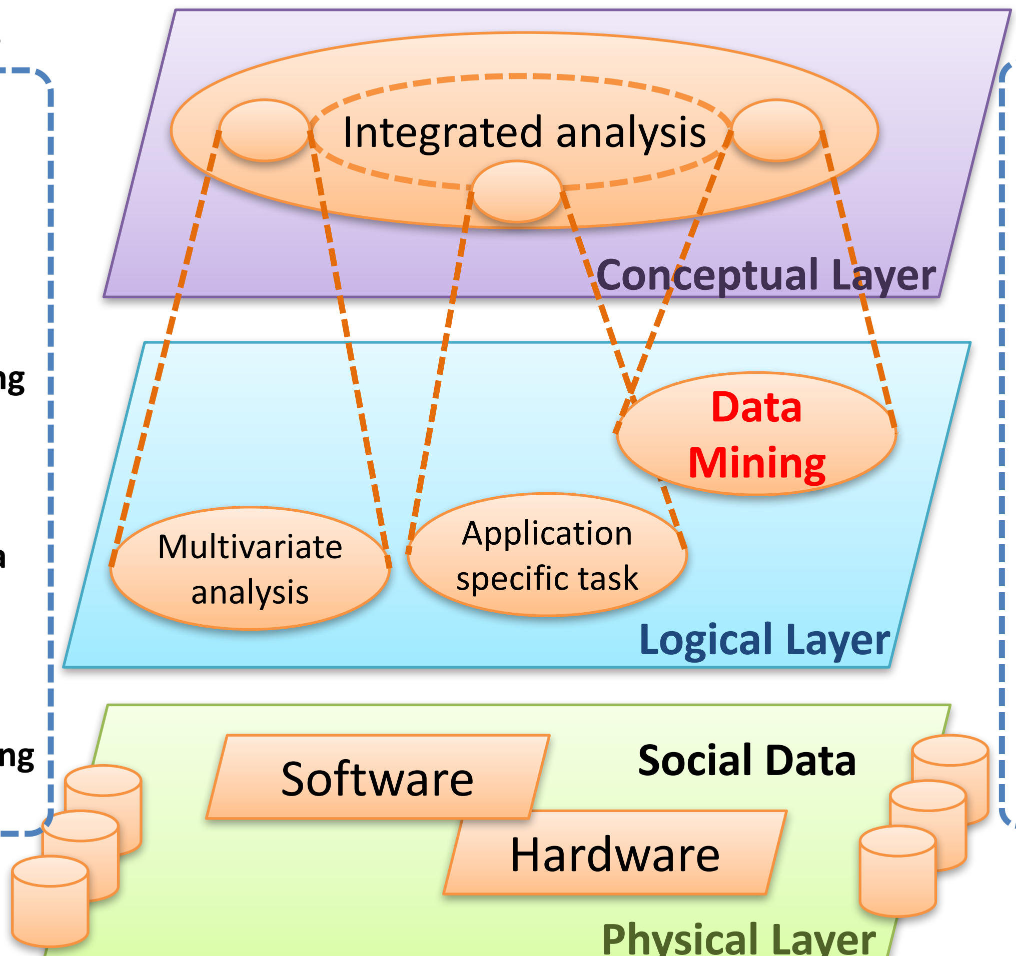
Source: http://www.amazon.com/Social-Data-Mining-Hiroshi-Ishikawa/dp/149871093X

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**

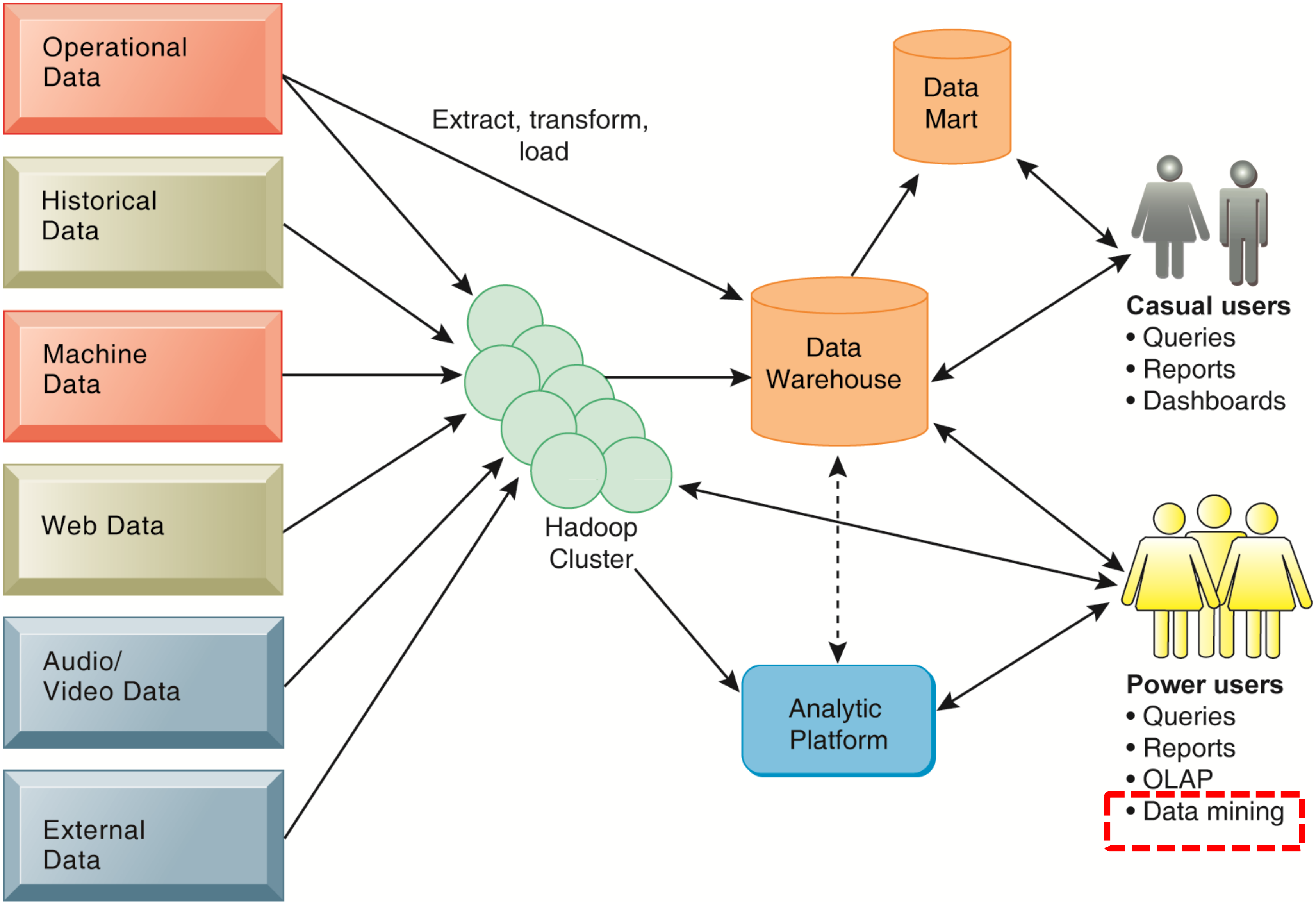


Analysts

- **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

Business Intelligence (BI) Infrastructure



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

LeCun, Yann,
Yoshua Bengio,
and Geoffrey Hinton.

"**Deep learning**."

Nature 521, no. 7553 (2015): 436-444.

REVIEW

doi:10.1038/nature14539

Deep learning

Yann LeCun[1,2], Yoshua Bengio[3] & Geoffrey Hinton[4,5]

Deep learning allows computational models that are composed of multiple processing layers to learn representations of data with multiple levels of abstraction. These methods have dramatically improved the state-of-the-art in speech recognition, visual object recognition, object detection and many other domains such as drug discovery and genomics. Deep learning discovers intricate structure in large data sets by using the backpropagation algorithm to indicate how a machine should change its internal parameters that are used to compute the representation in each layer from the representation in the previous layer. Deep convolutional nets have brought about breakthroughs in processing images, video, speech and audio, whereas recurrent nets have shone light on sequential data such as text and speech.

Machine-learning technology powers many aspects of modern society: from web searches to content filtering on social networks to recommendations on e-commerce websites, and it is increasingly present in consumer products such as cameras and smartphones. Machine-learning systems are used to identify objects in images, transcribe speech into text, match news items, posts or products with users' interests, and select relevant results of search. Increasingly, these applications make use of a class of techniques called deep learning.

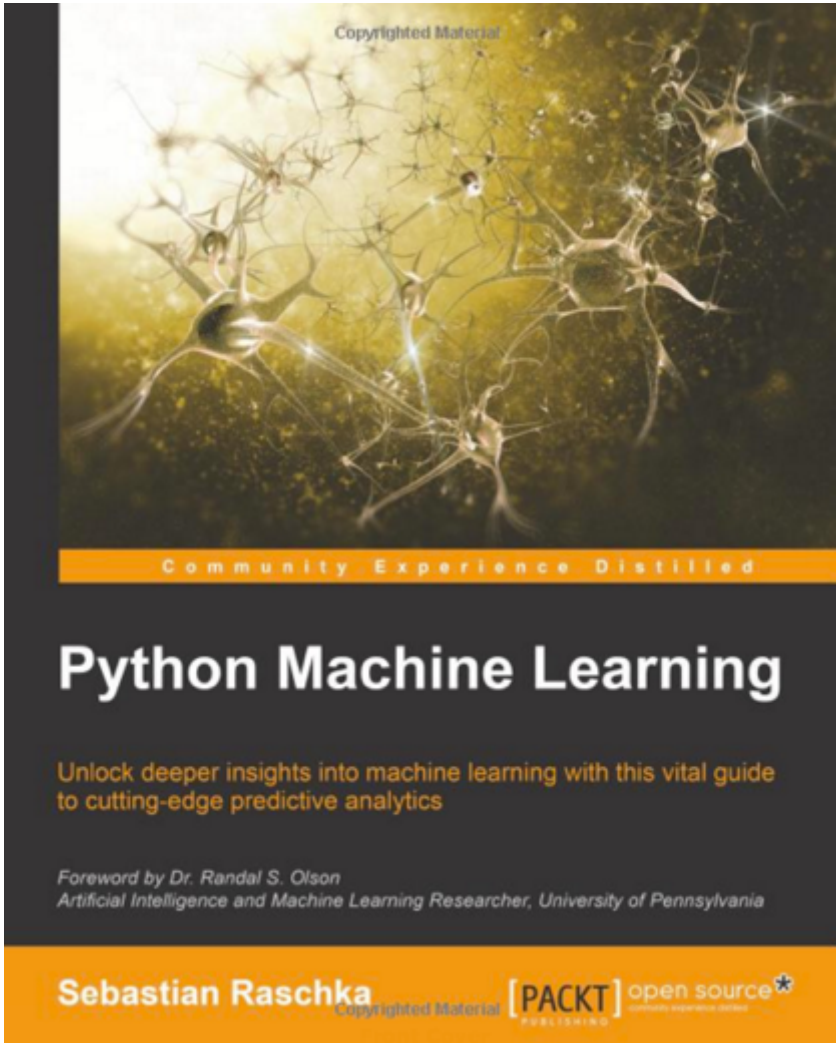
Conventional machine-learning techniques were limited in their ability to process natural data in their raw form. For decades, con- intricate structures in high-dimensional data and is therefore applicable to many domains of science, business and government. In addition to beating records in image recognition[1–4] and speech recognition[5–7], it has beaten other machine-learning techniques at predicting the activity of potential drug molecules[8], analysing particle accelerator data[9,10], reconstructing brain circuits[11], and predicting the effects of mutations in non-coding DNA on gene expression and disease[12,13]. Perhaps more surprisingly, deep learning has produced extremely promising results for various tasks in natural language understanding[14], particularly topic classification, sentiment analysis, question answering[15] and language translation[16,17].

Source: LeCun, Yann, Yoshua Bengio, and Geoffrey Hinton. "Deep learning." Nature 521, no. 7553 (2015): 436-444.

Sebastian Raschka (2015),

Python Machine Learning,

Packt Publishing

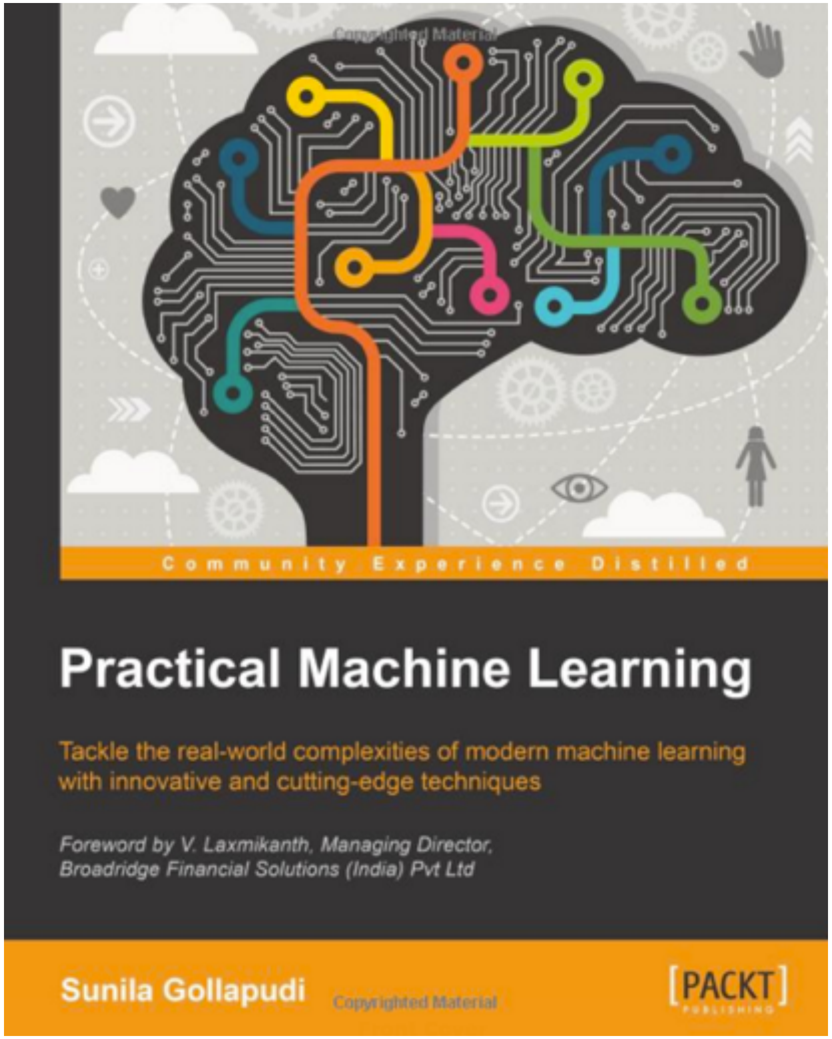


Source: http://www.amazon.com/Python-Machine-Learning-Sebastian-Raschka/dp/1783555130

Sunila Gollapudi (2016),

Practical Machine Learning,

Packt Publishing



Source: http://www.amazon.com/Practical-Machine-Learning-Sunila-Gollapudi/dp/178439968X

Machine Learning Models

- Deep Learning
- Kernel
- Association rules
- Ensemble
- Decision tree
- Dimensionality reduction
- Clustering
- Regression Analysis
- Bayesian
- Instance based

Source: Sunila Gollapudi (2016), Practical Machine Learning, Packt Publishing

Data Scientist

資料科學家

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

Deep Learning

Intelligence from Big Data

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

Big Data

Source: EMC Education Services, Data Science and Big Data Analytics: Discovering, Analyzing, Visualizing and Presenting Data, Wiley, 2015

Data Scientist:

The Sexiest Job of the 21st Century

(Davenport & Patil, 2012)(HBR)

Source: Davenport, T. H., & Patil, D. J. (2012). Data Scientist. *Harvard business review*

Data Scientist:

The Sexiest Job of the 21st Century

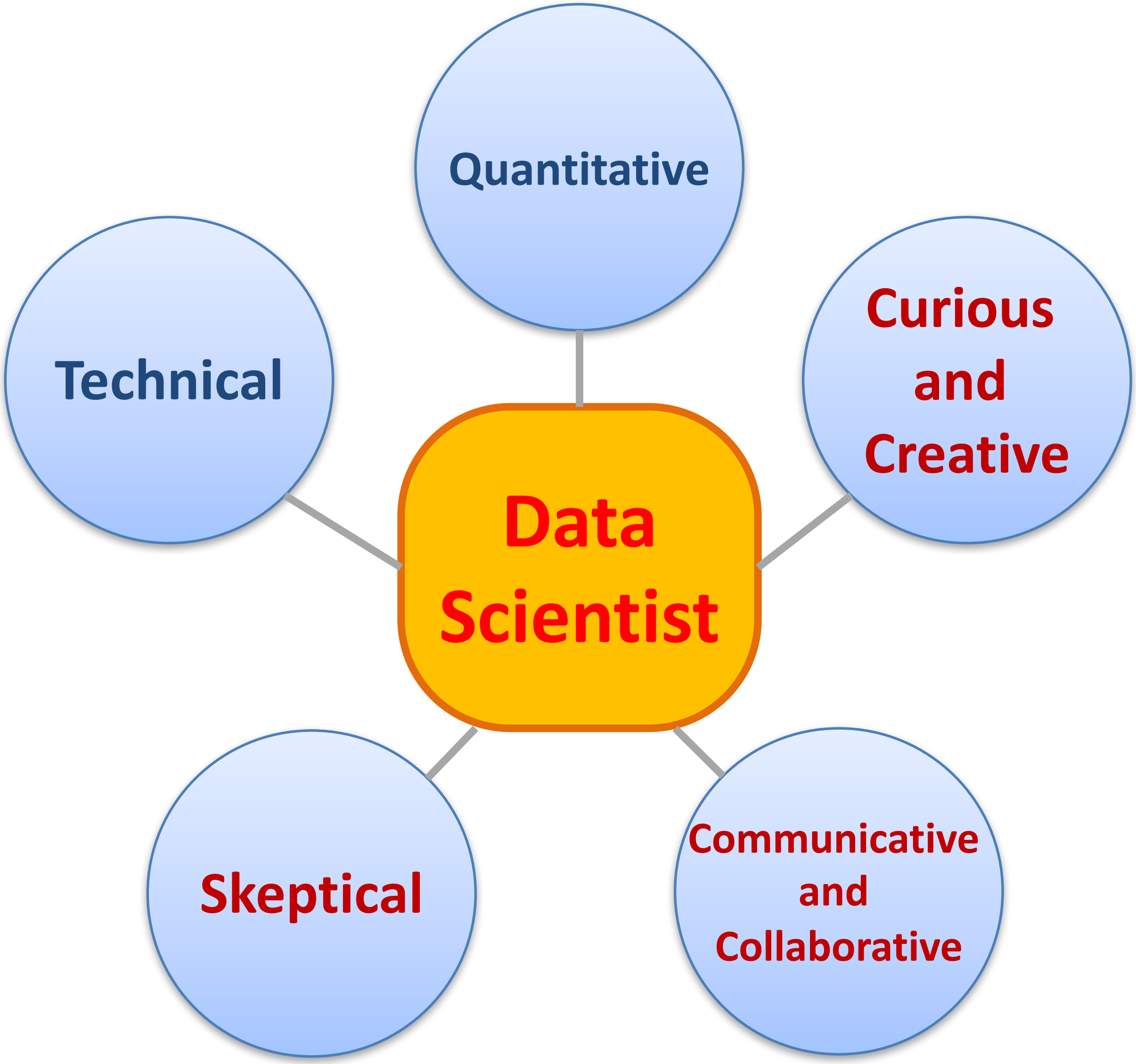
Meet the people who can coax treasure out of messy, unstructured data.

by Thomas H. Davenport and D.J. Patil

When Jonathan Goldman arrived for work in June 2006 at LinkedIn, the business networking site, the place still felt like a start-up. The company had just under 8 million accounts, and the number was growing quickly as existing members invited their friends and colleagues to join. But users weren't seeking out connections with the people who were already on the site at the rate executives had expected. Something was apparently missing in the social experience. As one LinkedIn manager put it, "It was like arriving at a conference reception and realizing you don't know anyone. So you just stand in the corner sipping your drink—and you probably leave early."

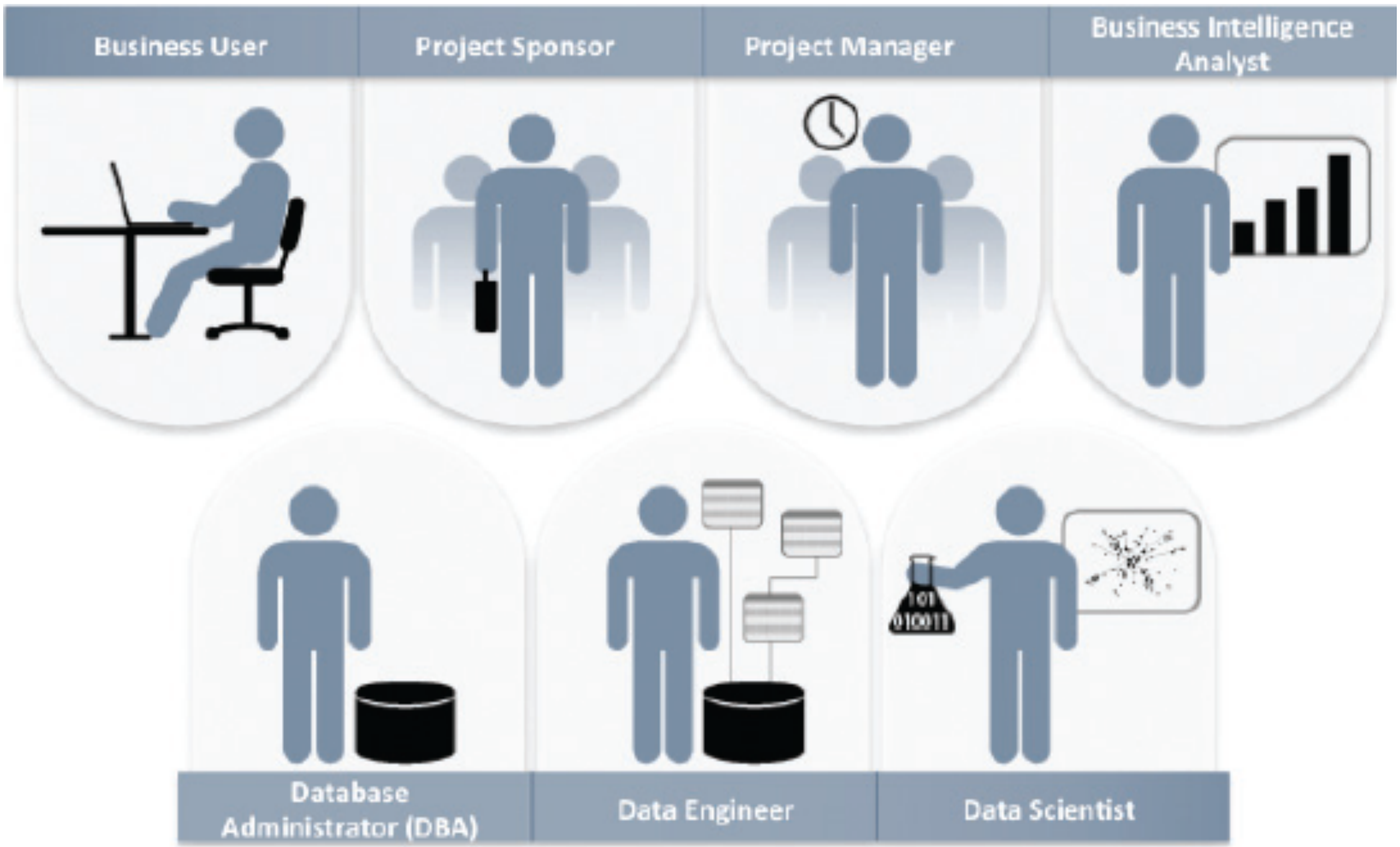
Source: Davenport, T. H., & Patil, D. J. (2012). Data Scientist. *Harvard business review*

Data Scientist Profile



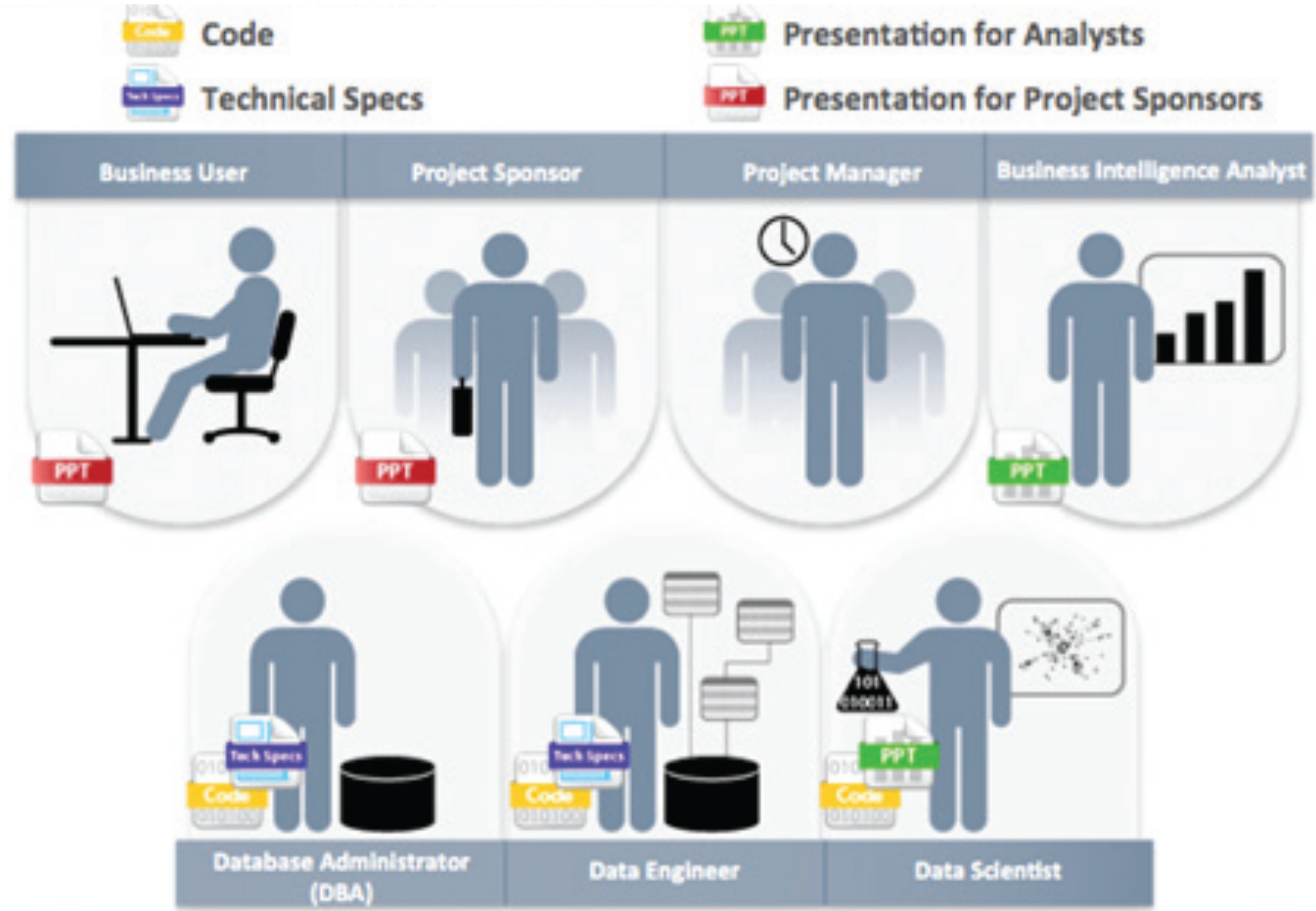
Source: EMC Education Services, Data Science and Big Data Analytics: Discovering, Analyzing, Visualizing and Presenting Data, Wiley, 2015

Key Roles for a Successful Analytics Project



Source: EMC Education Services, Data Science and Big Data Analytics: Discovering, Analyzing, Visualizing and Presenting Data, Wiley, 2015

Key Outputs from a Successful Analytics Project

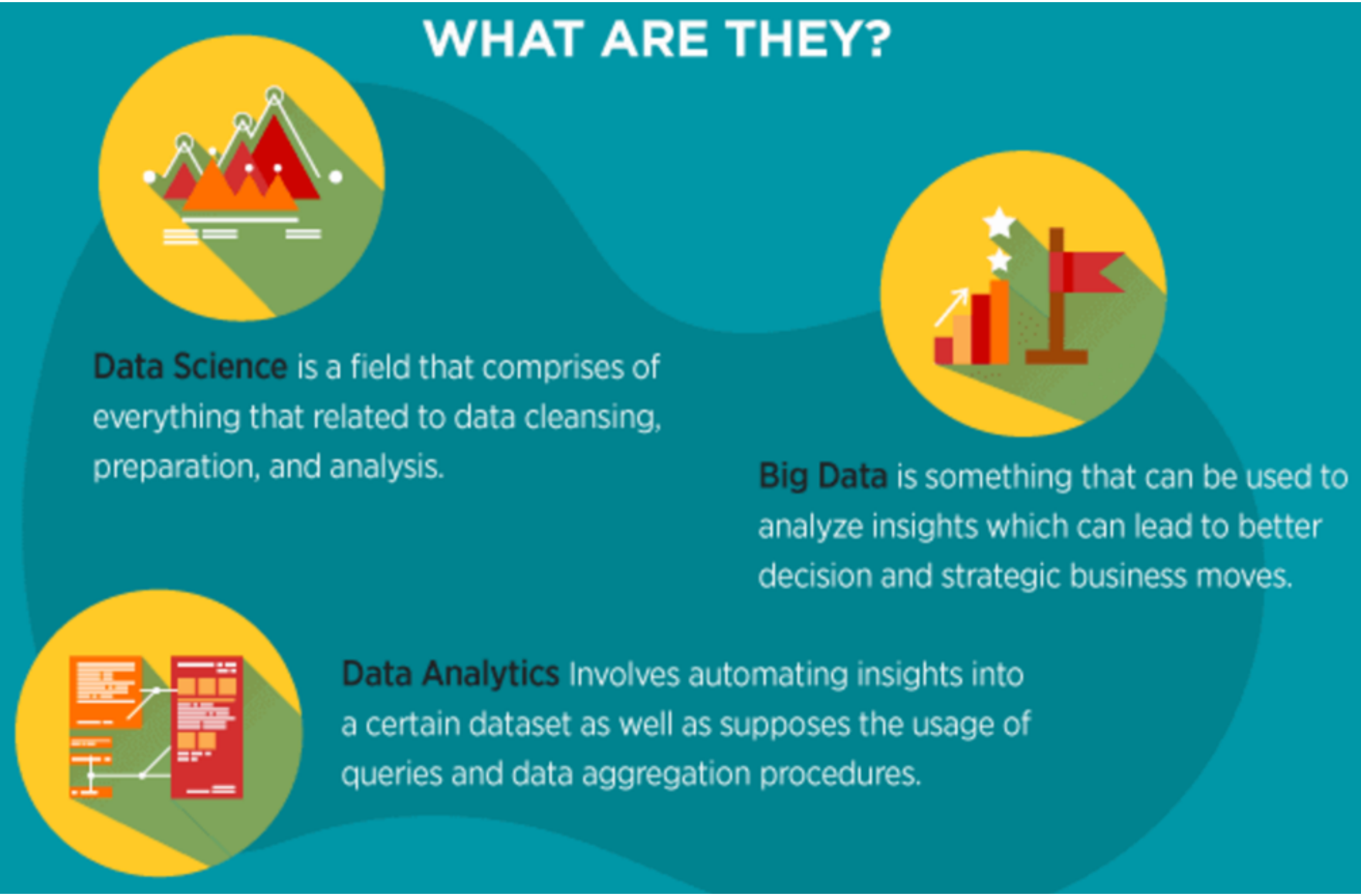


Source: EMC Education Services, Data Science and Big Data Analytics: Discovering, Analyzing, Visualizing and Presenting Data, Wiley, 2015

Data Science vs. Big Data vs. Data Analytics

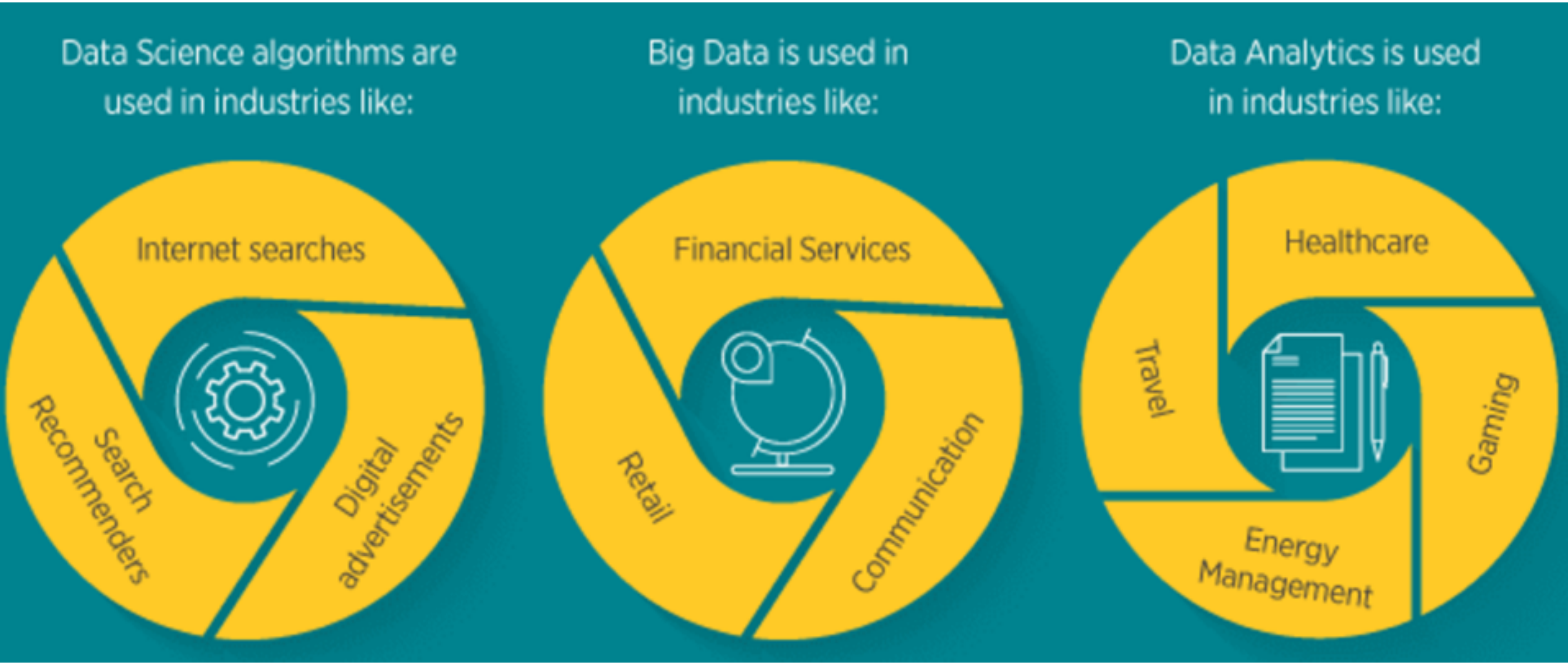
Source: https://www.simplilearn.com/data-science-vs-big-data-vs-data-analytics-article

Data Science vs. Big Data vs. Data Analytics



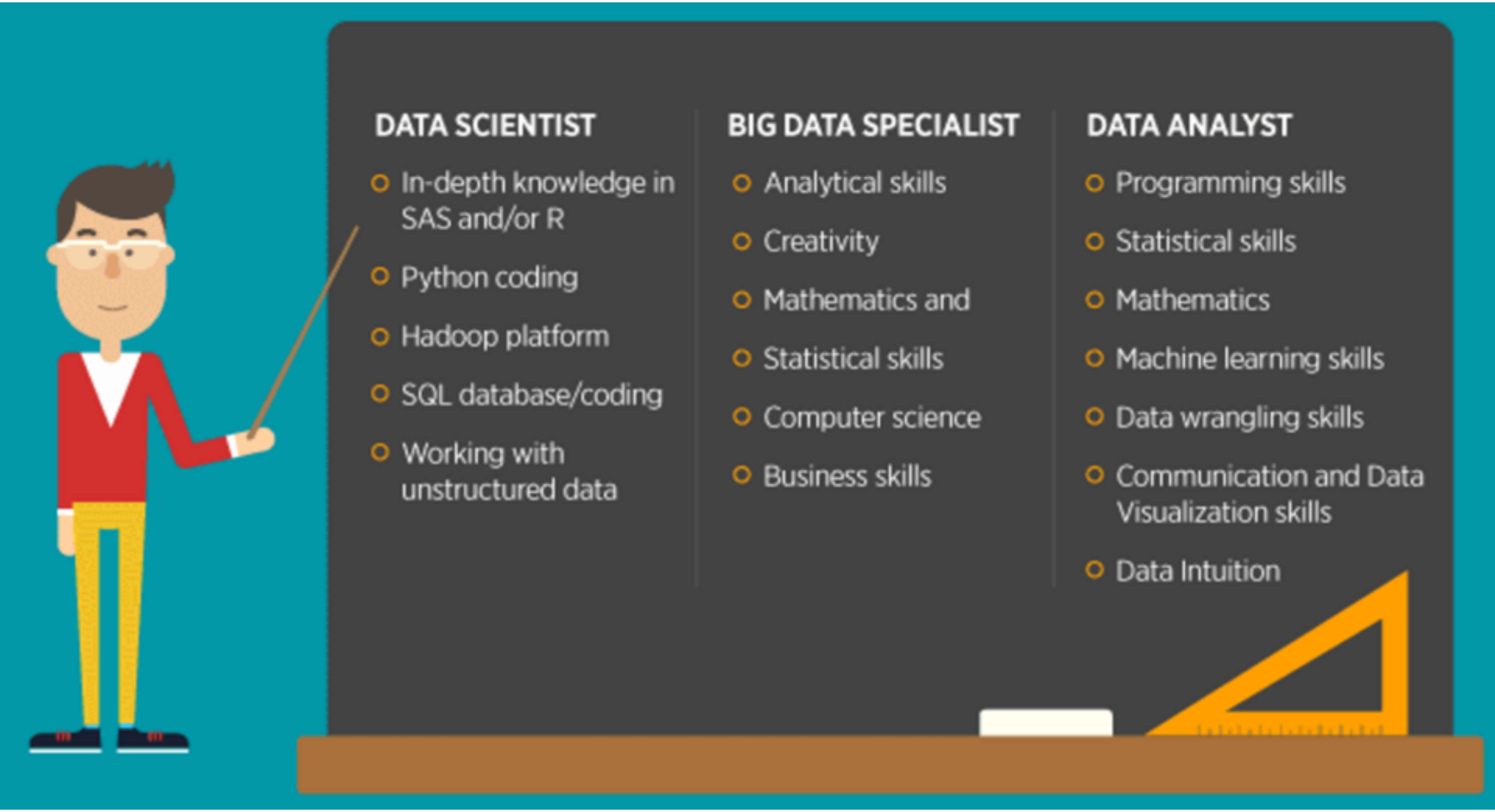
Source: https://www.simplilearn.com/data-science-vs-big-data-vs-data-analytics-article

What are they used?

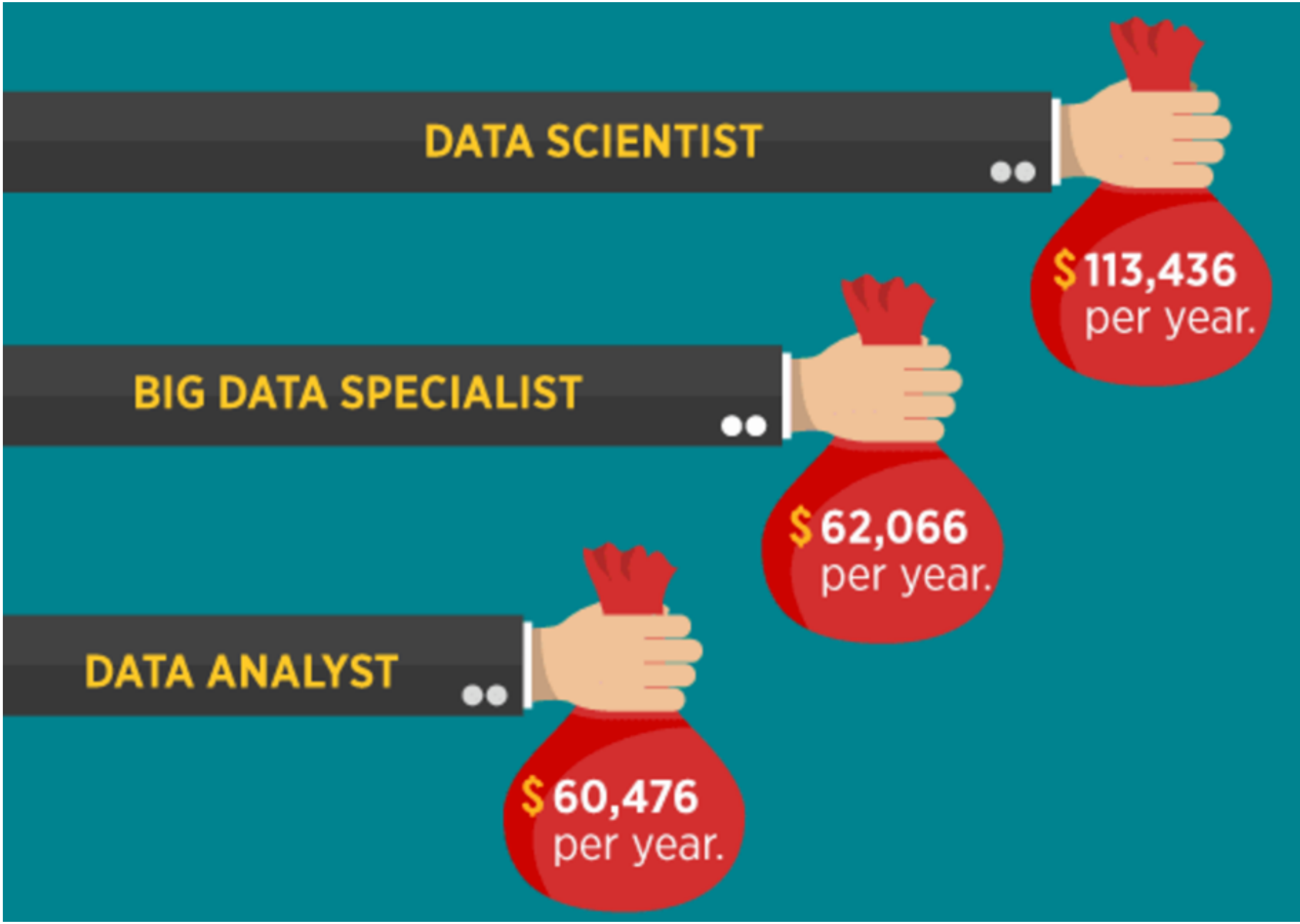


Source: https://www.simplilearn.com/data-science-vs-big-data-vs-data-analytics-article

Data Science
What are the Skills Required?



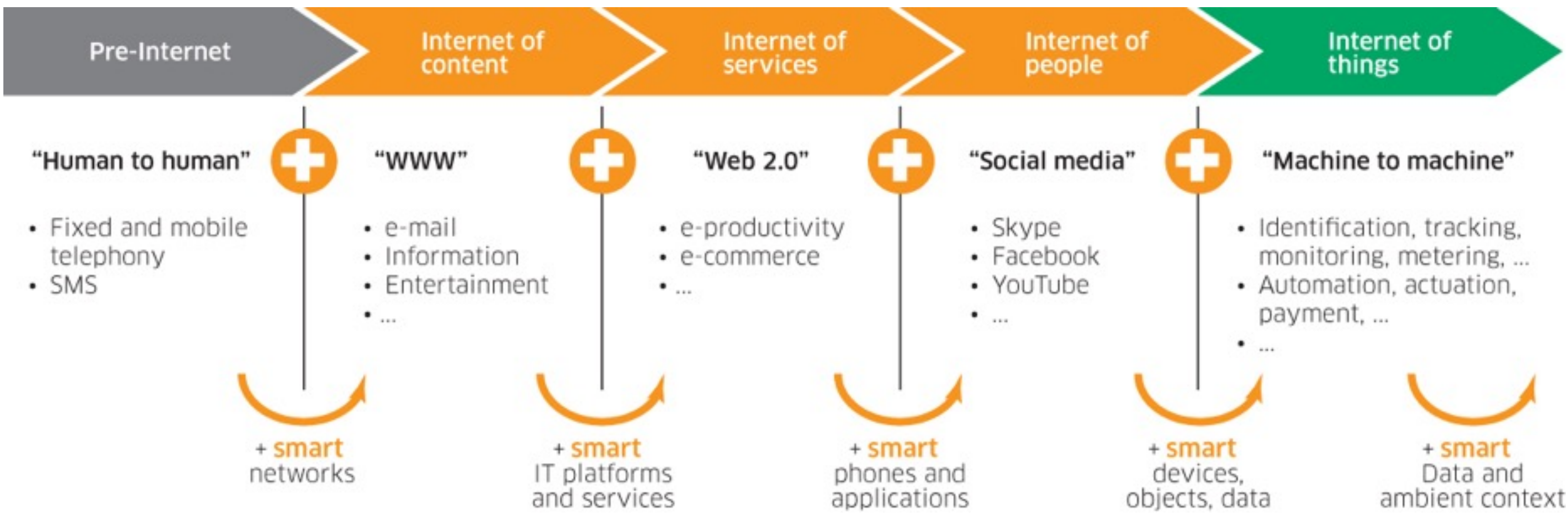
Source: https://www.simplilearn.com/data-science-vs-big-data-vs-data-analytics-article



Source: https://www.simplilearn.com/data-science-vs-big-data-vs-data-analytics-article

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/

Social Media

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

Emotions

Love

Anger

Joy

Sadness

Surprise

Fear

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

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**.

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

+Positive Opinion

(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,

How consumers think, feel, and act

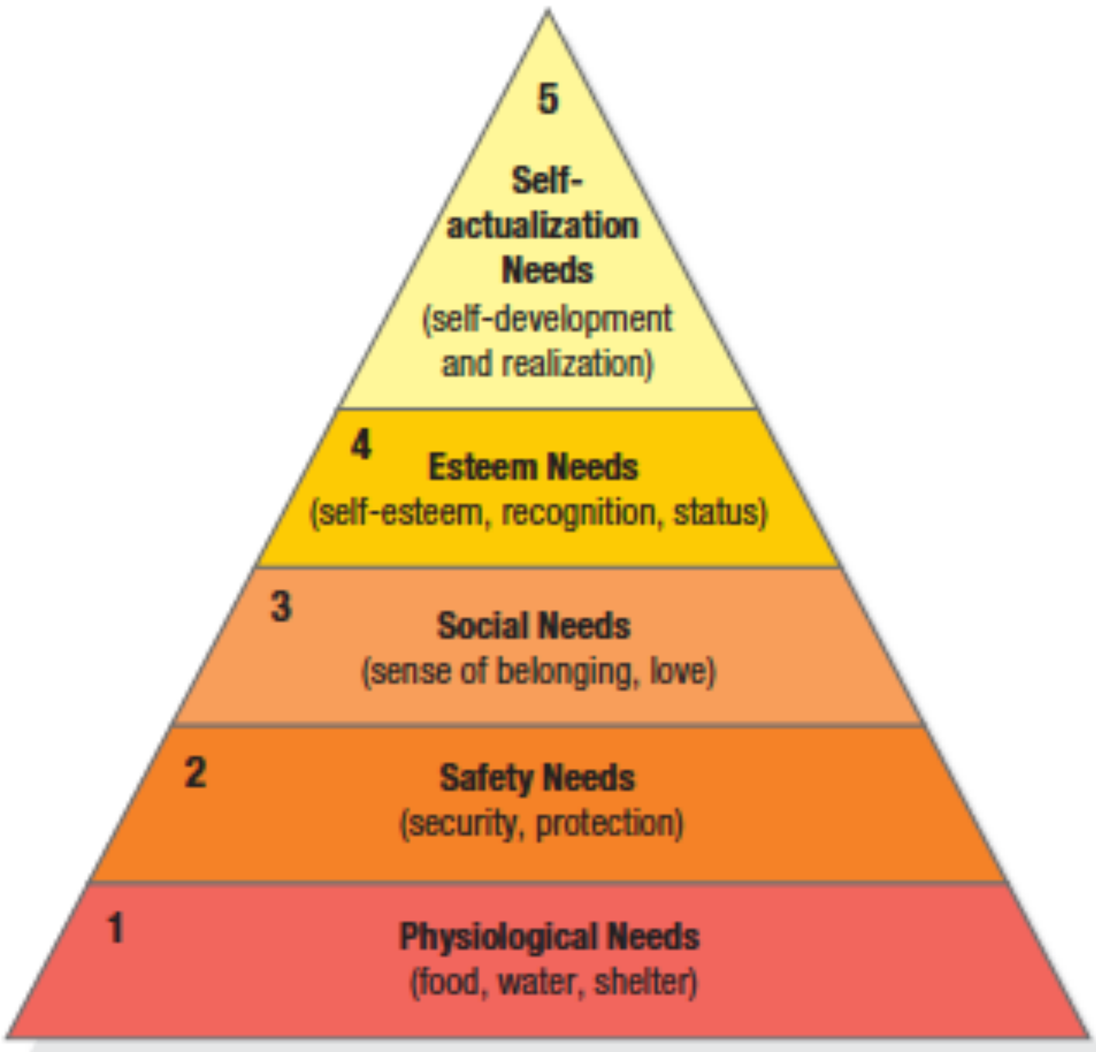
Source: Philip Kotler & Kevin Lane Keller, Marketing Management, 14th ed., Pearson, 2012

Emotions

Love	Anger
Joy	Sadness
Surprise	Fear

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

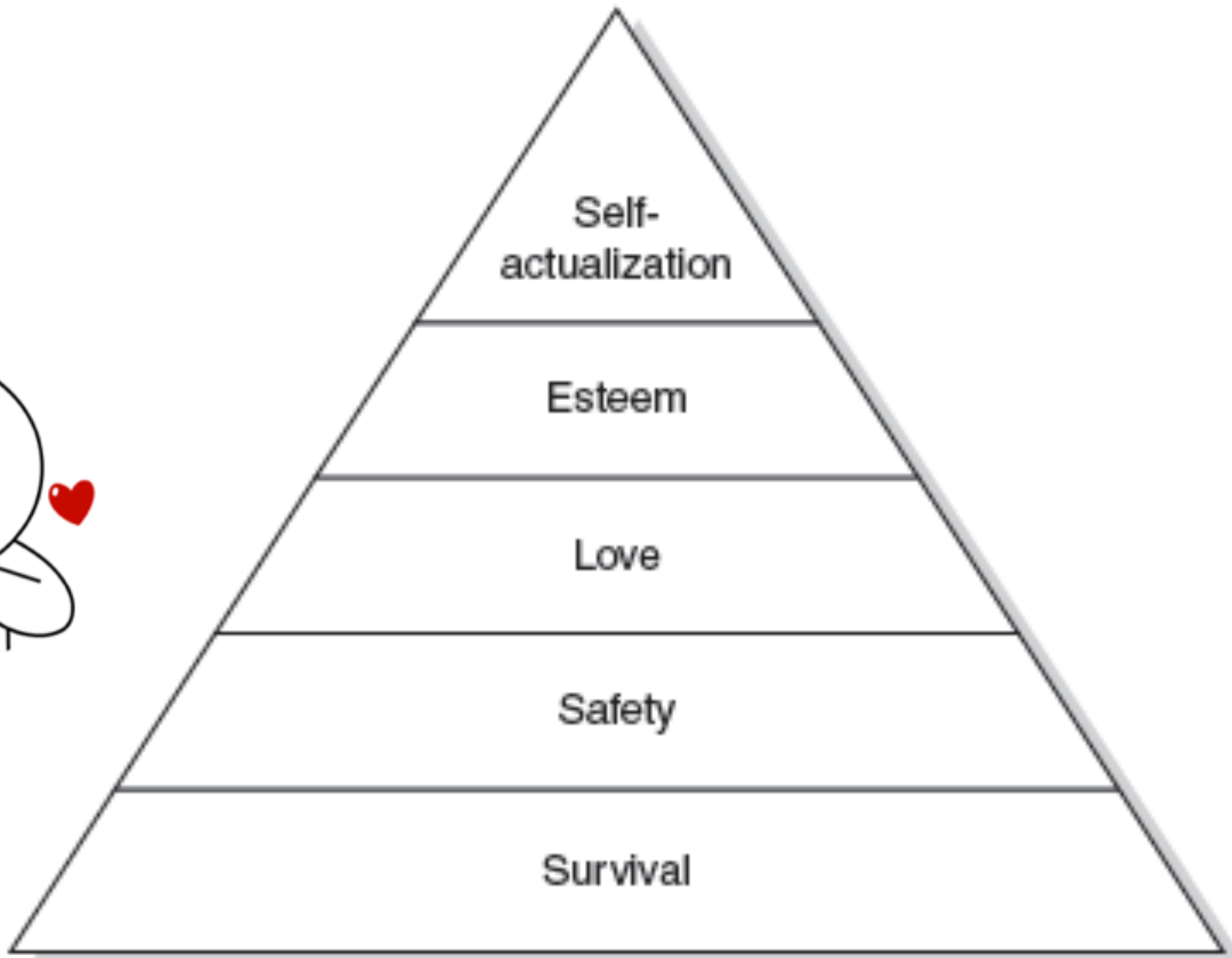
Maslow's Hierarchy of Needs



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

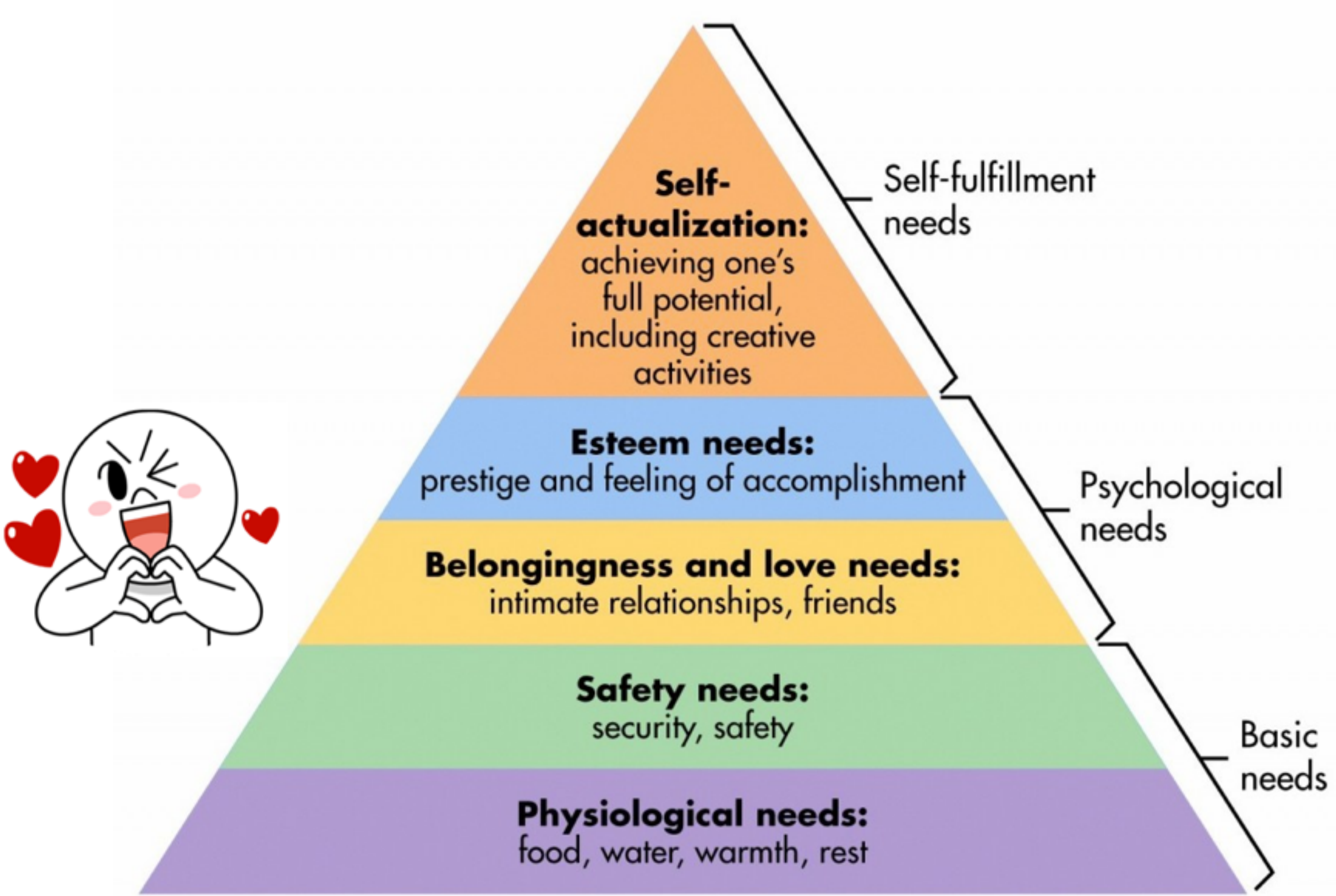
Maslow's hierarchy of human needs

(Maslow, 1943)



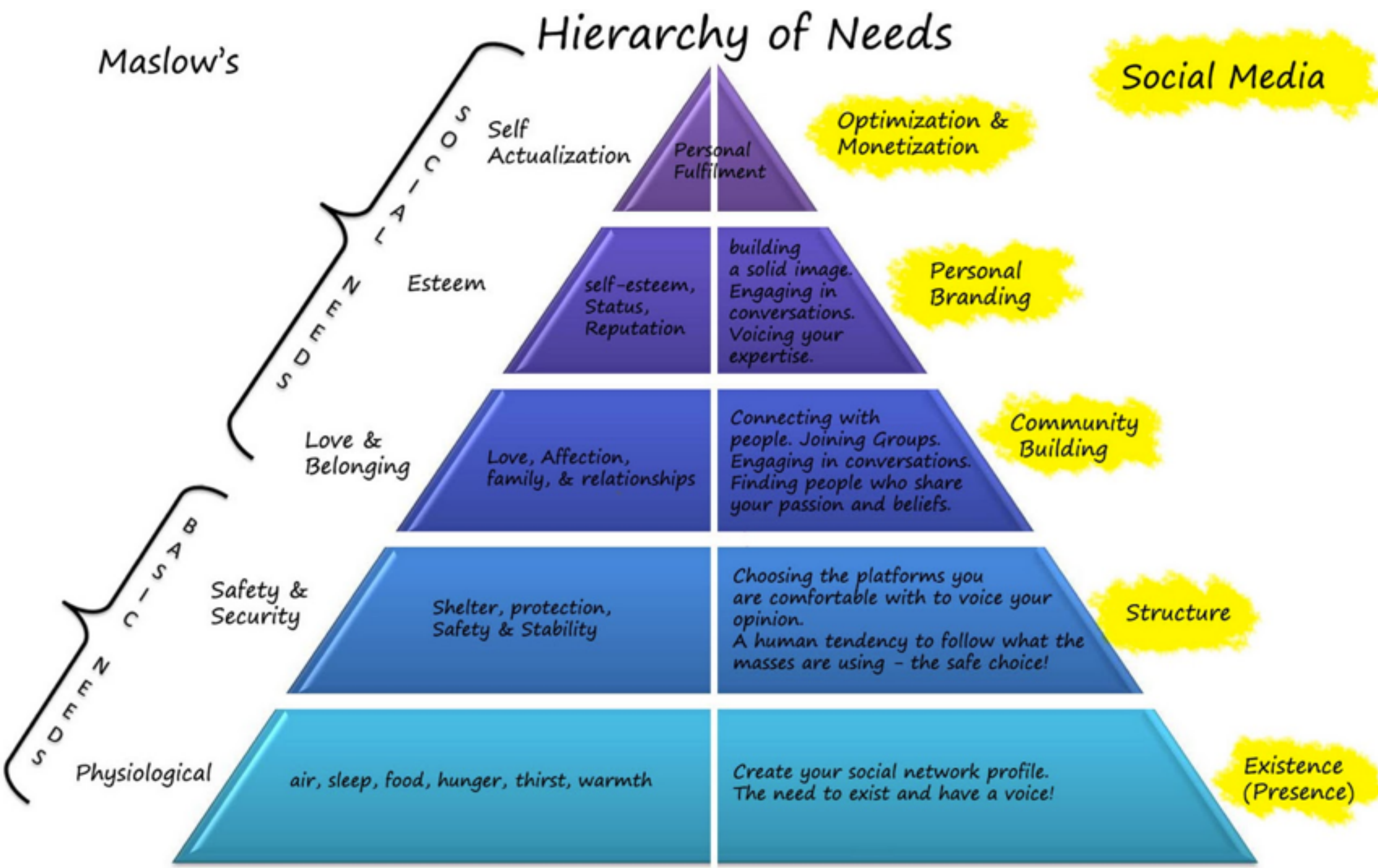
Source: Backer & Saren (2009), Marketing Theory: A Student Text, 2nd Edition, Sage

Maslow's Hierarchy of Needs



Source: http://sixstoriesup.com/social-psyche-what-makes-us-go-social/

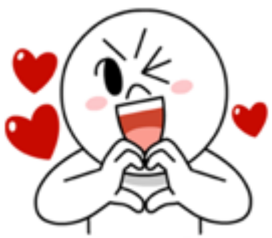
Social Media Hierarchy of Needs

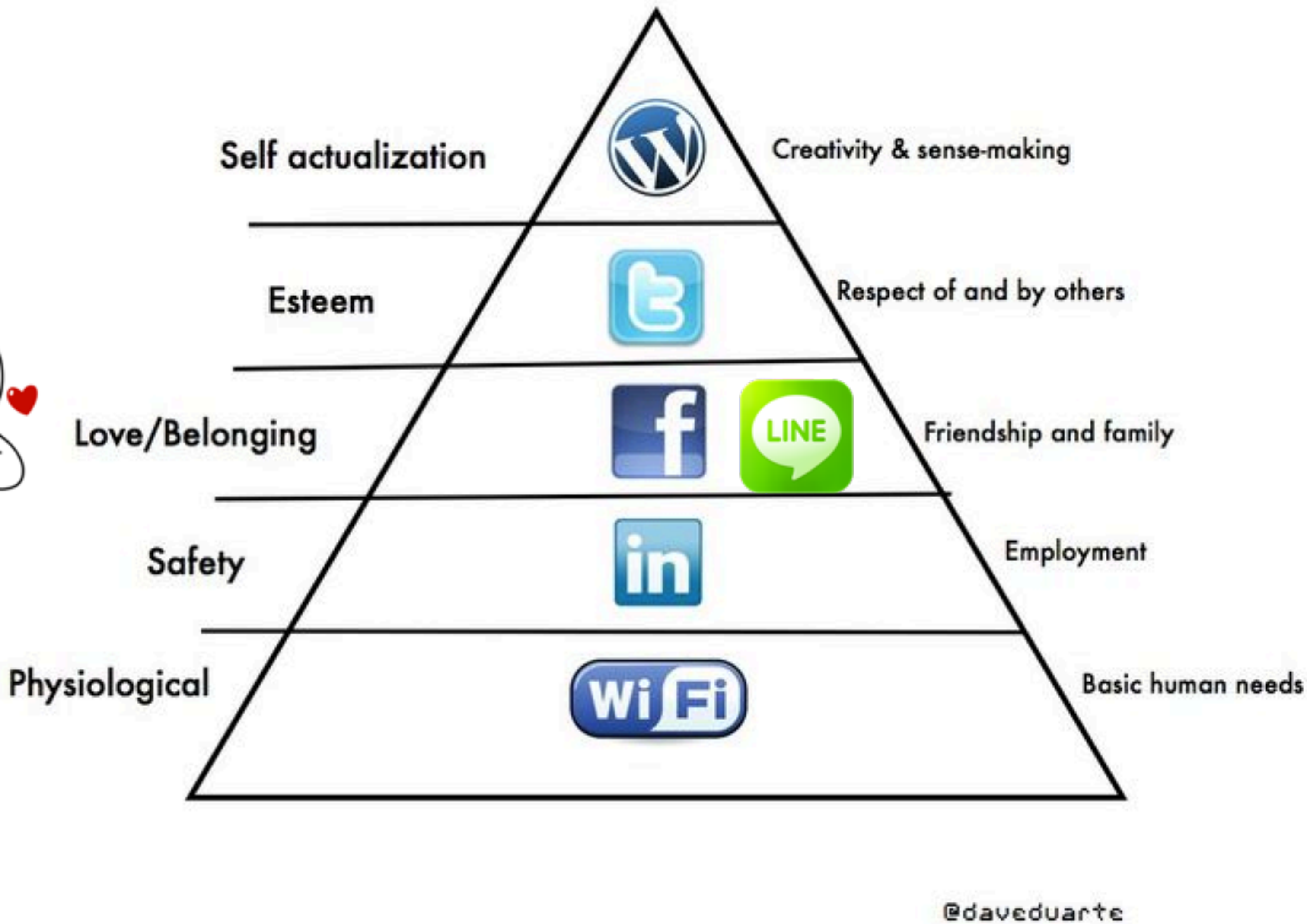


Social Media Hierarchy of Needs - by John Antonios

Source: http://2.bp.blogspot.com/_Rta1VZltiMk/TPavcanFtfI/AAAAAAAAACo/OBGnRL5arSU/s1600/social-media-heirarchy-of-needs1.jpg

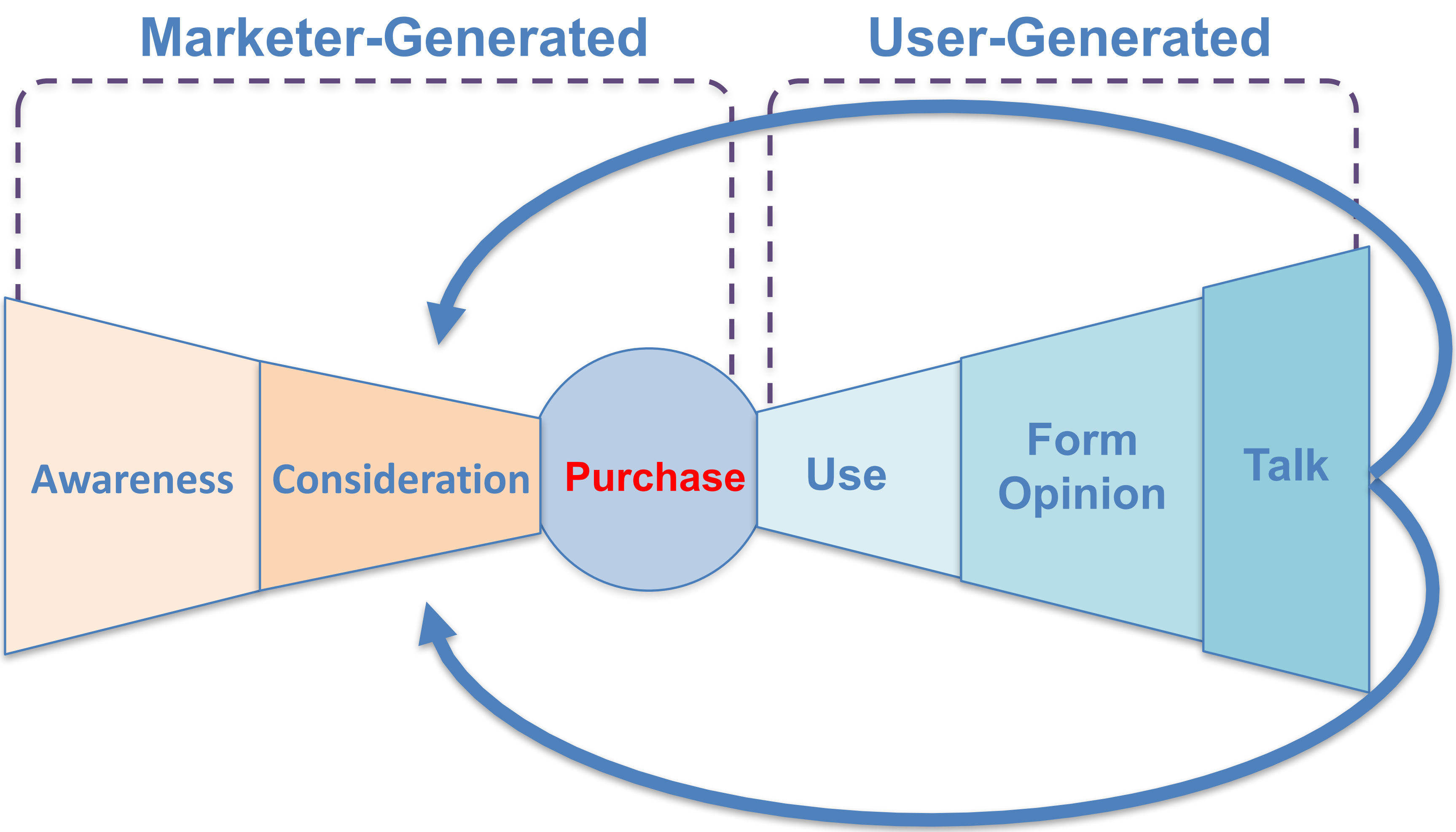
Social Media Hierarchy of Needs





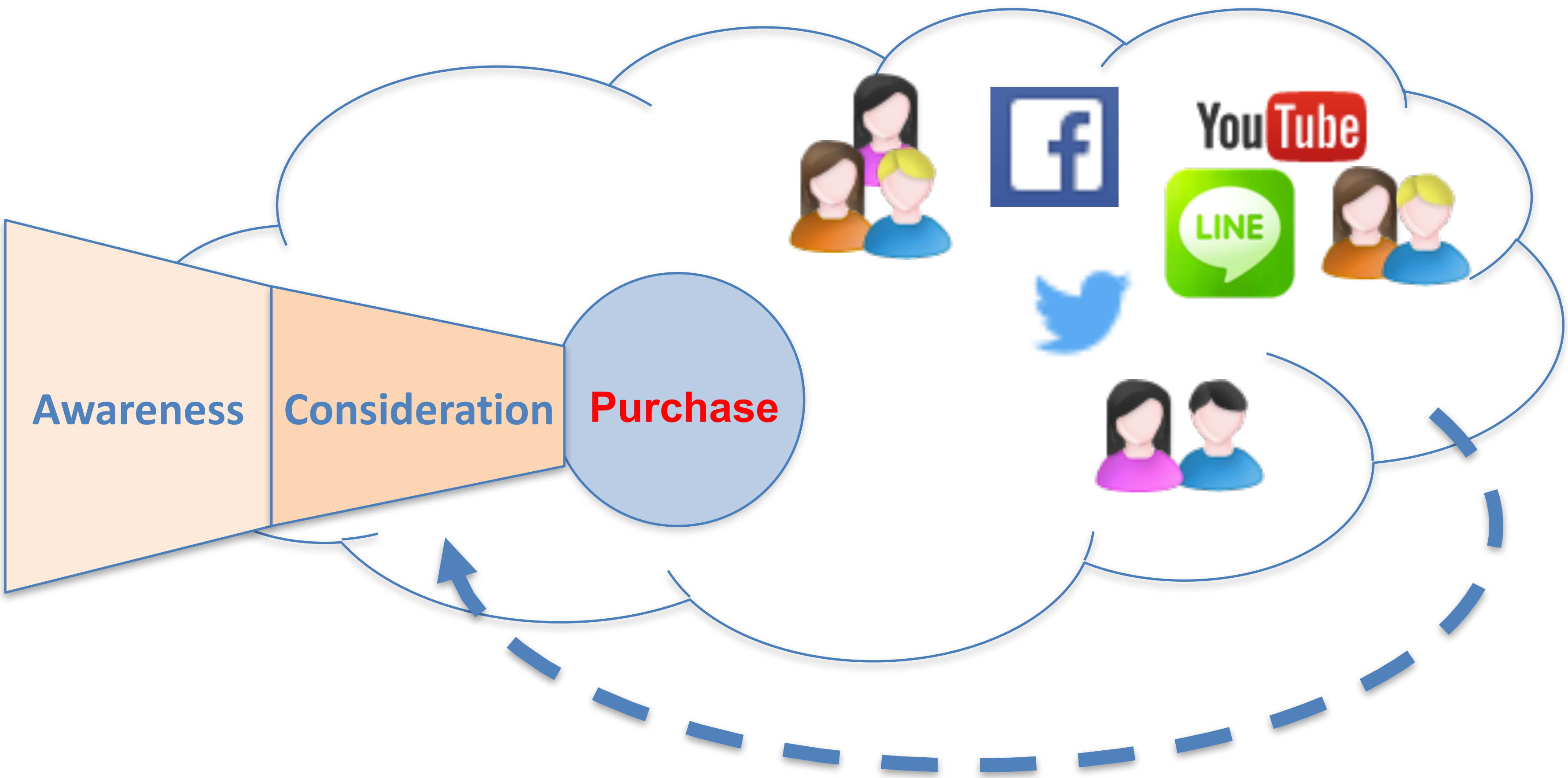
Source: http://www.pinterest.com/pin/186477859309035585/

The Social Feedback Cycle
Consumer Behavior on Social Media



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

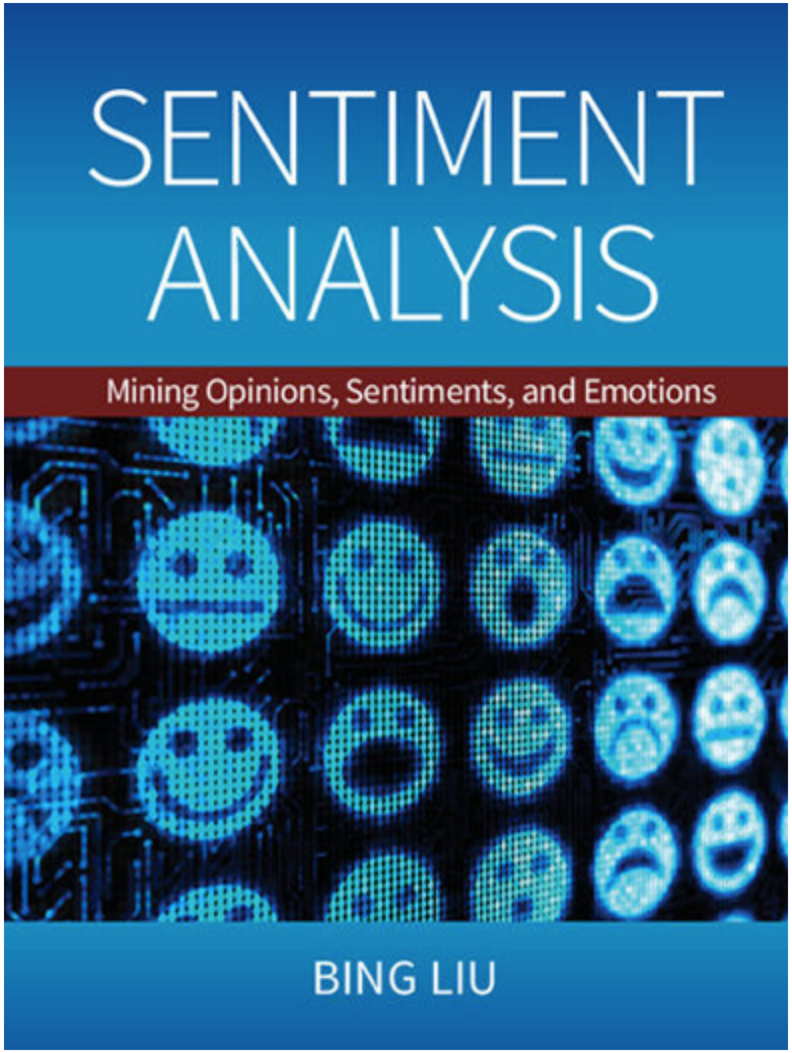
The New Customer Influence Path



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

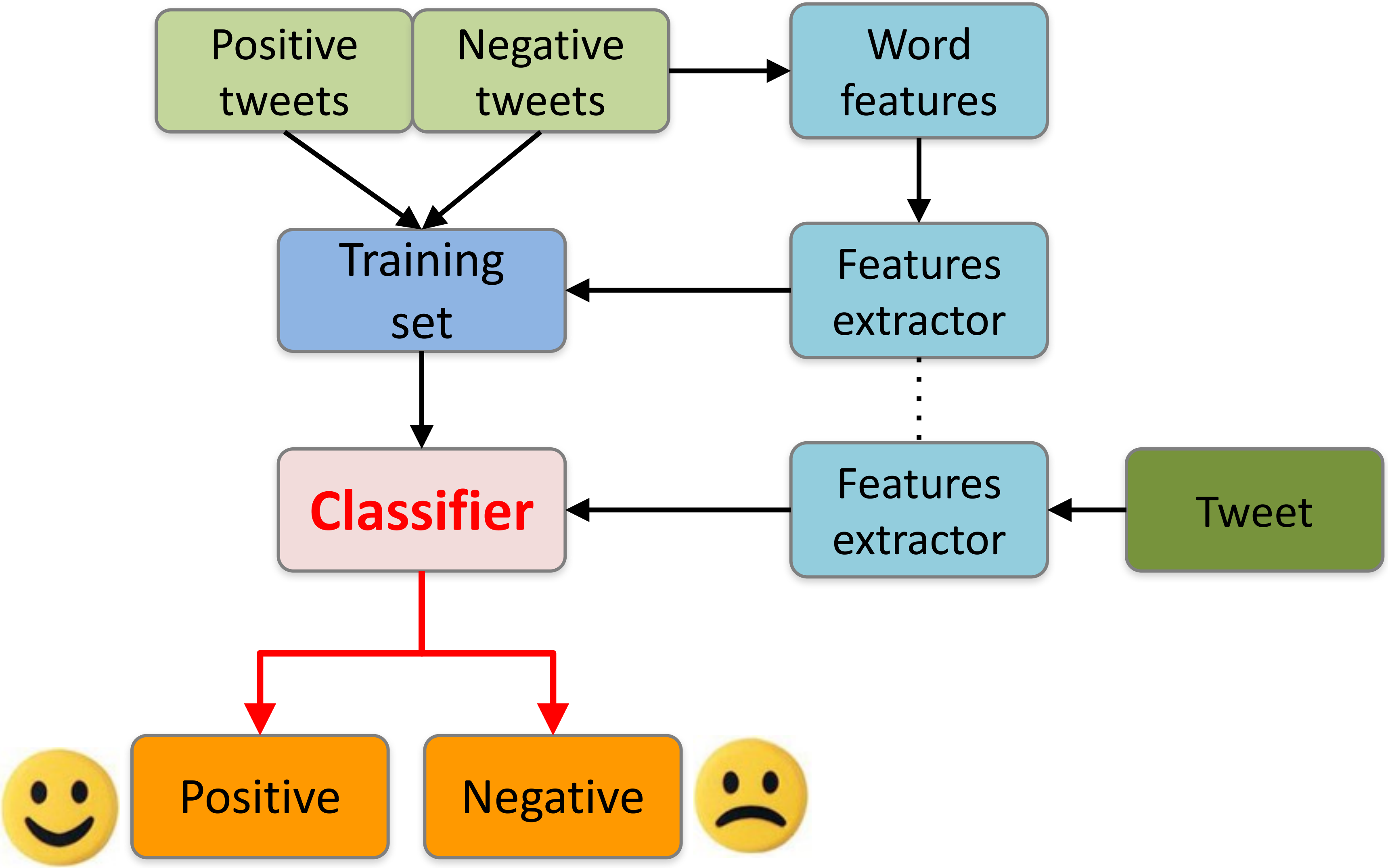
Architectures of Sentiment Analytics

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



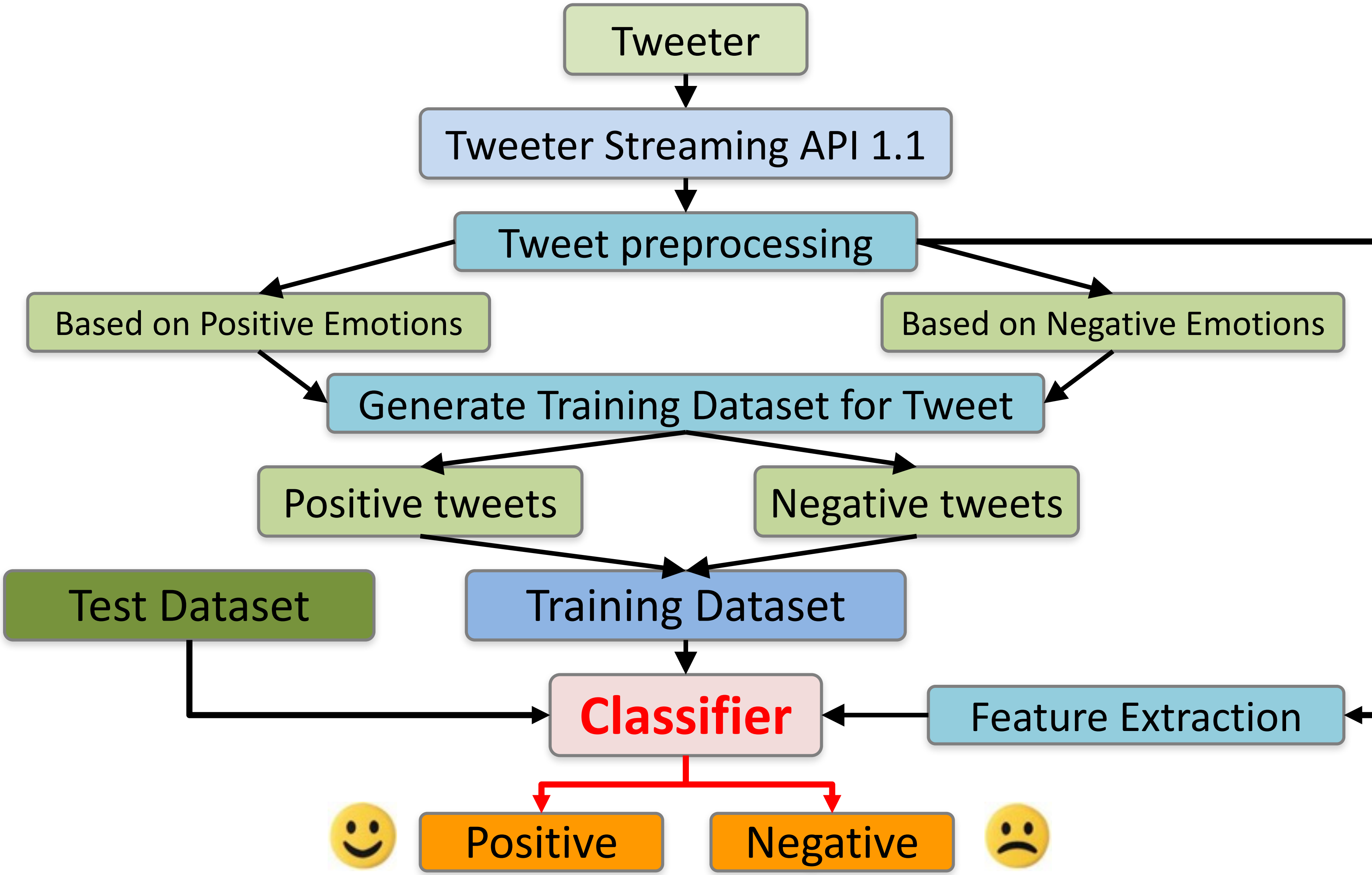
http://www.amazon.com/Sentiment-Analysis-Opinions-Sentiments-Emotions/dp/1107017890

Sentiment Analysis Architecture



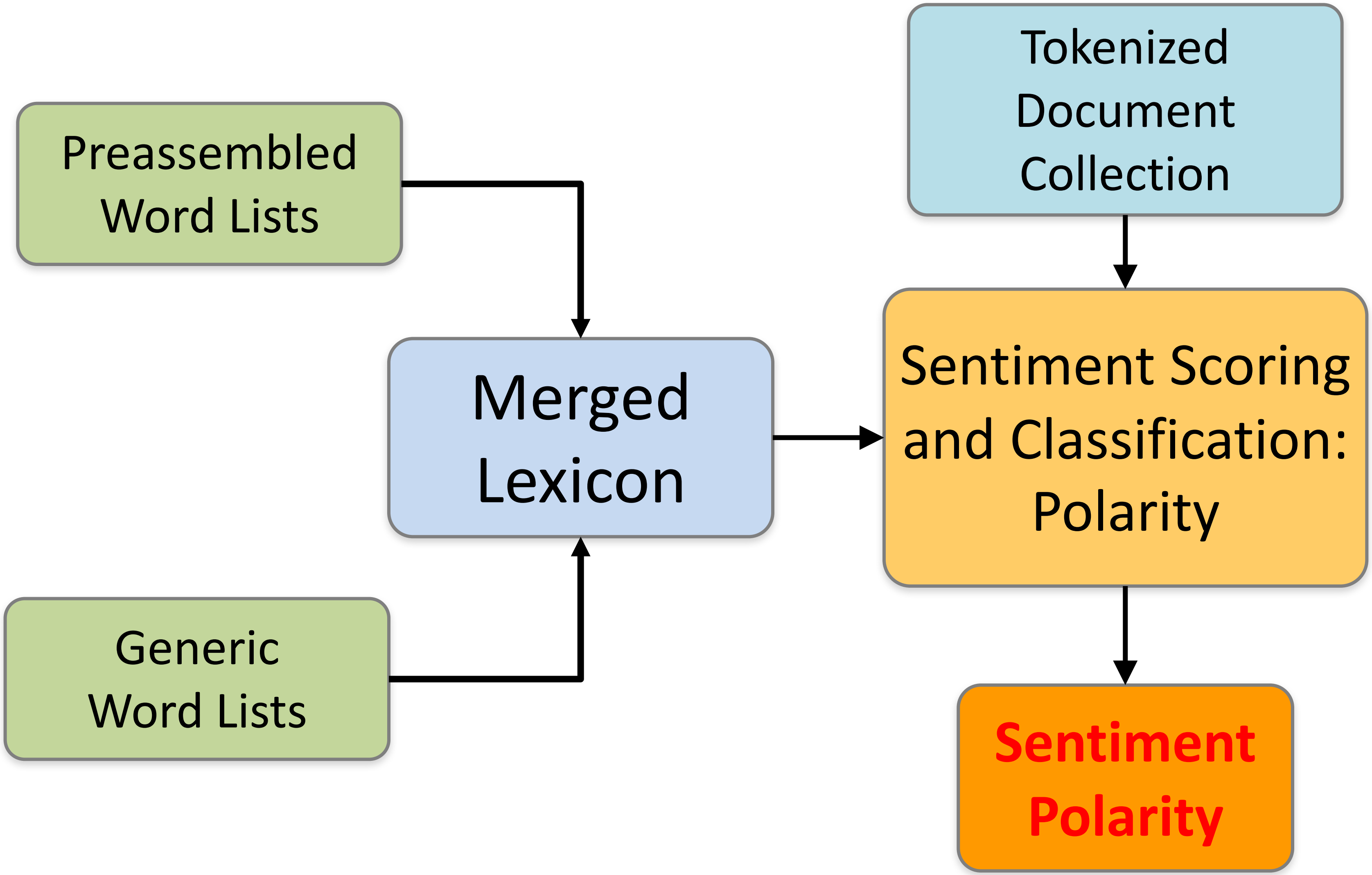
Vishal Kharde and Sheetal Sonawane (2016), "Sentiment Analysis of Twitter Data: A Survey of Techniques," International Journal of Computer Applications, Vol 139, No. 11, 2016. pp.5-15

Sentiment Classification Based on Emoticons



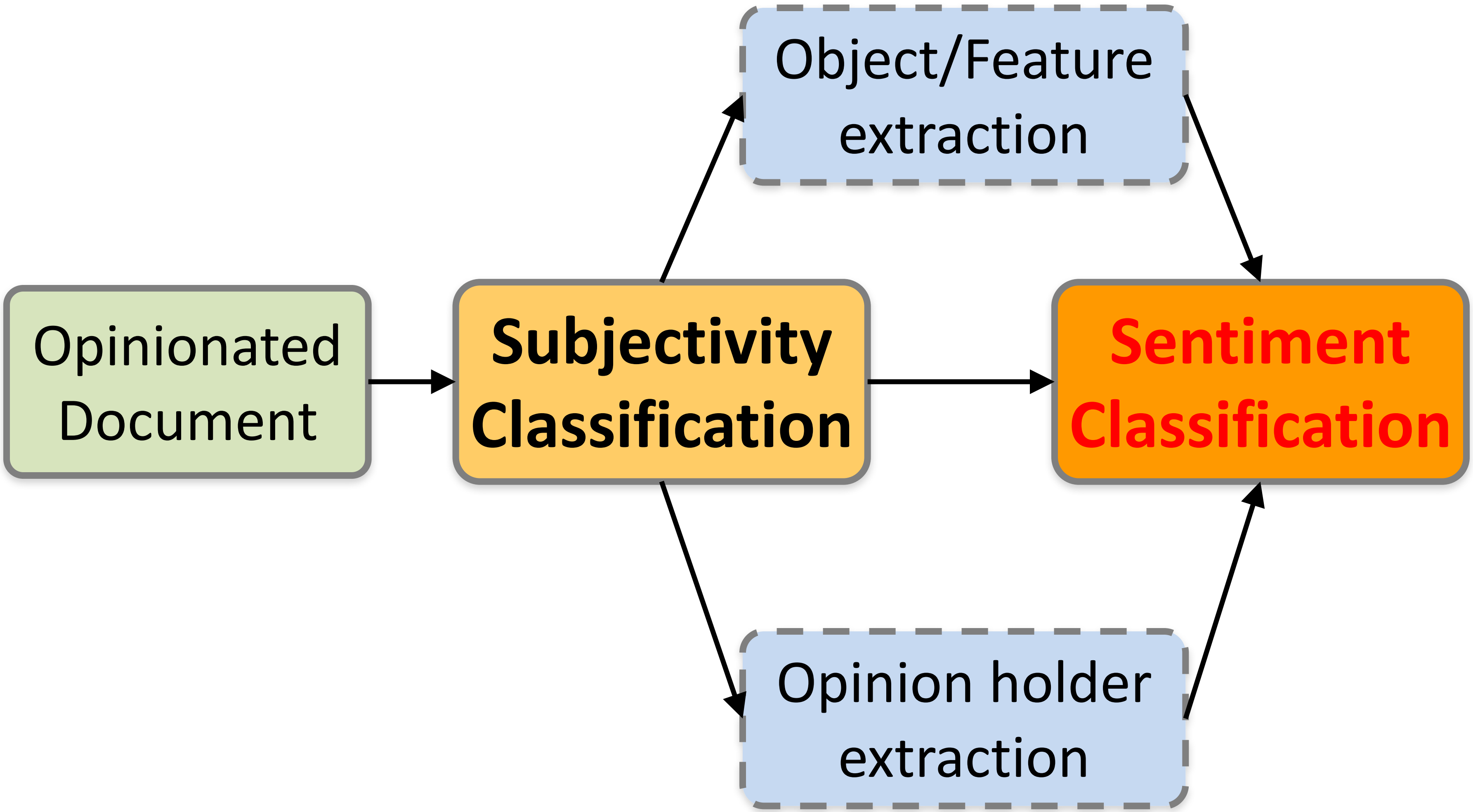
Vishal Kharde and Sheetal Sonawane (2016), "Sentiment Analysis of Twitter Data: A Survey of Techniques," International Journal of Computer Applications, Vol 139, No. 11, 2016. pp.5-15

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

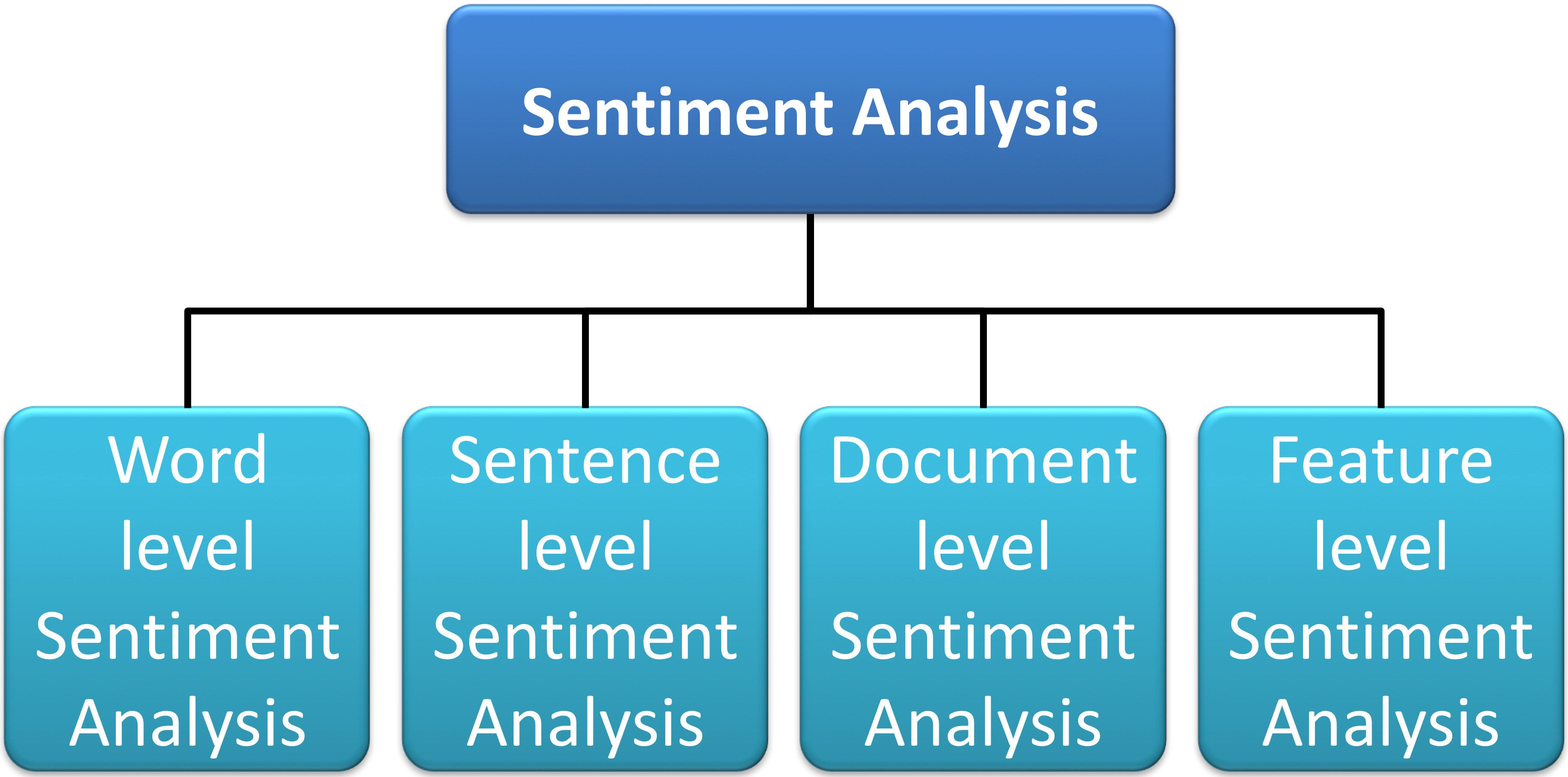


Vishal Kharde and Sheetal Sonawane (2016), "Sentiment Analysis of Twitter Data: A Survey of Techniques," International Journal of Computer Applications, Vol 139, No. 11, 2016. pp.5-15

Sentiment Analysis vs. Subjectivity Analysis

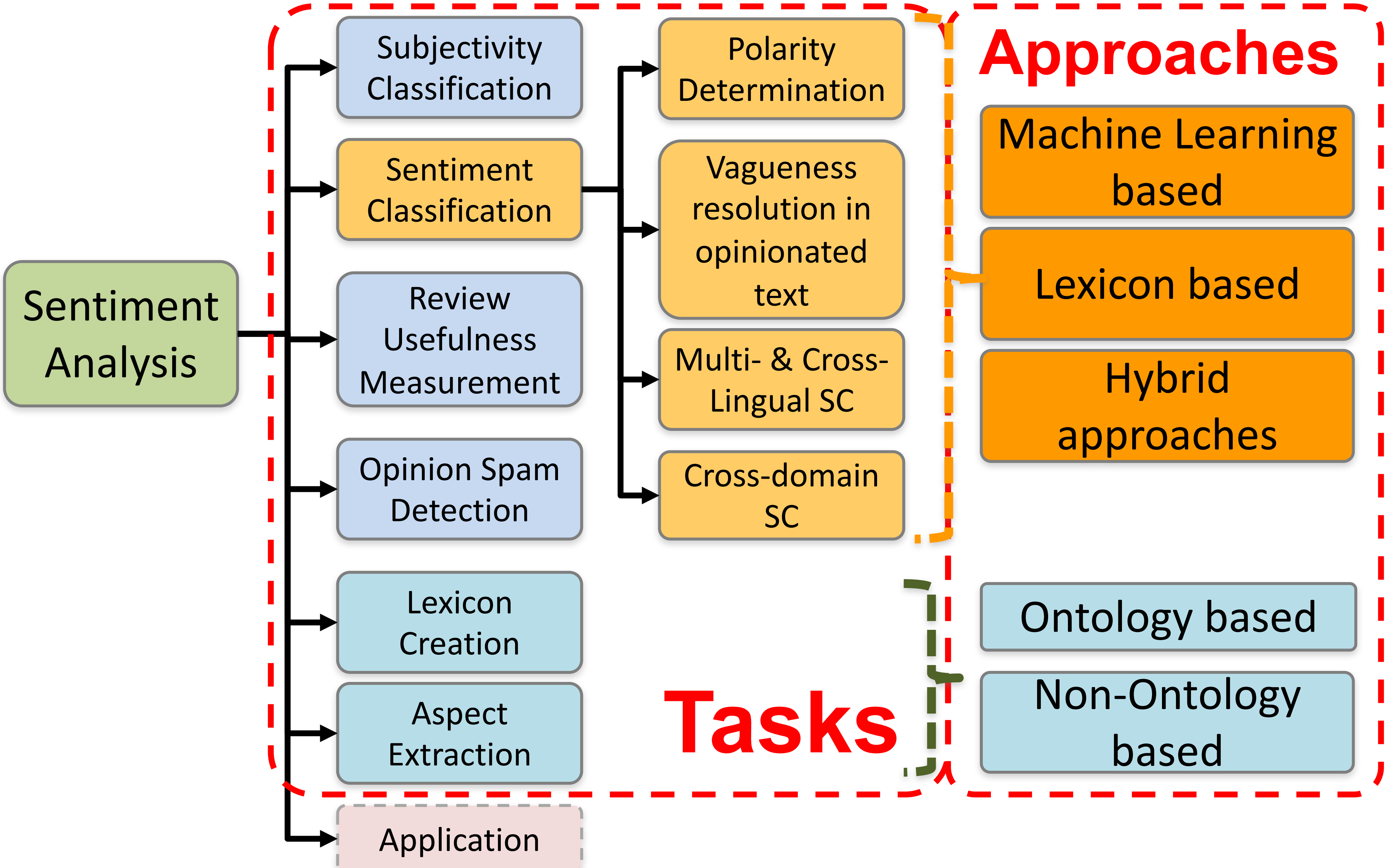
<table>
<tr><th>Sentiment Analysis</th><th>Subjectivity Analysis</th></tr>
<tr><td>Positive</td><td rowspan="2">Subjective</td></tr>
<tr><td>Negative</td></tr>
<tr><td>Neutral</td><td>Objective</td></tr>
</table>

Levels of Sentiment Analysis



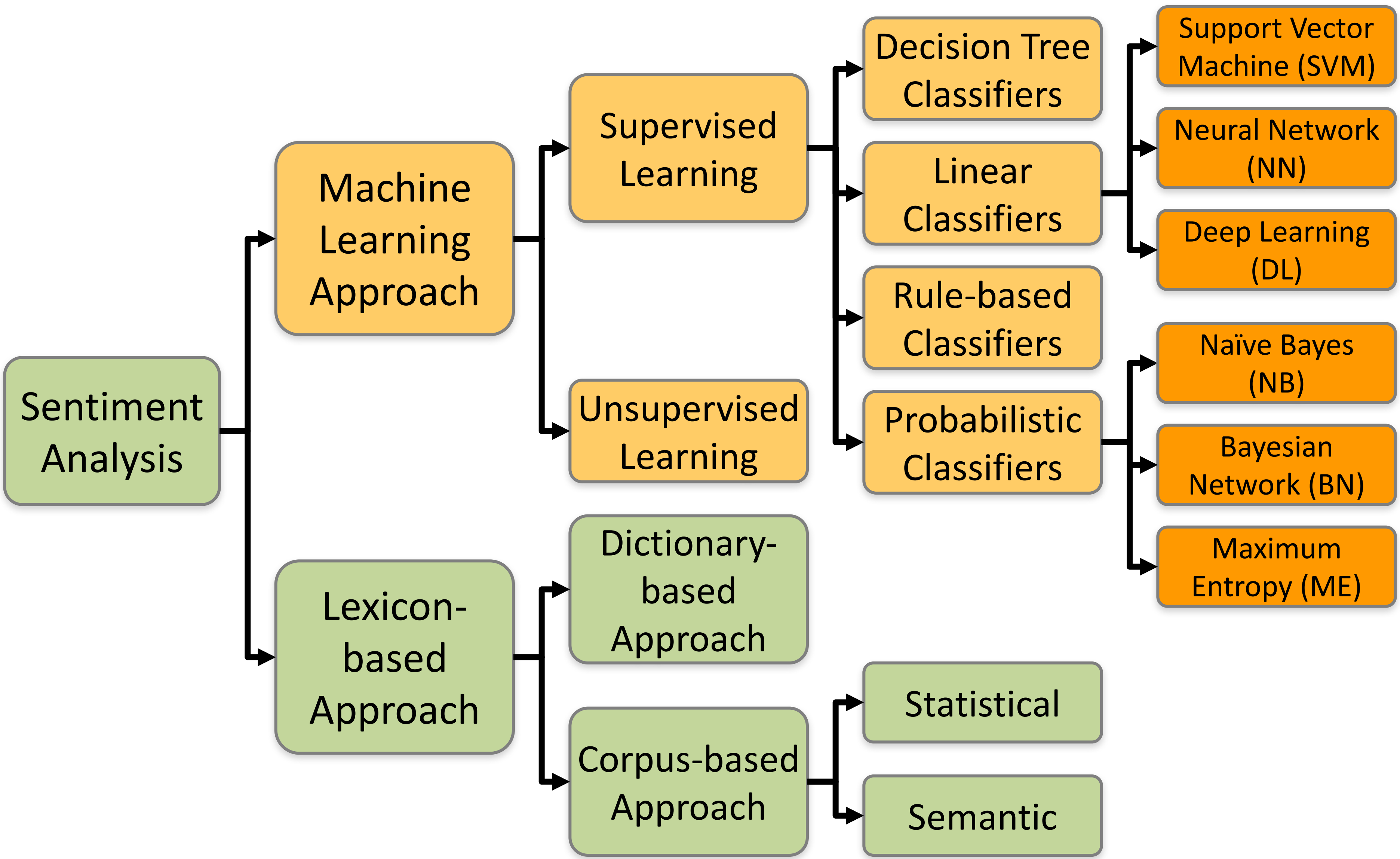
Vishal Kharde and Sheetal Sonawane (2016), "Sentiment Analysis of Twitter Data: A Survey of Techniques," International Journal of Computer Applications, Vol 139, No. 11, 2016. pp.5-15

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.

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,

Sentiment Analysis

- Sentiment
  - A thought, view, or attitude, especially one based mainly on emotion instead of reason
- Sentiment Analysis
  - opinion mining
  - use of natural language processing (NLP) and computational techniques to automate the extraction or classification of sentiment from typically unstructured text

Applications of Sentiment Analysis

- Consumer information
  - Product reviews
- Marketing
  - Consumer attitudes
  - Trends
- Politics
  - Politicians want to know voters’ views
  - Voters want to know policitians’ stances and who else supports them
- Social
  - Find like-minded individuals or communities

Sentiment detection

- How to interpret features for sentiment detection?
  - Bag of words (IR)
  - Annotated lexicons (WordNet, SentiWordNet)
  - Syntactic patterns
- Which features to use?
  - Words (unigrams)
  - Phrases/n-grams
  - Sentences

Problem statement of Opinion Mining

- Two aspects of abstraction
  - Opinion definition
    - What is an opinion?
    - What is the structured definition of opinion?
  - Opinion summarization
    - Opinion are subjective
      - An opinion from a single person (unless a VIP) is often not sufficient for action
    - We need opinions from many people, and thus opinion summarization.

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

What is an opinion?

- Id: **Abc123** on **5-1-2008** "*I bought an iPhone a few days ago. It is such a nice phone. The touch screen is really cool. The voice quality is clear too. It is much better than my old Blackberry, which was a terrible phone and so difficult to type with its tiny keys. However, my mother was mad with me as I did not tell her before I bought the phone. She also thought the phone was too expensive, …*"
- One can look at this review/blog at the
  - Document level
    - Is this review + or -?
  - Sentence level
    - Is each sentence + or -?
  - Entity and feature/aspect level

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

Entity and aspect/feature level

- Id: **Abc123** on **5-1-2008** "*I bought an iPhone a few days ago. It is such a nice phone. The touch screen is really cool. The voice quality is clear too. It is much better than my old Blackberry, which was a terrible phone and so difficult to type with its tiny keys. However, my mother was mad with me as I did not tell her before I bought the phone. She also thought the phone was too expensive*, …"
- What do we see?
  - Opinion targets: entities and their features/aspects
  - Sentiments: positive and negative
  - Opinion holders: persons who hold the opinions
  - Time: when opinion are expressed

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

Two main types of opinions

- Regular opinions: Sentiment/Opinion expressions on some target entities
  - Direct opinions: sentiment expressions on one object:
    - “The touch screen is really cool.”
    - “The picture quality of this camera is great”
  - Indirect opinions: comparisons, relations expressing similarities or differences (objective or subjective) of more than one object
    - “phone X is cheaper than phone Y.” (objective)
    - “phone X is better than phone Y.” (subjective)
- Comparative opinions: comparisons of more than one entity.
  - “iPhone is better than Blackberry.”

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

Subjective and Objective

- Objective
  - An objective sentence expresses some factual information about the world.
  - “I returned the phone yesterday.”
  - Objective sentences can implicitly indicate opinions
    - “The earphone broke in two days.”
- Subjective
  - A subjective sentence expresses some personal feelings or beliefs.
  - “The voice on my phone was not so clear”
  - Not every subjective sentence contains an opinion
    - “I wanted a phone with good voice quality”
- ➔ Subjective analysis

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

Sentiment Analysis vs. Subjectivity Analysis

Sentiment Analysis	Subjectivity Analysis
Positive	Subjective
Negative	
Neutral	Objective

A (regular) opinion

- Opinion (a restricted definition)
  - An opinion (regular opinion) is simply a positive or negative sentiment, view, attitude, emotion, or appraisal about an entity or an aspect of the entity from an opinion holder.
- Sentiment orientation of an opinion
  - Positive, negative, or neutral (no opinion)
  - Also called:
    - Opinion orientation
    - Semantic orientation
    - Sentiment polarity

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

Entity and aspect

- Definition of Entity:
  - An *entity e* is a product, person, event, organization, or topic.
  - e is represented as
    - A hierarchy of components, sub-components.
    - Each node represents a components and is associated with a set of attributes of the components
- An opinion can be expressed on any node or attribute of the node
- Aspects(features)
  - represent both components and attribute

Opinion Definition

- An opinion is a quintuple
  $(e_j, a_{jk}, so_{ijkl}, h_i, t_l)$
  where
  - e_j is a target entity.
  - a_{jk} is an aspect/feature of the entity e_j .
  - so_{ijkl} is the sentiment value of the opinion from the opinion holder on feature of entity at time.
    so_{ijkl} is +ve, -ve, or neu, or more granular ratings
  - h_i is an opinion holder.
  - t_l is the time when the opinion is expressed.
- (e_j, a_{jk}) is also called opinion target

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

Terminologies

- Entity: object
- Aspect: feature, attribute, facet
- Opinion holder: opinion source

- Topic: entity, aspect

- Product features, political issues

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

Subjectivity and Emotion

- Sentence subjectivity
  - An objective sentence presents some factual information, while a subjective sentence expresses some personal feelings, views, emotions, or beliefs.
- Emotion
  - Emotions are people's subjective feelings and thoughts.

Classification Based on Supervised Learning

- Sentiment classification
  - Supervised learning Problem
  - Three classes
    - *Positive*
    - *Negative*
    - *Neutral*

Opinion words in Sentiment classification

- topic-based classification
  - topic-related words are important
    - e.g., *politics, sciences, sports*
- Sentiment classification
  - topic-related words are unimportant
  - **opinion words** (also called **sentiment words)**
    - **that indicate positive or negative opinions** are important,
      e.g., *great, excellent, amazing, horrible, bad, worst*

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

Features in Opinion Mining

- *Terms and their frequency*
  - *TF-IDF*
- *Part of speech (POS)*
  - Adjectives
- *Opinion words and phrases*
  - *beautiful, wonderful, good, and amazing are positive opinion words*
  - *bad, poor, and terrible are negative opinion words.*
  - opinion phrases and idioms,
    e.g., *cost someone an arm and a leg*
- *Rules of opinions*
- *Negations*
- *Syntactic dependency*

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

A Brief Summary of Sentiment Analysis Methods

Study	Analysis Task	Sentiment Identification		Sentiment Aggregation		Nature of Measure
		Method	Level	Method	Level	
Hu and Li, 2011	Polarity	ML (Probabilistic model)	Snippet			Valence
Li and Wu, 2010	Polarity	Lexicon/Rule	Phrase	Sum	Snippet	Valence
Thelwall et al., 2010	Polarity	Lexicon/Rule	Sentence	Max & Min	Snippet	Range
Boiy and Moens, 2009	Both	ML (Cascade ensemble)	Sentence			Valence
Chung 2009	Polarity	Lexicon	Phrase	Average	Sentence	Valence
Wilson, Wiebe, and Hoffmann, 2009	Both	ML (SVM, AdaBoost, Rule, etc.)	Phrase			Valence
Zhang et al., 2009	Polarity	Lexicon/Rule	Sentence	Weighted average	Snippet	Valence
Abbasi, Chen, and Salem, 2008	Polarity	ML (GA + feature selection)	Snippet			Valence
Subrahmanian and Reforgiato, 2008	Polarity	Lexicon/Rule	Phrase	Rule	Snippet	Valence
Tan and Zhang 2008	Polarity	ML (SVM, Winnow, NB, etc.)	Snippet			Valence
Airoldi, Bai, and Padman, 2007	Polarity	ML (Markov Blanket)	Snippet			Valence
Das and Chen, 2007	Polarity	ML (Bayesian, Discriminate, etc.)	Snippet	Average	Daily	Valence
Liu et al., 2007	Polarity	ML (PLSA)	Snippet			Valence
Kennedy and Inkpen, 2006	Polarity	Lexicon/Rule, ML (SVM)	Phrase	Count	Snippet	Valence
Mishne 2006	Polarity	Lexicon	Phrase	Average	Snippet	Valence
Liu et al., 2005	Polarity	Lexicon/Rule	Phrase	Distribution	Object	Range
Mishne 2005	Polarity	ML (SVM)	Snippet			Valence
Popescu and Etzioni 2005	Polarity	Lexicon/Rule	Phrase			Valence
Efron 2004	Polarity	ML (SVN, NB)	Snippet			Valence
Wilson, Wiebe, and Hwa, 2004	Both	ML (SVM, AdaBoost, Rule, etc.)	Sentence			Valence
Nigam and Hurst 2004	Polarity	Lexicon/Rule	Chunk	Rule	Sentence	Valence
Dave, Lawrence, and Pennock, 2003	Polarity	ML (SVM, Rainbow, etc.)	Snippet			Valence
Nasukawa and Yi 2003	Polarity	Lexicon/Rule	Phrase	Rule	Sentence	Valence
Yi et al., 2003	Polarity	Lexicon/Rule	Phrase	Rule	Sentence	Valence
Yu and Hatzivassiloglou 2003	Both	ML (NB) + Lexicon/Rule	Phrase	Average	Sentence	Valence
Pang, Lee, and Vaithyanathan 2002	Polarity	ML (SVM, MaxEnt, NB)	Snippet			Valence
Subasic and Huettner 2001	Polarity	Lexicon/Fuzzy logic	Phrase	Average	Snippet	Valence
Turney 2001	Polarity	Lexicon/Rule	Phrase	Average	Snippet	Valence

(Both = Subjectivity and Polarity; ML= Machine Learning; Lexicon/Rule= Lexicon enhanced by linguistic rules)

Source: Zhang, Z., Li, X., and Chen, Y. (2012), "Deciphering word-of-mouth in social media: Text-based metrics of consumer reviews," ACM Trans. Manage. Inf. Syst. (3:1) 2012, pp 1-23.,

Word-of-Mouth (WOM)

- “This book is the best written documentary thus far, yet sadly, there is no soft cover edition.”

- “This book is the best written documentary thus far, yet sadly, there is no soft cover edition.”

Source: Zhang, Z., Li, X., and Chen, Y. (2012), "Deciphering word-of-mouth in social media: Text-based metrics of consumer reviews," ACM Trans. Manage. Inf. Syst. (3:1) 2012, pp 1-23.,

This
book
is
the
best
written
documentary
thus
far
,
yet
sadly
,
there
is
no
soft
cover
edition
.

Word	POS
This	DT
book	NN
is	VBZ
the	DT
best	JJS
written	VBN
documentary	NN
thus	RB
far	RB
,	,
yet	RB
sadly	RB
,	,
there	EX
is	VBZ
no	DT
soft	JJ
cover	NN
edition	NN
.	.

Source: Zhang, Z., Li, X., and Chen, Y. (2012), "Deciphering word-of-mouth in social media: Text-based metrics of consumer reviews," ACM Trans. Manage. Inf. Syst. (3:1) 2012, pp 1-23.,

Conversion of text representation

Word Vector (WV)	Polarity Score Vector (PSV) *pscore*	*nscore*		Microstate Sequence (MS)
This	0	0	Neutral (0)	0
book	0	0	Neutral (0)	0
is	0	0	Neutral (0)	0
the	0	0	Neutral (0)	0
best	0.75	0	Positive (0.75)	1
written	0	0	Neutral (0)	0
documentary	0	0	Neutral (0)	0
thus	0.375	0	Positive (0.375)	1
far	0.375	0	Positive (0.375)	1
,				
yet	0	0.125	Negative (0.125)	-1
sadly	0.25	0.5	Negative (0.25)	-1
,				
there	0	0	Neutral (0)	0
is	0	0	Neutral (0)	0
no	0	0.75	Negative (0.75)	-1
soft	0	0	Neutral (0)	0
cover	0	0	Neutral (0)	0
edition	0	0	Neutral (0)	0
.				

SentiWordNet Lookup

Microstate Mapping

Probability Mapping

Probability Distribution (P)

P("1")=3/17

P("-1")=3/17

P("0")=11/17

Source: Zhang, Z., Li, X., and Chen, Y. (2012), "Deciphering word-of-mouth in social media: Text-based metrics of consumer reviews," ACM Trans. Manage. Inf. Syst. (3:1) 2012, pp 1-23.,

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"

SenticNet

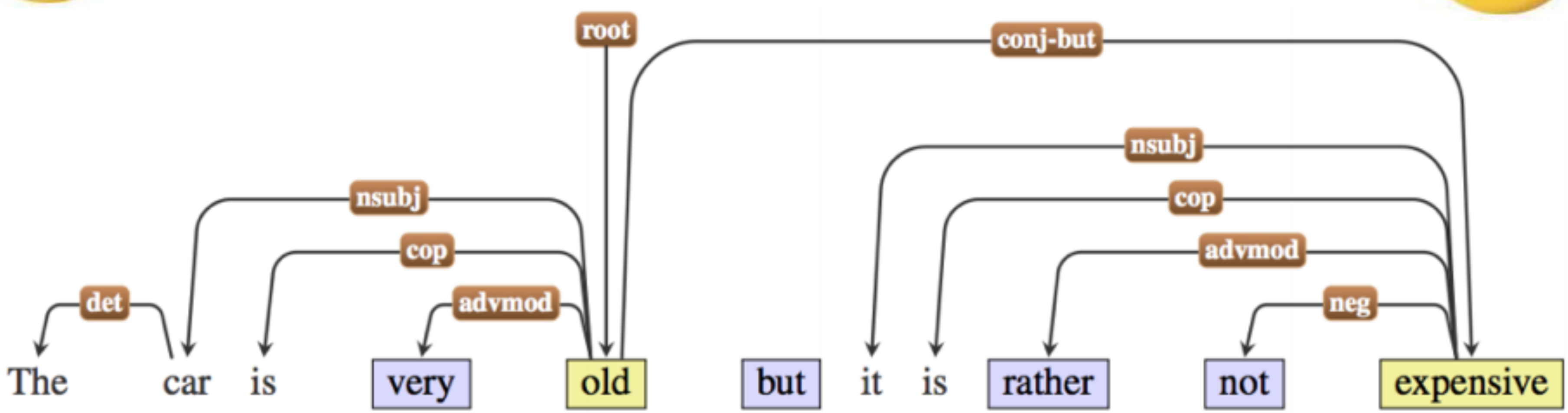
The car is very old but it is rather not expensive.

The car is very old but it is rather not expensive.

The car is very old but it is rather not expensive.

Source: Cambria, Erik, Soujanya Poria, Rajiv Bajpai, and Björn Schuller. "SenticNet 4: A semantic resource for sentiment analysis based on conceptual primitives." In *the 26th International Conference on Computational Linguistics (COLING), Osaka*. 2016.

Polarity Detection with SenticNet



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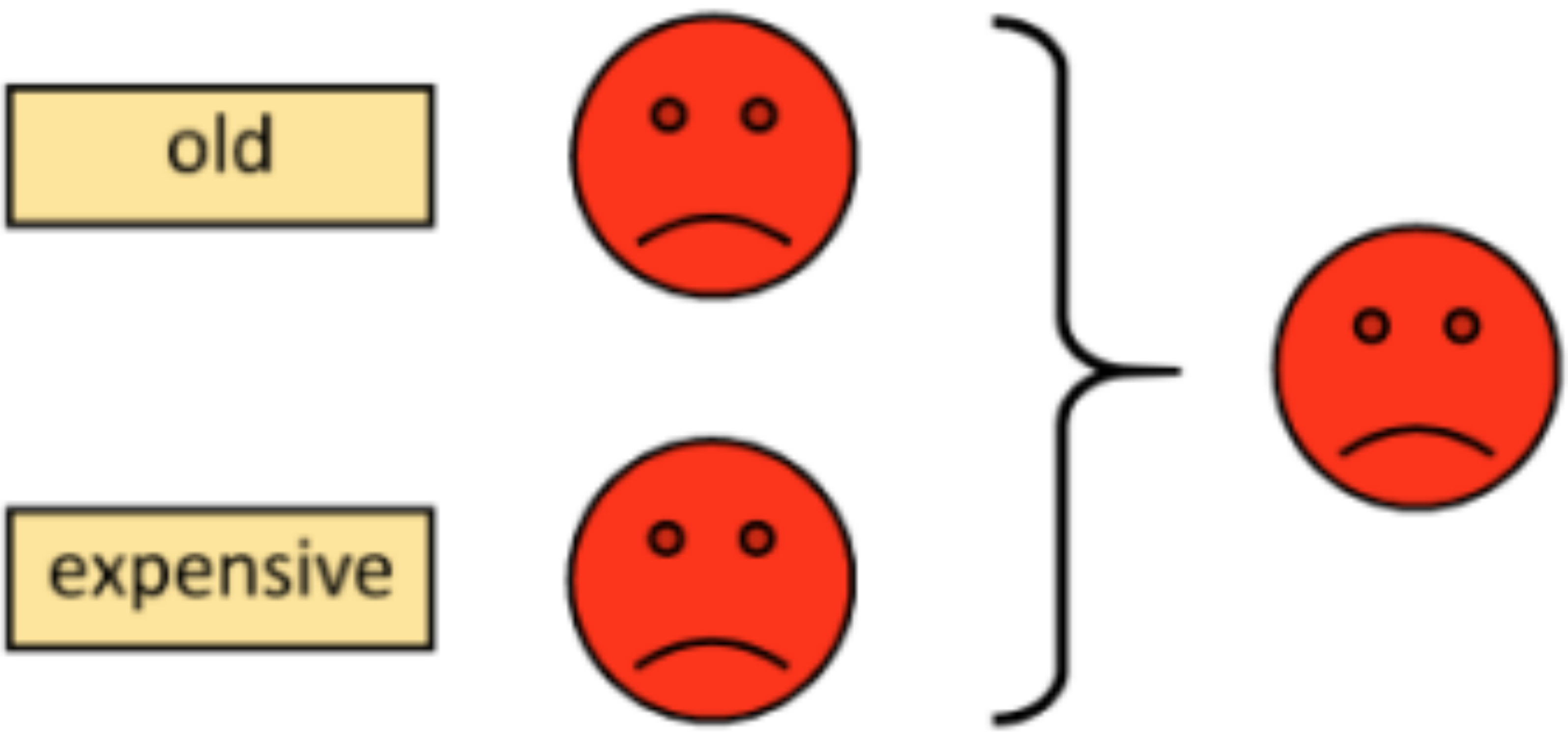
Polarity Detection with SenticNet



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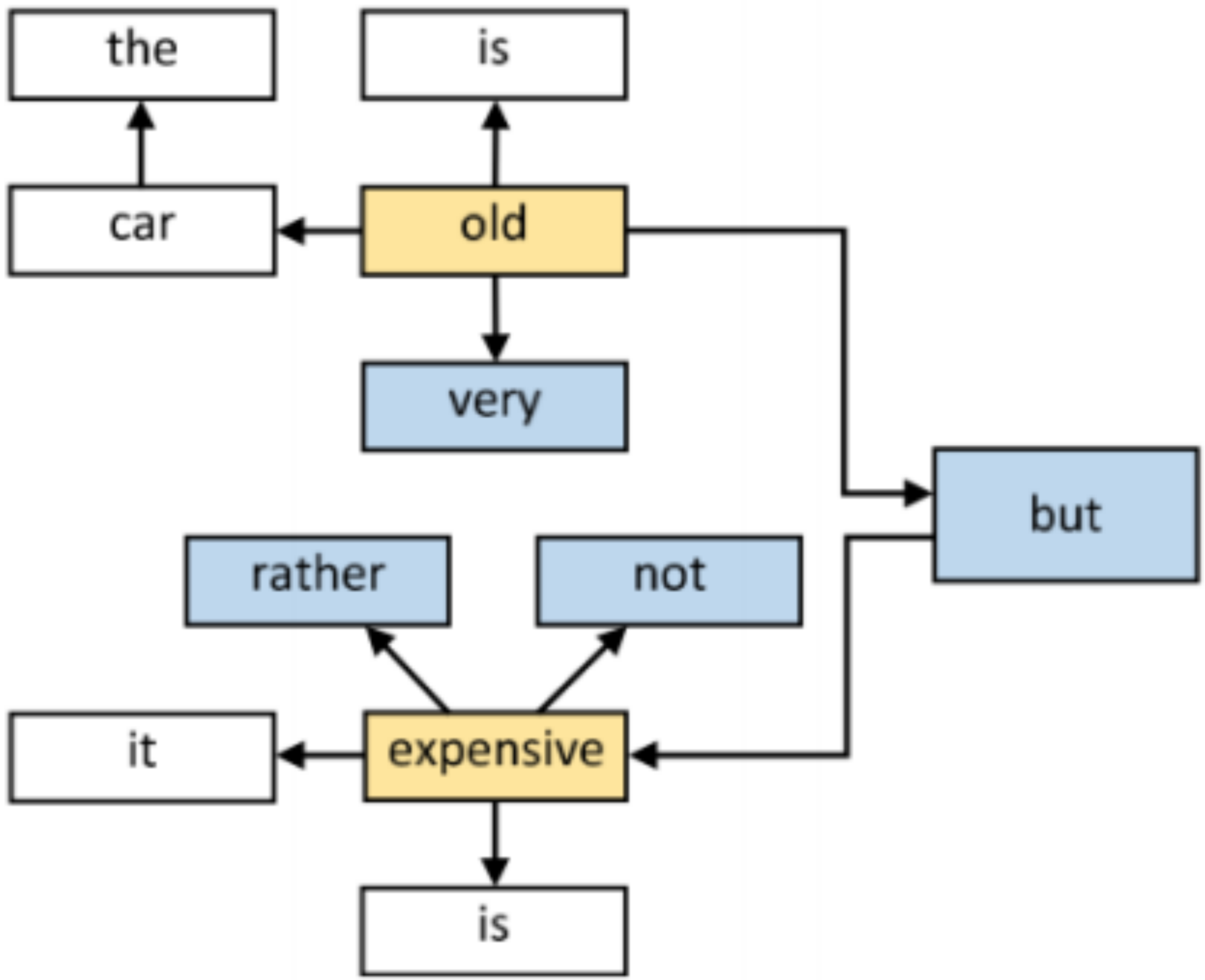
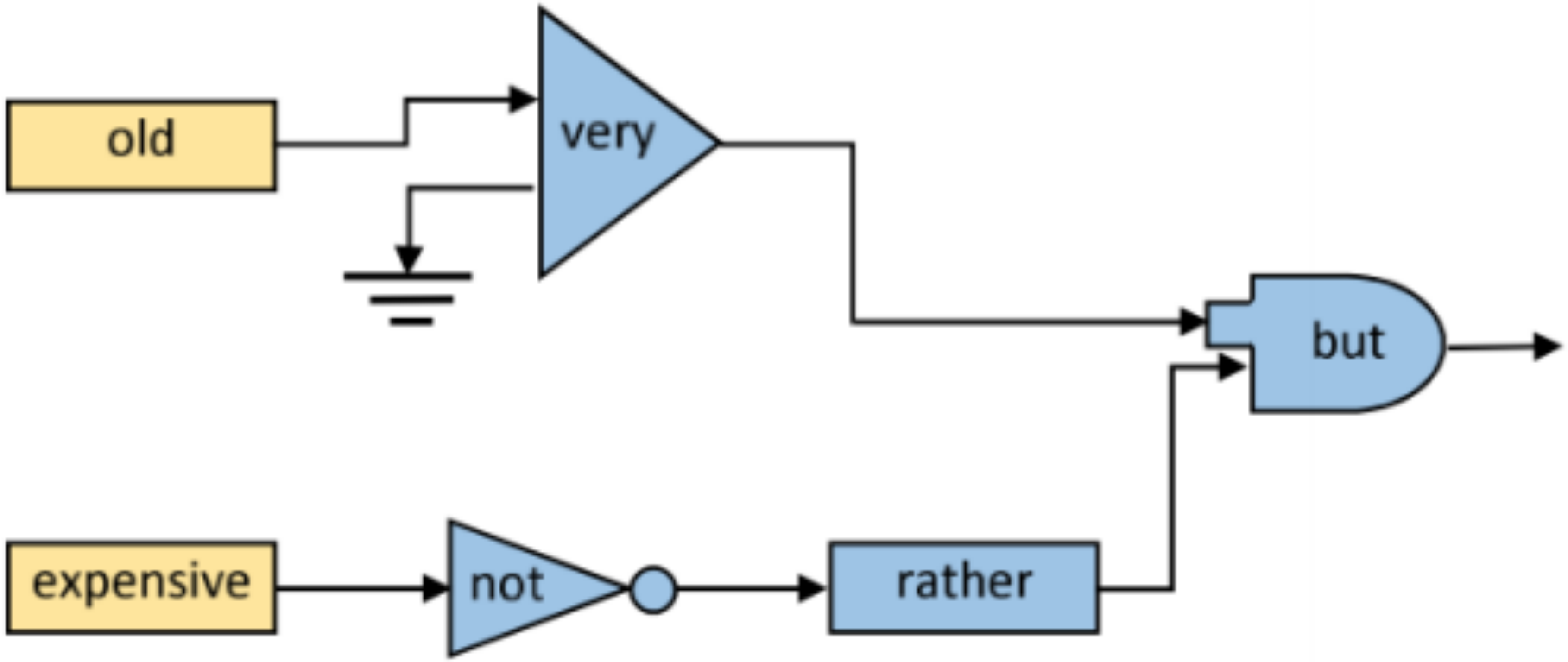


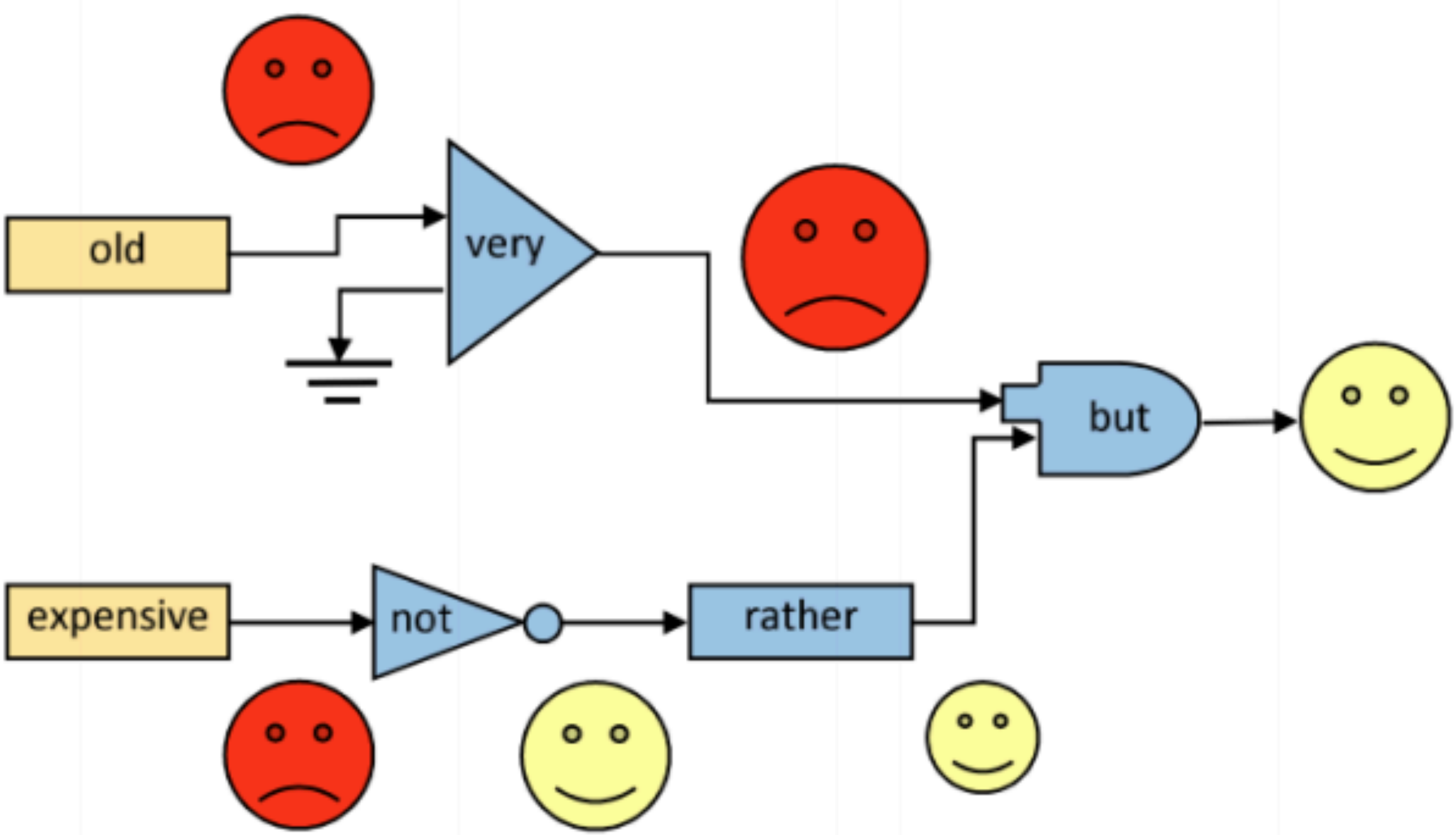
Source: Cambria, Erik, Soujanya Poria, Rajiv Bajpai, and Björn Schuller. "SenticNet 4: A semantic resource for sentiment analysis based on conceptual primitives." In *the 26th International Conference on Computational Linguistics (COLING), Osaka*. 2016.

Polarity Detection with SenticNet



Source: Cambria, Erik, Soujanya Poria, Rajiv Bajpai, and Björn Schuller. "SenticNet 4: A semantic resource for sentiment analysis based on conceptual primitives." In *the 26th International Conference on Computational Linguistics (COLING), Osaka*. 2016.

Polarity Detection with SenticNet



Source: Cambria, Erik, Soujanya Poria, Rajiv Bajpai, and Björn Schuller. "SenticNet 4: A semantic resource for sentiment analysis based on conceptual primitives." In *the 26th International Conference on Computational Linguistics (COLING), Osaka*. 2016.

Evaluation of Text Mining and Sentiment Analysis

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

Deep Learning for Sentiment Analytics

Recursive Deep Models for Semantic Compositionality Over a Sentiment Treebank

Recursive Deep Models for Semantic Compositionality Over a Sentiment Treebank

Richard Socher, Alex Perelygin, Jean Y. Wu, Jason Chuang, Christopher D. Manning, Andrew Y. Ng and Christopher Potts
Stanford University, Stanford, CA 94305, USA
richard@socher.org,{aperelyg,jcchuang,ang}@cs.stanford.edu
{jeaneis,manning,cgpotts}@stanford.edu

Abstract

Semantic word spaces have been very useful but cannot express the meaning of longer phrases in a principled way. Further progress towards understanding compositionality in tasks such as sentiment detection requires richer supervised training and evaluation resources and more powerful models of composition. To remedy this, we introduce a Sentiment Treebank. It includes fine grained sentiment labels for 215,154 phrases in the parse trees of 11,855 sentences and presents new challenges for sentiment compositionality. To address them, we introduce the Recursive Neural Tensor Network. When trained on the new treebank, this model out-

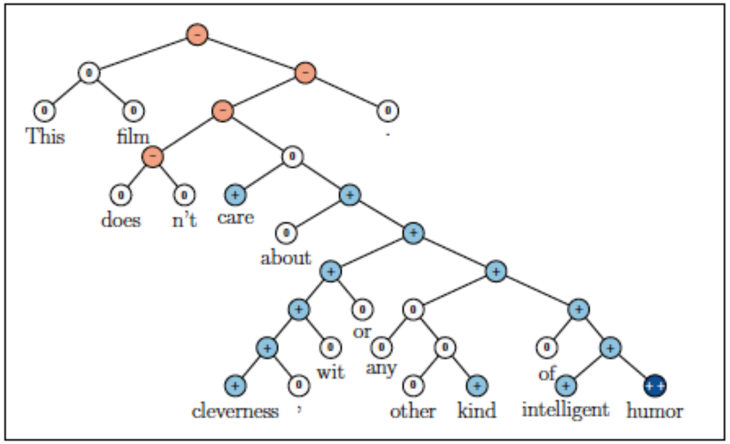
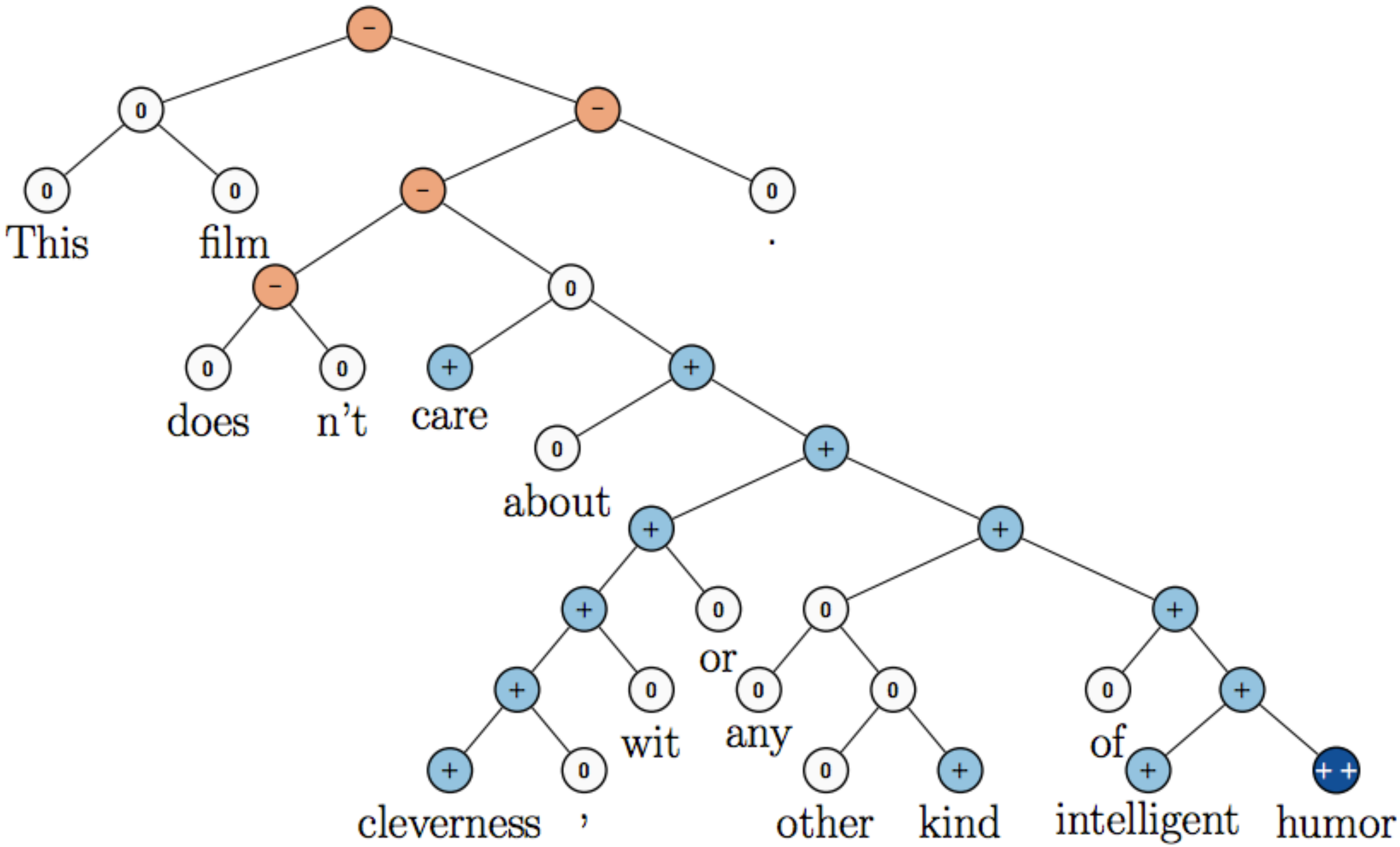


Figure 1: Example of the Recursive Neural Tensor Network accurately predicting 5 sentiment classes, very negative to very positive (– –, –, 0, +, + +), at every node of a parse tree and capturing the negation and its scope in this sentence.

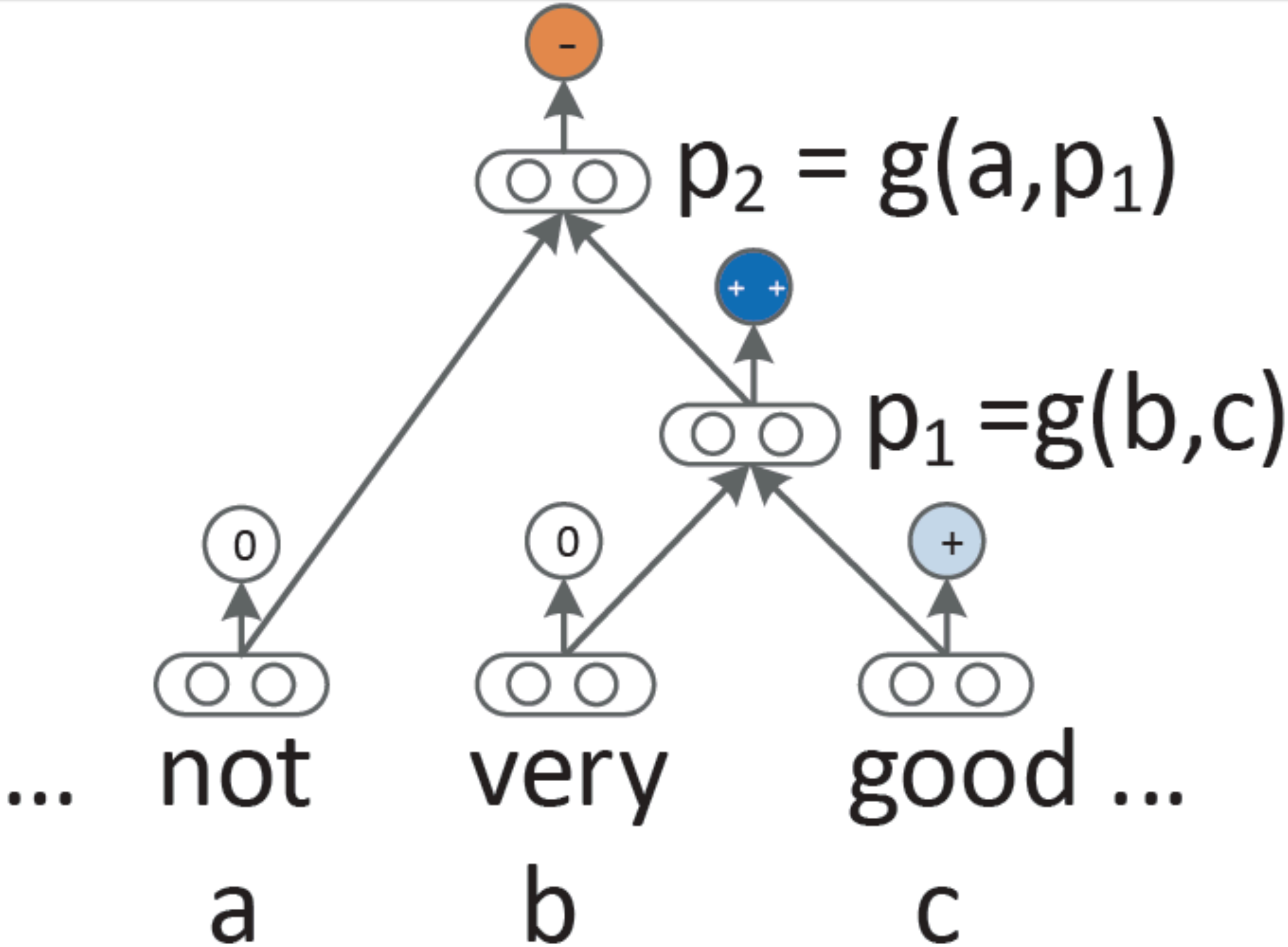
Source: Richard Socher et al. (2013) "Recursive Deep Models for Semantic Compositionality Over a Sentiment Treebank", EMNLP 2013

Recursive Neural Tensor Network (RNTN)



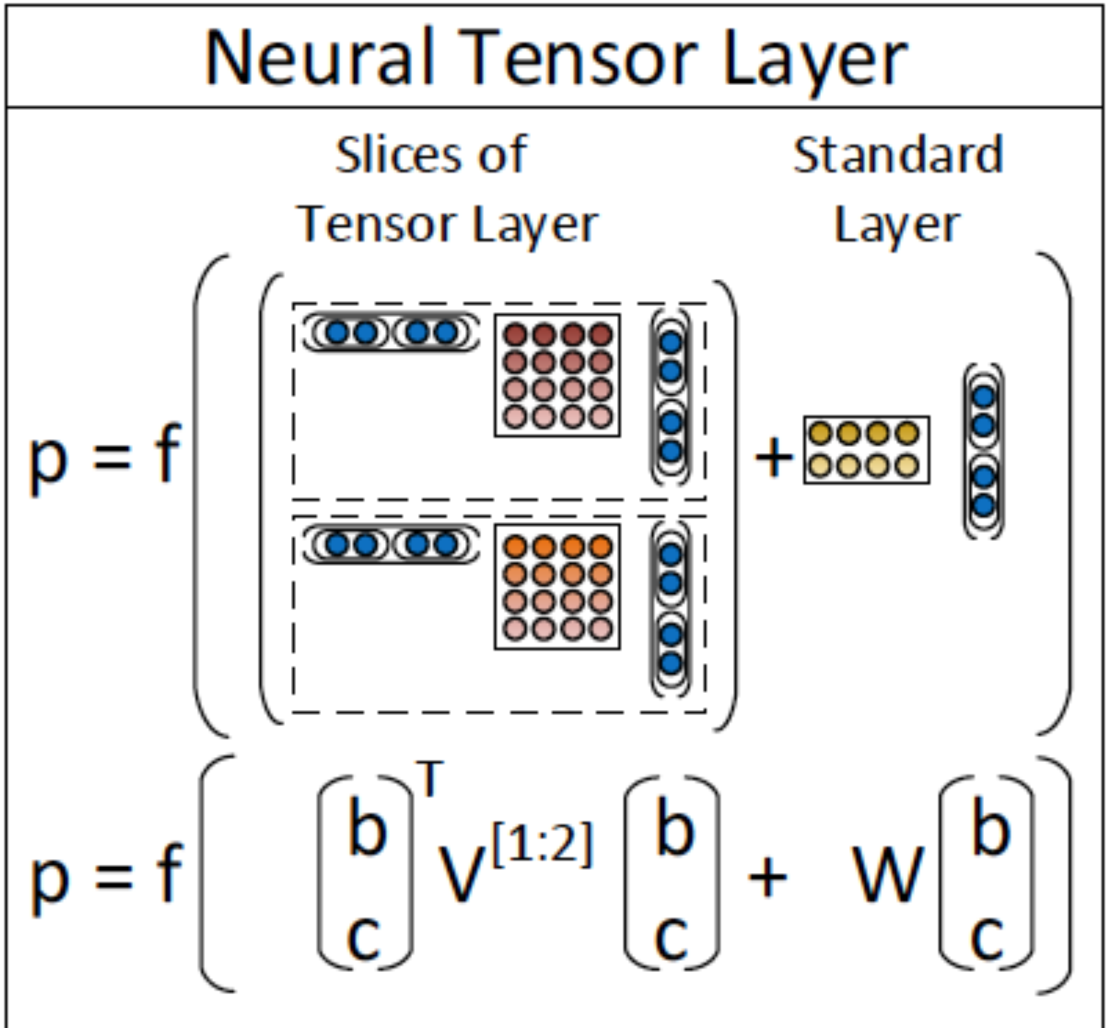
Source: Richard Socher et al. (2013) "Recursive Deep Models for Semantic Compositionality Over a Sentiment Treebank", EMNLP 2013

Recursive Neural Network (RNN) models for sentiment



Source: Richard Socher et al. (2013) "Recursive Deep Models for Semantic Compositionality Over a Sentiment Treebank", EMNLP 2013

Recursive Neural Tensor Network (RNTN)



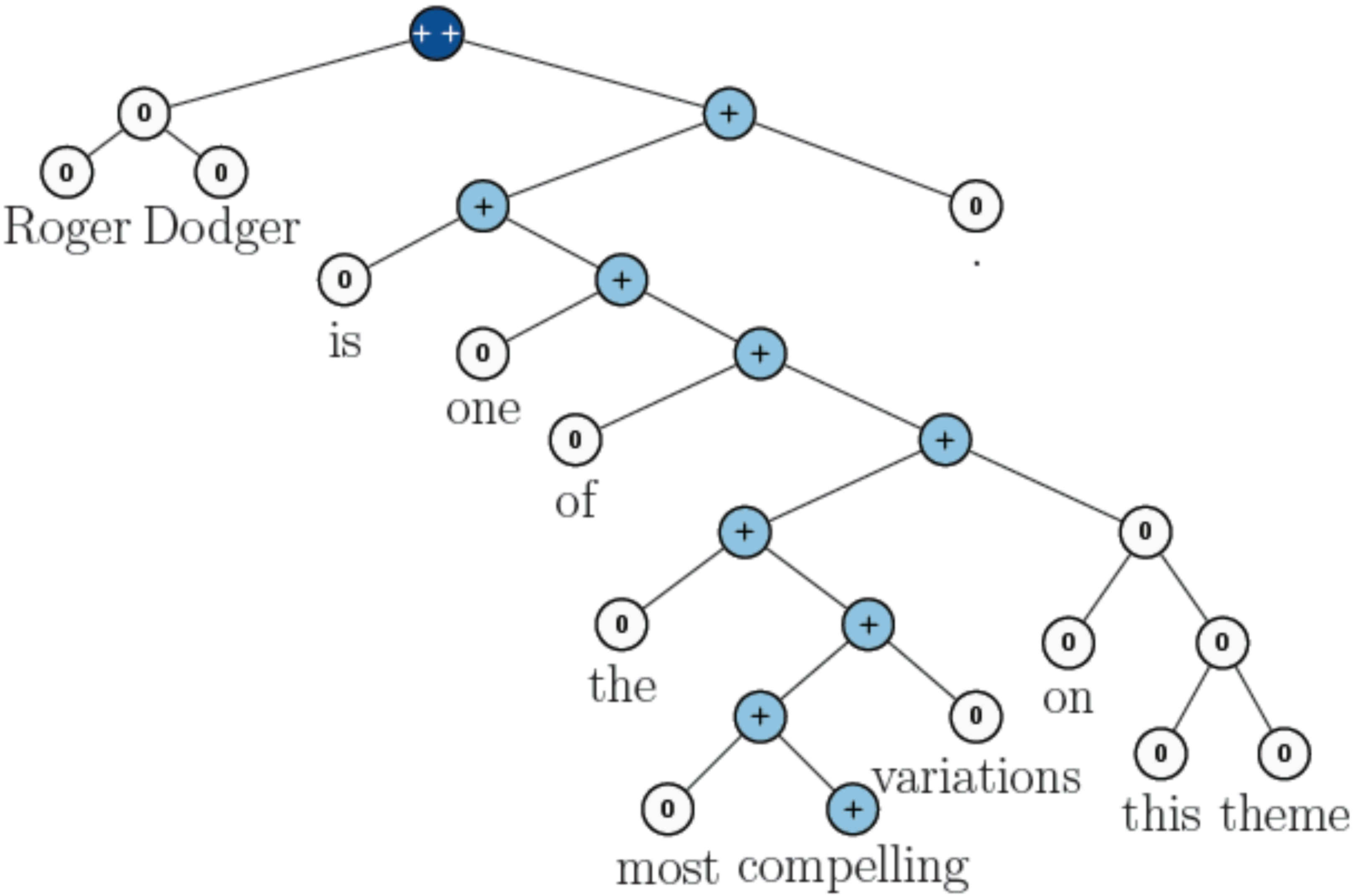
Source: Richard Socher et al. (2013) "Recursive Deep Models for Semantic Compositionality Over a Sentiment Treebank", EMNLP 2013

Roger Dodger is one of the most compelling variations on this theme.

Roger Dodger is one of the least compelling variations on this theme.

Source: Richard Socher et al. (2013) "Recursive Deep Models for Semantic Compositionality Over a Sentiment Treebank", EMNLP 2013

RNTN for Sentiment Analysis



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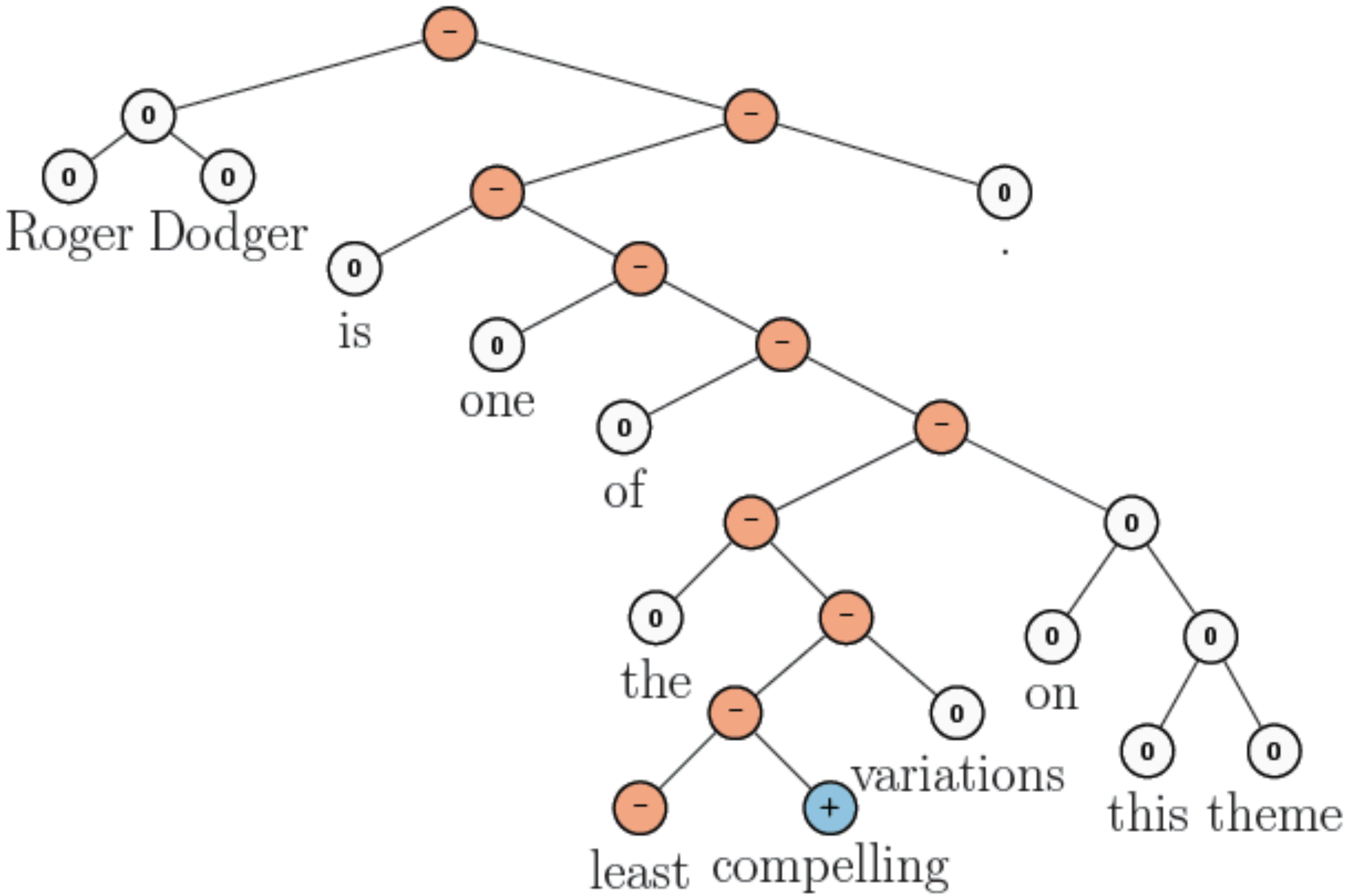
RNTN for Sentiment Analysis



Roger Dodger is one of the least compelling variations on this theme.

Source: Richard Socher et al. (2013) "Recursive Deep Models for Semantic Compositionality Over a Sentiment Treebank", EMNLP 2013

Accuracy for fine grained (5-class) and binary predictions at the sentence level (root) and for all nodes

Model	Fine-grained		Positive/Negative	
	All	Root	All	Root
NB	67.2	41.0	82.6	81.8
SVM	64.3	40.7	84.6	79.4
BiNB	71.0	41.9	82.7	83.1
VecAvg	73.3	32.7	85.1	80.1
RNN	79.0	43.2	86.1	82.4
MV-RNN	78.7	44.4	86.8	82.9
RNTN	**80.7**	**45.7**	**87.6**	**85.4**

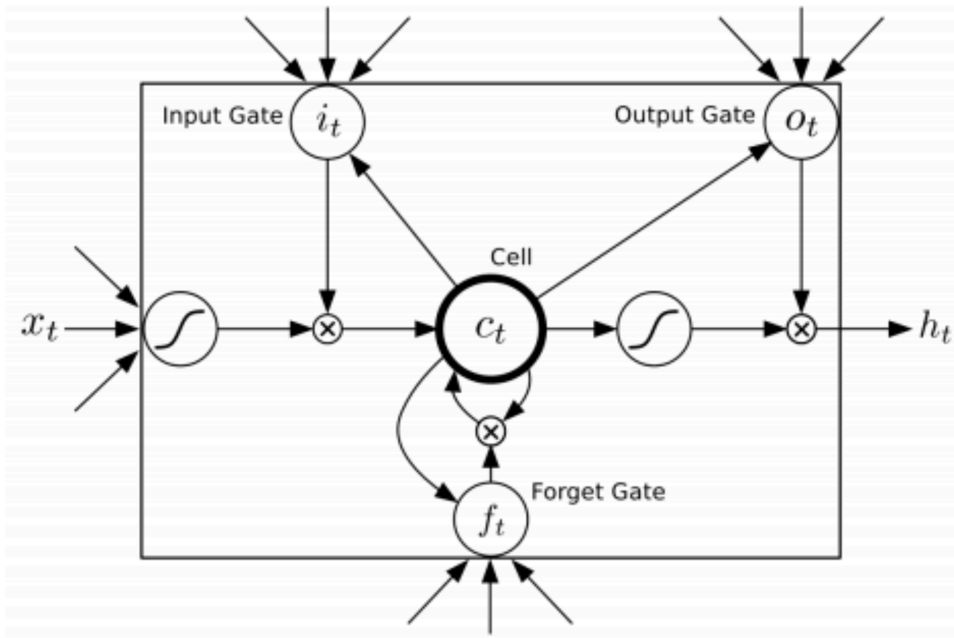
Source: Richard Socher et al. (2013) "Recursive Deep Models for Semantic Compositionality Over a Sentiment Treebank", EMNLP 2013

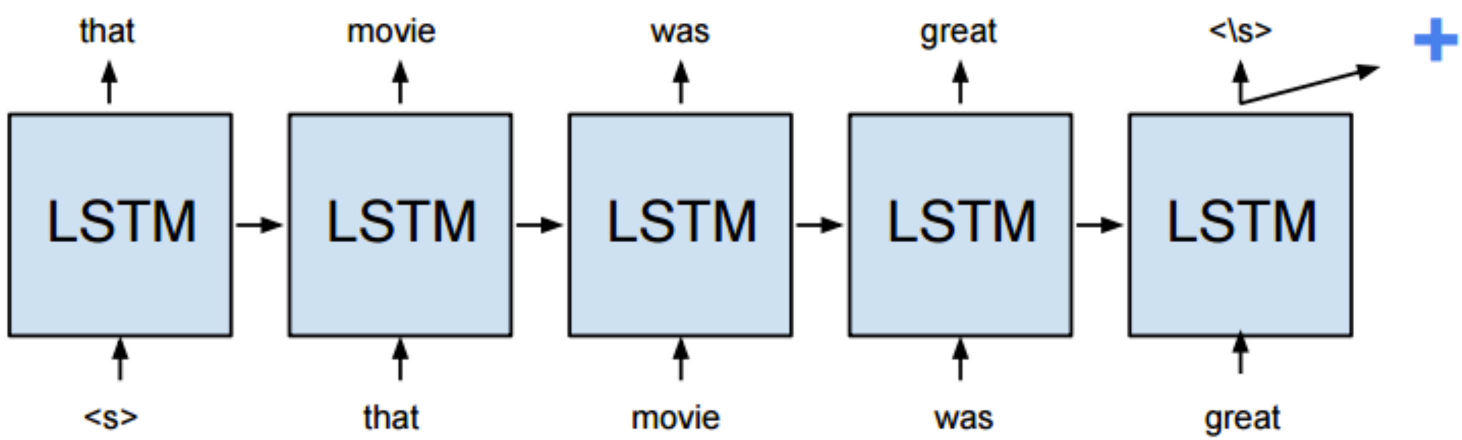
Accuracy of negation detection

Model	Accuracy	
	Negated Positive	Negated Negative
biNB	19.0	27.3
RNN	33.3	45.5
MV-RNN	52.4	54.6
RNTN	**71.4**	**81.8**

Source: Richard Socher et al. (2013) "Recursive Deep Models for Semantic Compositionality Over a Sentiment Treebank", EMNLP 2013

Long Short-Term Memory (LSTM)





Source: https://cs224d.stanford.edu/reports/HongJames.pdf

Deep Learning for Sentiment Analysis CNN RNTN LSTM

Model	Fine (5-class)	Binary
DCNN (Blunsom, et al. 2014)	0.485	0.868
RNTN (Socher, et al. 2013)	0.457	0.854
CNN-non-static (Kim, 2014)	0.480	0.872
CNN-multi-channel (Kim, 2014)	0.474	0.881
DRNN w. pretrained word-embeddings (Irsoy and Cardie, 2014)	0.498	0.866
Paragraph Vector (Le and Mikolov. 2014)	0.487	0.878
Dependency Tree-LSTM (Tai, et al, 2015)	0.484	0.857
Constituency Tree-LSTM (Tai, et al, 2015)	0.439	0.820
Constituency Tree-LSTM (Glove vectors) (Tai, et al, 2015)	0.510	0.880
Paragraph Vector	0.391	0.798
LSTM	0.456	0.843
Deep Recursive-NN	0.469	0.847

Source: https://cs224d.stanford.edu/reports/HongJames.pdf

Performance Comparison of Sentiment Analysis Methods

	Method	Data Set	Acc.	Author
Machine Learning	SVM	Movie reviews	86.40%	Pang, Lee[23]
	CoTraining SVM	Twitter	82.52%	Liu[14]
	Deep learning	Stanford Sentiment Treebank	80.70%	Richard[18]
Lexical based	Corpus	Product reviews	74.00%	Turkey
	Dictionary	Amazon's Mechanical Turk	---	Taboada[20]
Cross-lingual	Ensemble	Amazon	81.00%	Wan,X[16]
	Co-Train	Amazon, ITI68	81.30%	Wan,X.[16]
	EWGA	IMDb movie review	>90%	Abbasi,A.
	CLMM	MPQA,NTCIR,ISI	83.02%	Mengi
Cross-domain	Active Learning	Book, DVD, Electronics, Kitchen	80% (avg)	Li, S
	Thesaurus			Bollegala[22]
	SFA			Pan S J[15]

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

Resources of Opinion Mining

Datasets of Opinion Mining

- Blog06
  - 25GB TREC test collection
  - http://ir.dcs.gla.ac.uk/test collections/access to data.html
- Cornell movie-review datasets
  - http://www.cs.cornell.edu/people/pabo/movie-review-data/
- Customer review datasets
  - http://www.cs.uic.edu/~liub/FBS/CustomerReviewData.zip
- Multiple-aspect restaurant reviews
  - http://people.csail.mit.edu/bsnyder/naacl07
- NTCIR multilingual corpus
  - NTCIR Multilingual Opinion-Analysis Task (MOAT)

Source: Bo Pang and Lillian Lee (2008), "Opinion mining and sentiment analysis," Foundations and Trends in Information Retrieval

Lexical Resources of Opinion Mining

- SentiWordnet
  - http://sentiwordnet.isti.cnr.it/
- General Inquirer
  - http://www.wjh.harvard.edu/~inquirer/
- OpinionFinder’s Subjectivity Lexicon
  - http://www.cs.pitt.edu/mpqa/
- NTU Sentiment Dictionary (NTUSD)
  - http://nlg18.csie.ntu.edu.tw:8080/opinion/
- Hownet Sentiment
  - http://www.keenage.com/html/c_bulletin_2007.htm

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“

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《知網》情感分析用詞語集（beta版）

- “中英文情感分析用詞語集”
  - 包含詞語約 17887
- “中文情感分析用詞語集”
  - 包含詞語約 9193
- “英文情感分析用詞語集”
  - 包含詞語 8945

Source: http://www.keenage.com/html/c_bulletin_2007.htm

中文情感分析用詞語集

中文正面情感詞語	836
中文負面情感詞語	1254
中文正面評價詞語	3730
中文負面評價詞語	3116
中文程度級別詞語	219
中文主張詞語	38
Total	9193

Source: http://www.keenage.com/html/c_bulletin_2007.htm

中文情感分析用詞語集

- “正面情感”詞語
  - 如：
    愛，讚賞，快樂，感同身受，好奇，喝彩，魂牽夢縈，嘉許 ...
- “負面情感”詞語
  - 如：
    哀傷，半信半疑，鄙視，不滿意，不是滋味兒，後悔，大失所望 ...

Source: http://www.keenage.com/html/c_bulletin_2007.htm

中文情感分析用詞語集

- “正面評價”詞語
  - 如：
    不可或缺，部優，才高八斗，沉魚落雁，催人奮進，動聽，對勁兒…
- “負面評價”詞語
  - 如：
    醜，苦，超標，華而不實，荒涼，混濁，畸輕畸重，價高，空洞無物…

Source: http://www.keenage.com/html/c_bulletin_2007.htm

中文情感分析用詞語集

- “程度級別” 詞語
  - 1. “極其|extreme / 最|most”
    - 非常，極，極度，無以倫比，最為
  - 2. “很|very”
    - 多麼，分外，格外，著實
  - …
- “主張” 詞語
  - 1. {perception|感知}
    - 感覺，覺得，預感
  - 2. {regard|認為}
    - 認為，以為，主張

Source: http://www.keenage.com/html/c_bulletin_2007.htm

Social Computing

Social Network Analysis

Social Computing

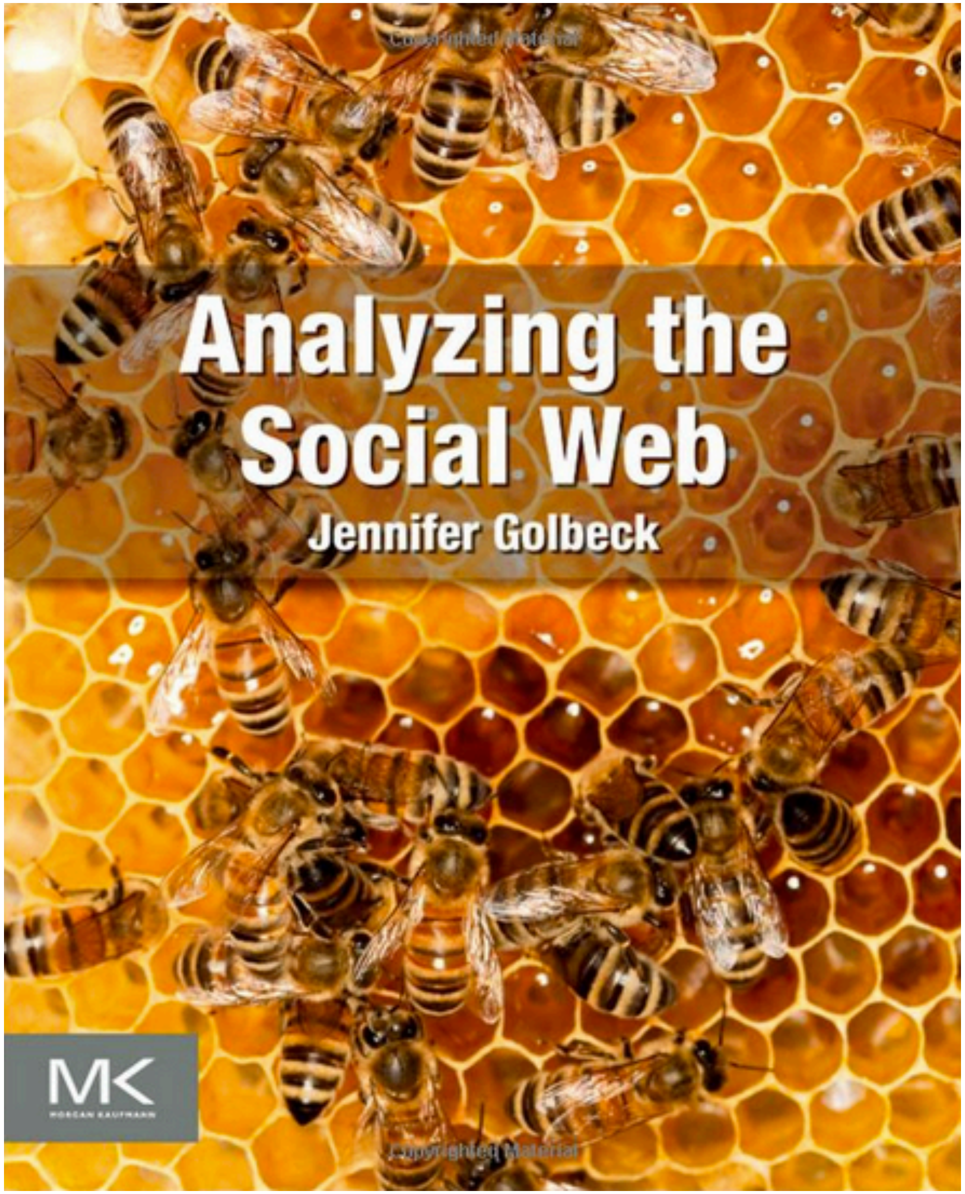
- Social Network Analysis
- Link mining
- Community Detection
- Social Recommendation

Business Insights with Social Analytics

Analyzing the Social Web:

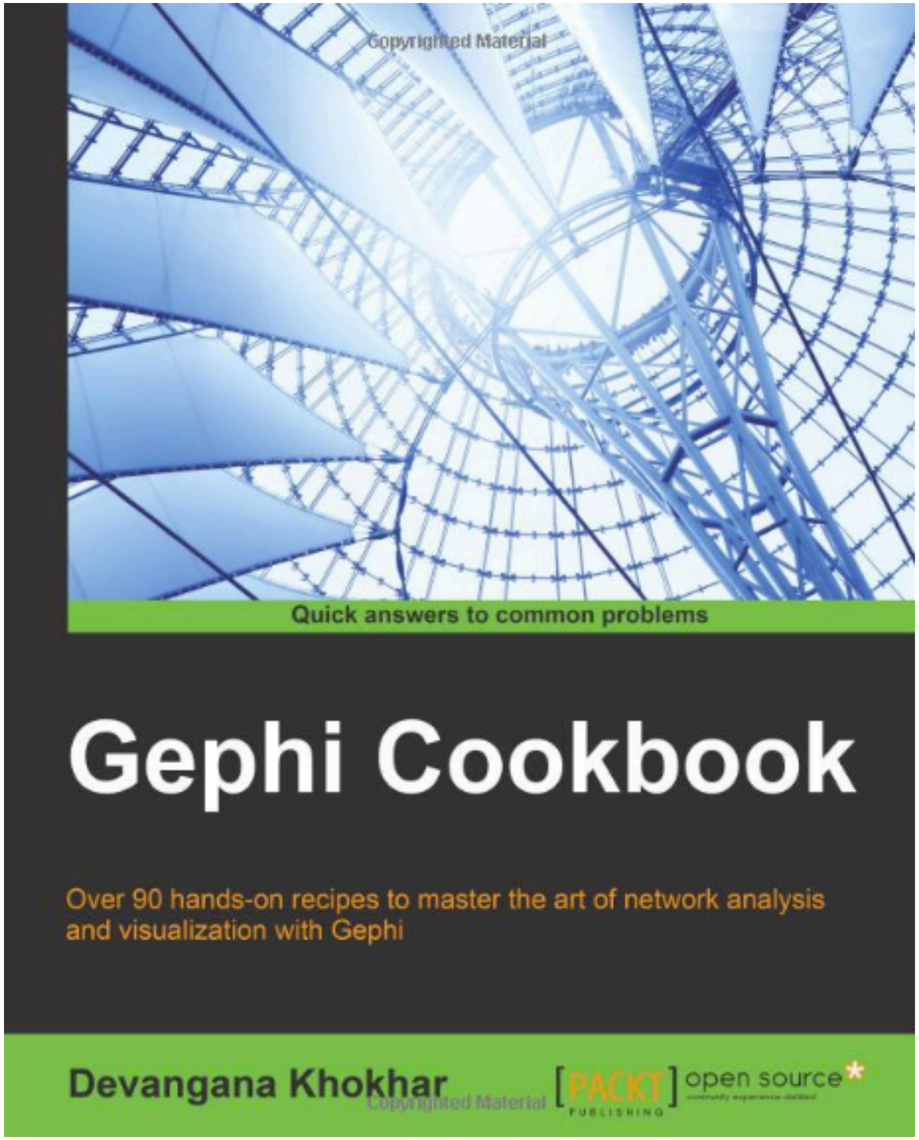
Social Network Analysis

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



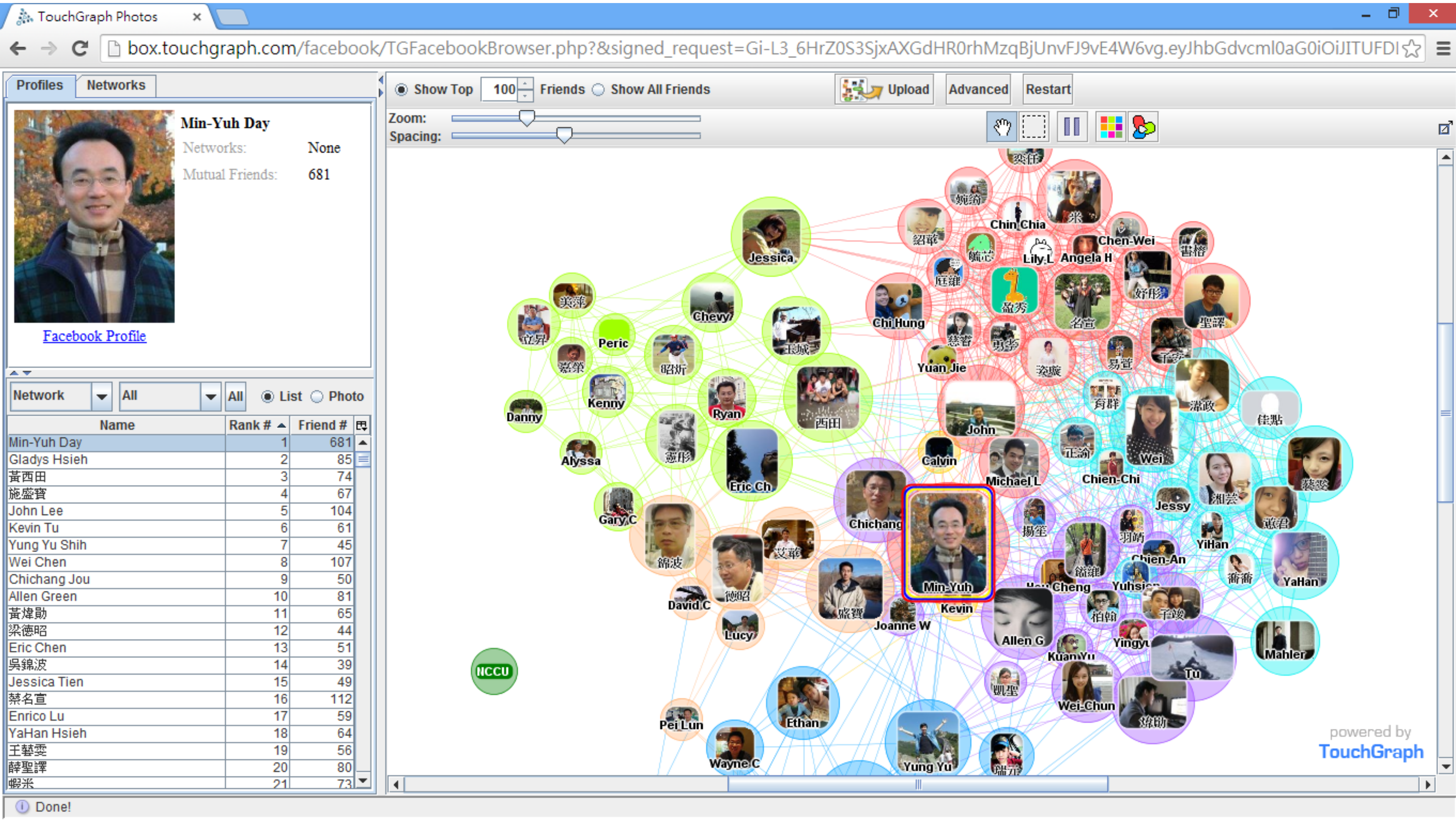
Source: http://www.amazon.com/Analyzing-Social-Web-Jennifer-Golbeck/dp/0124055311

Devangana Khokhar (2015),
Gephi Cookbook, Packt Publishing



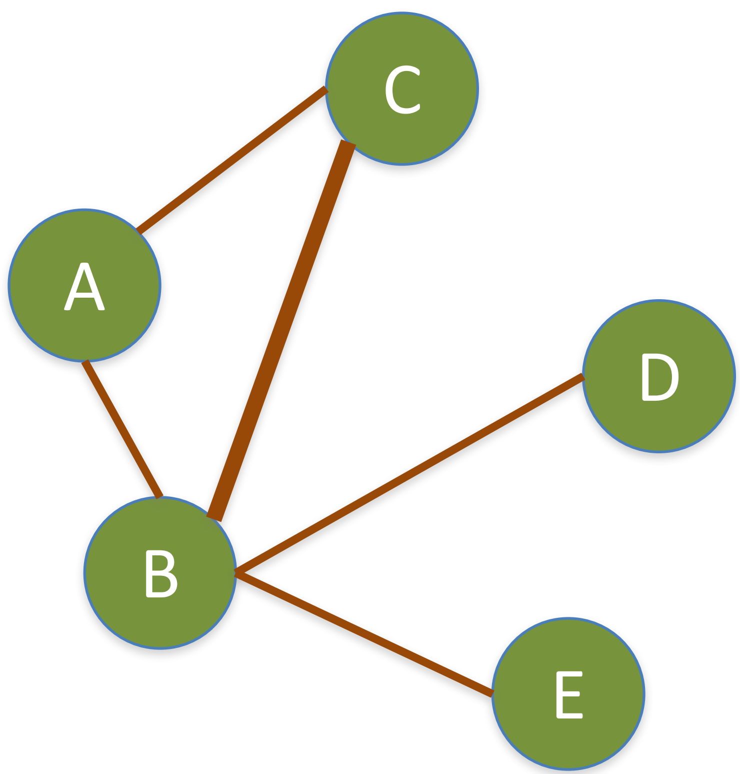
Source: http://www.amazon.com/Gephi-Cookbook-Devangana-Khokhar/dp/1783987405

Social Network Analysis (SNA)
Facebook TouchGraph



Graph Theory

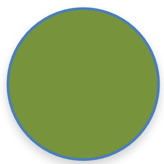
Graph



Graph

$$g = (V, E)$$

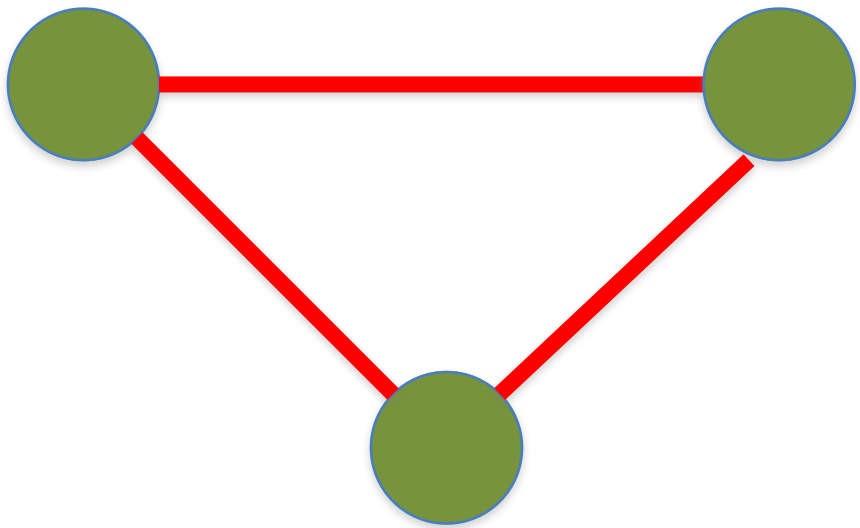
Vertex (Node)



Vertices (Nodes)

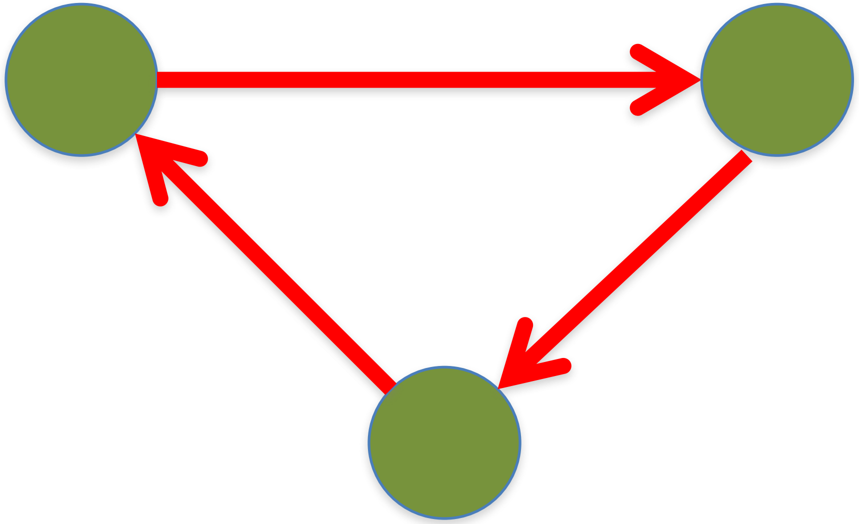
Edge

Edges

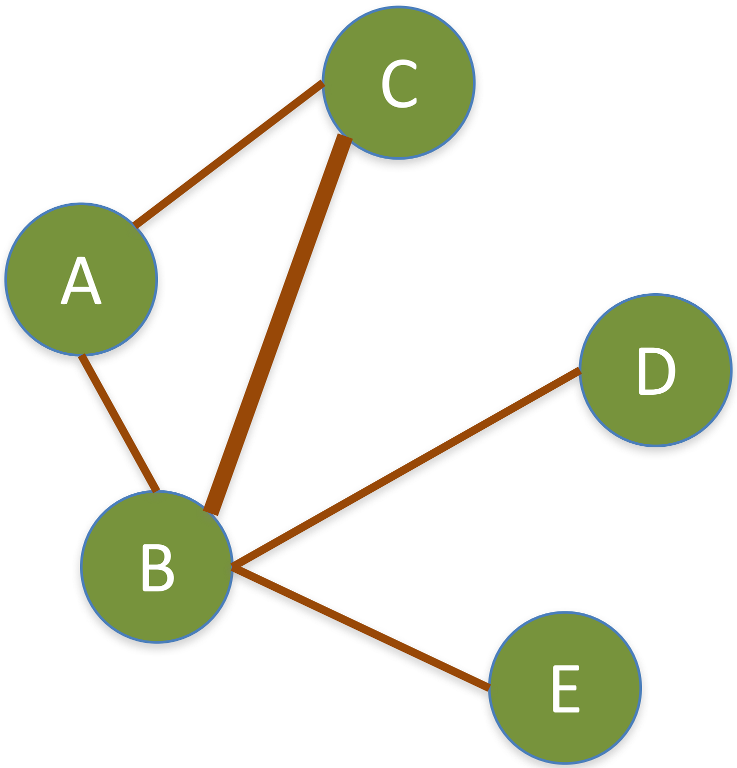


Arc

Arcs

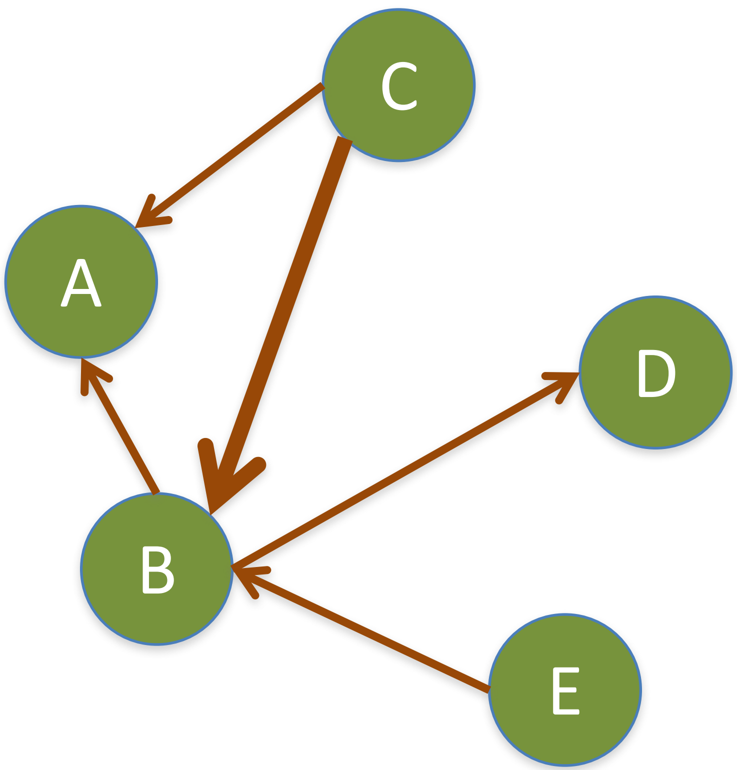


Undirected Graph



Source: https://www.youtube.com/watch?v=89mxOdwPfxA

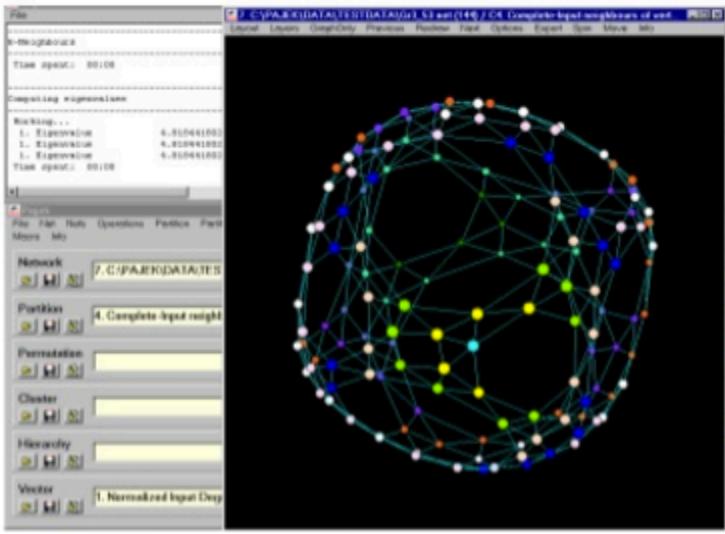
Directed Graph

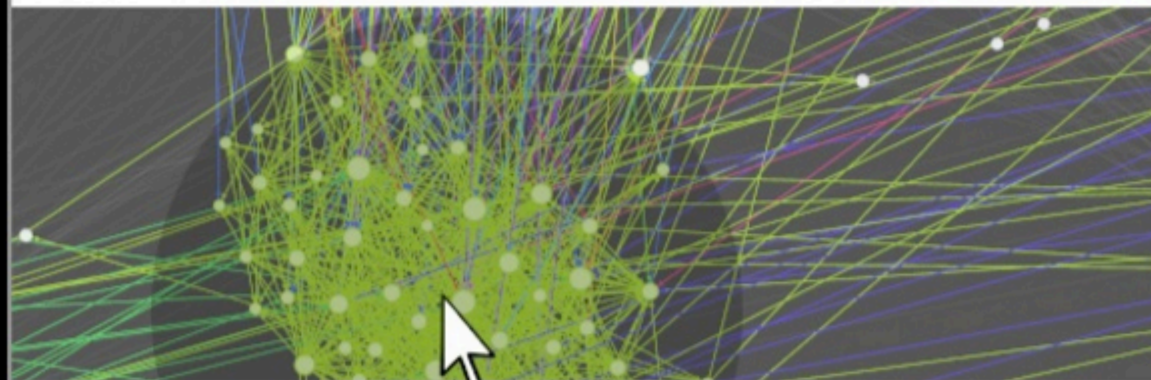


Source: https://www.youtube.com/watch?v=89mxOdwPfxA

Measurements of Social Network Analysis

Exploratory Network Analysis





2 interact in real time

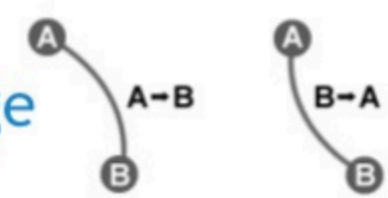
Gephi prototype (2008)
group, filter, compute metrics…

1 see the network

1st graph viz tool: Pajek (1996)
Vladimir Batagelj, Andrej Mrvar

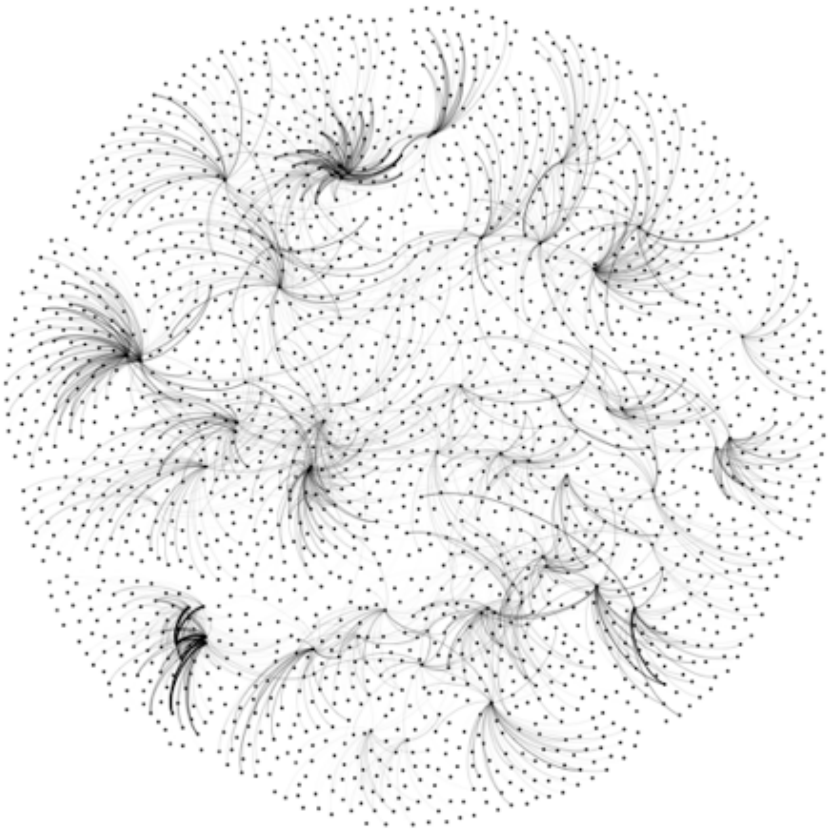
3 build a visual language

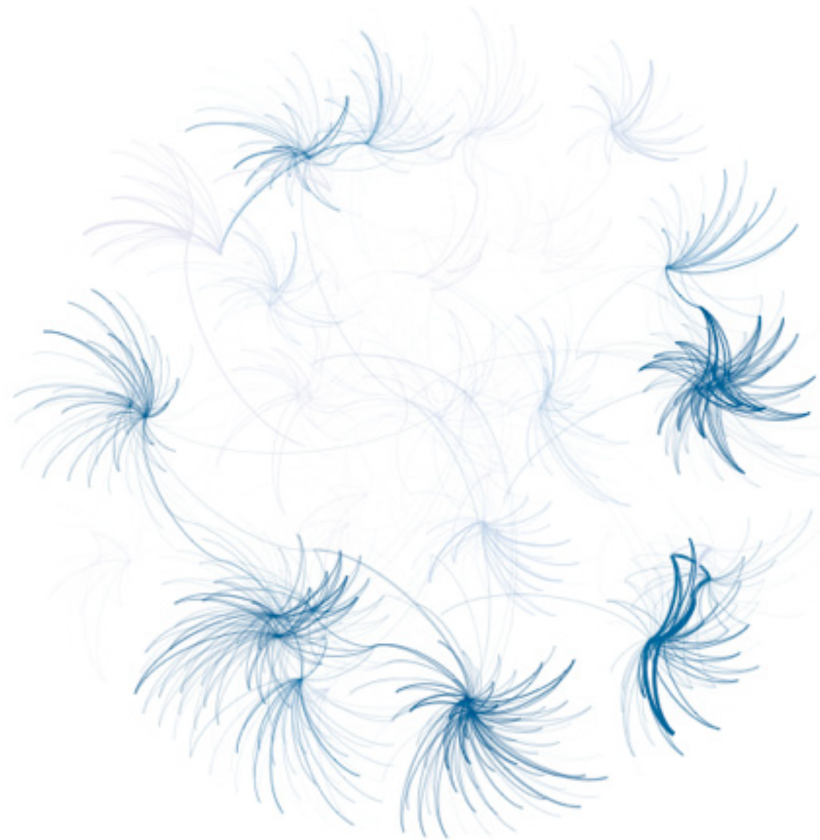
size by rank, color by partition,
label, curved edges, thickness…



Source: http://sebastien.pro/gephi-icwsm-tutorial.pdf

Looking for a "Simple Small Truth"? What Data Visualization Should Do?





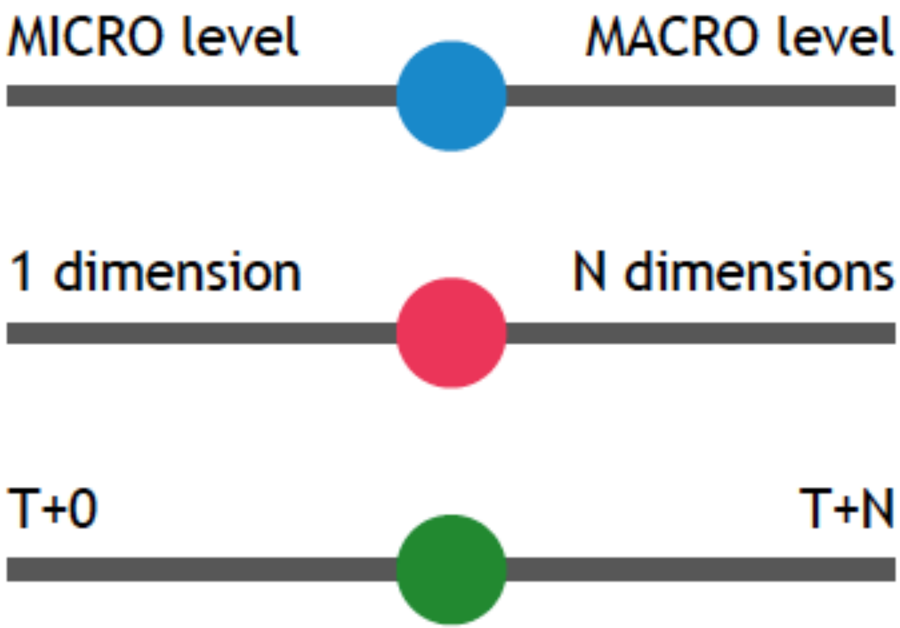
1. Make complex things **simple**
2. Extract **small** information from large data
3. Present **truth**, do not deceive

Source: http://sebastien.pro/gephi-icwsm-tutorial.pdf

Measurements

Looking for Orderness in Data

Make varying 3 cursors simultaneously to extract meaningful patterns



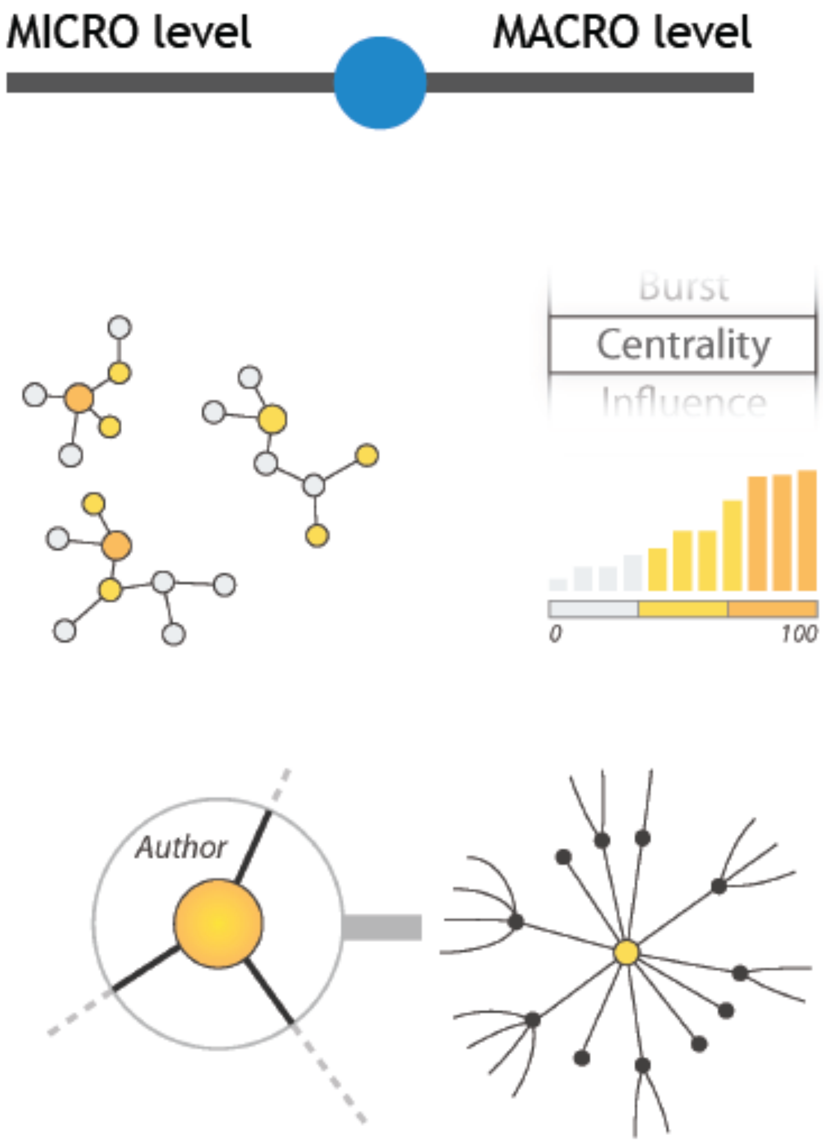
at different levels

on multiple dimensions

at time scale

Source: http://sebastien.pro/gephi-icwsm-tutorial.pdf

“Zoom” cursor on Quantitative Data



Global

- connectivity
- density
- centralization

Local

- communities
- bridges between communities
- local centers vs periphery

Individual

- centrality
- distances
- neighborhood
- location
- local authority vs hub

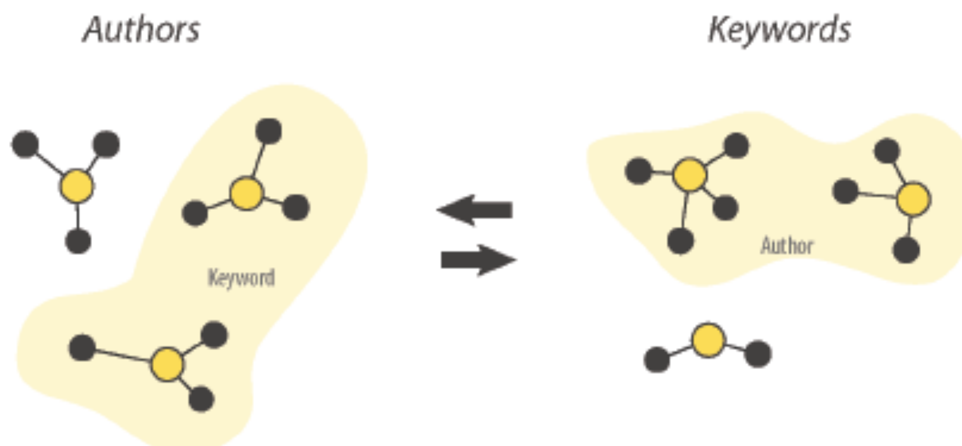
Source: http://sebastien.pro/gephi-icwsm-tutorial.pdf

"Crossing" cursor on Quantitative Data

Social
- who with whom
- communities
- brokerage
- influence and power
- homophily

Semantic
- topics
- thematic clusters

Geographic
- spatial phenomena



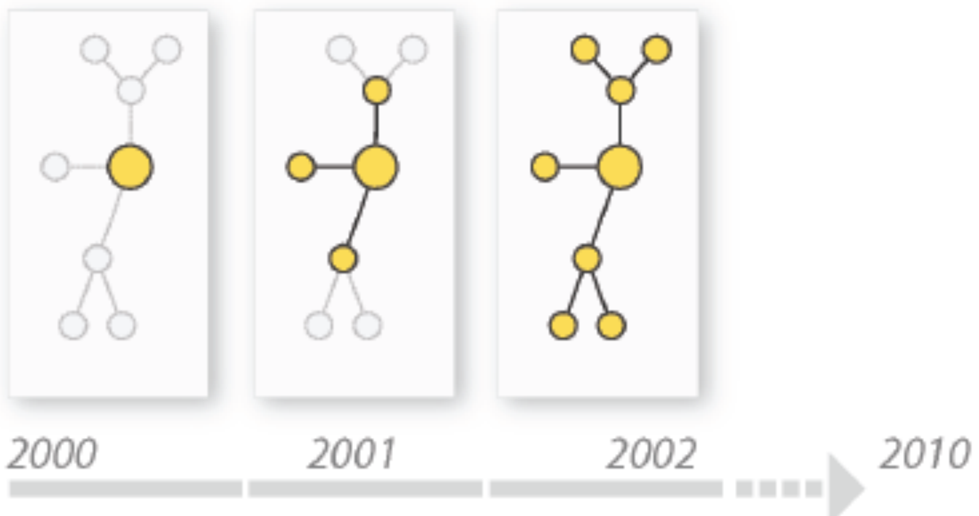
Source: http://sebastien.pro/gephi-icwsm-tutorial.pdf

“Timeline” cursor on Temporal Data

Evolution of social ties

Evolution of communities

Evolution of topics



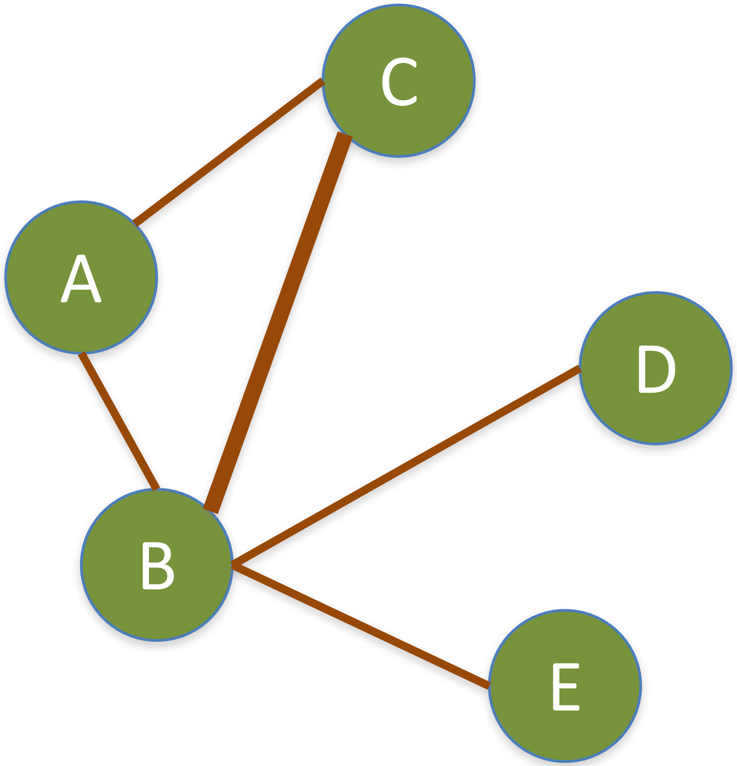
Source: http://sebastien.pro/gephi-icwsm-tutorial.pdf

SNA Guideline

# nodes	
1 - 100	lists + edges in bonus, focus on qualitative data
100 - 1,000	How attributes explain the structure? • easy to read, “obvious” patterns • focus on entities (in context) • metrics are tools to describe the graph (centrality, bridging…) • links help to build and interpret categories of entities challenge: mix attribute crossing and connectivity
1,000 - 50,000	How the structure explains attributes? • hard to read, problem of “**hidden signals**”: track patterns with various layouts and filtering • focus on structures • metrics are tools to build the graph (cosine similarity…) • categories help to understand the structure challenge: pattern recognition
> 50,000	require high computational power

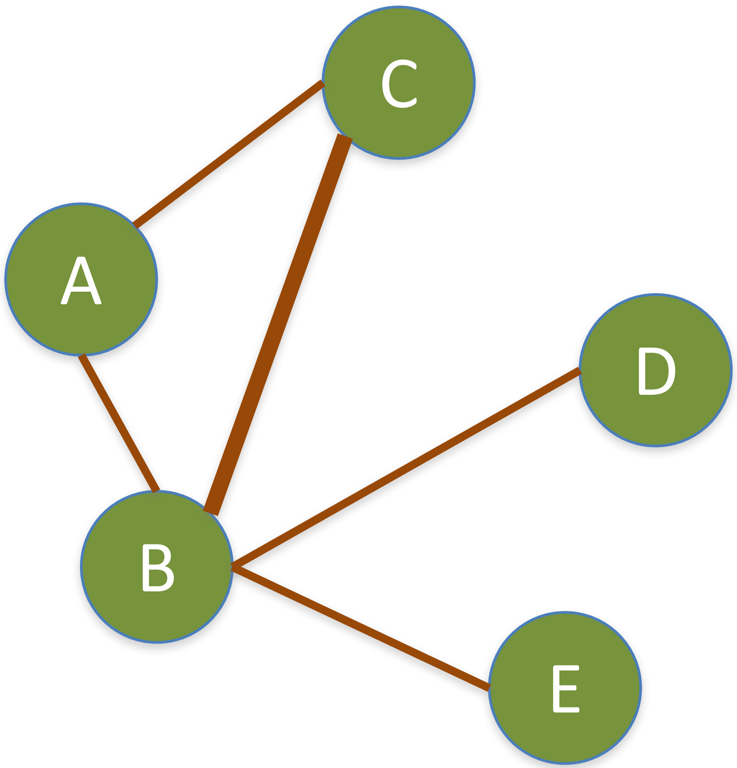
Source: http://sebastien.pro/gephi-icwsm-tutorial.pdf

Degree



Source: https://www.youtube.com/watch?v=89mxOdwPfxA

Degree



A: 2

<u>B: 4</u>

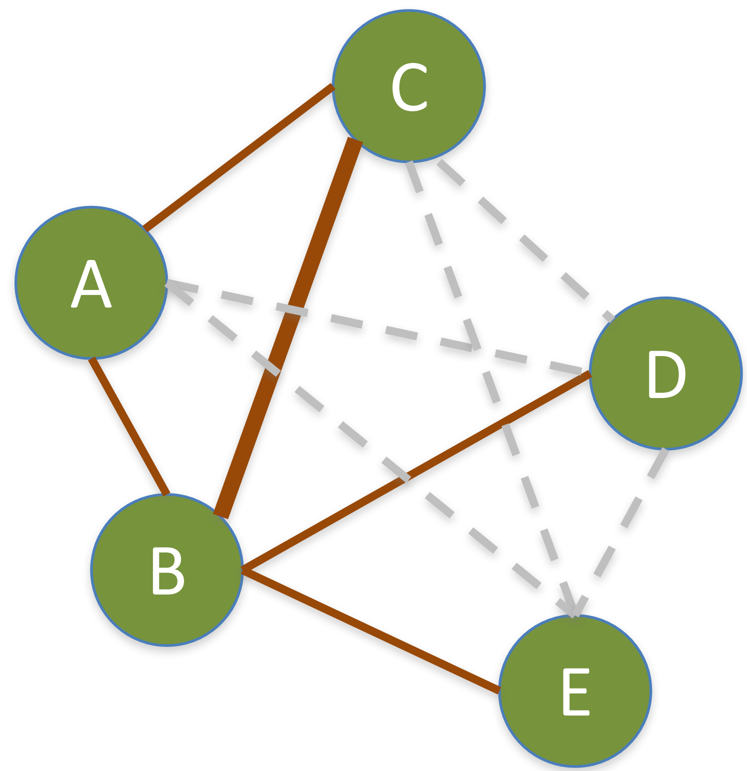
C: 2

D:1

E: 1

Source: https://www.youtube.com/watch?v=89mxOdwPfxA

Density



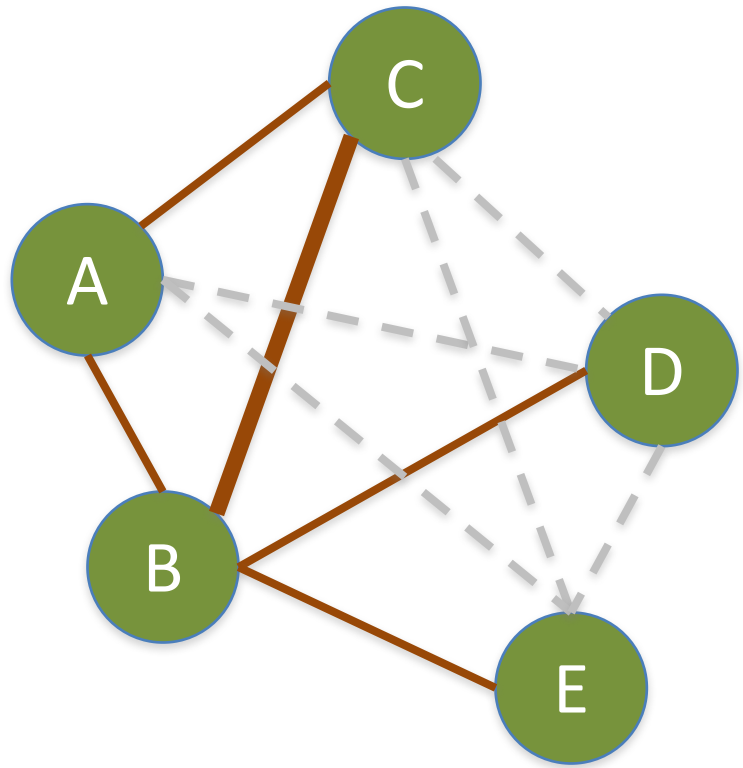
Source: https://www.youtube.com/watch?v=89mxOdwPfxA

Density

Edges (Links): 5

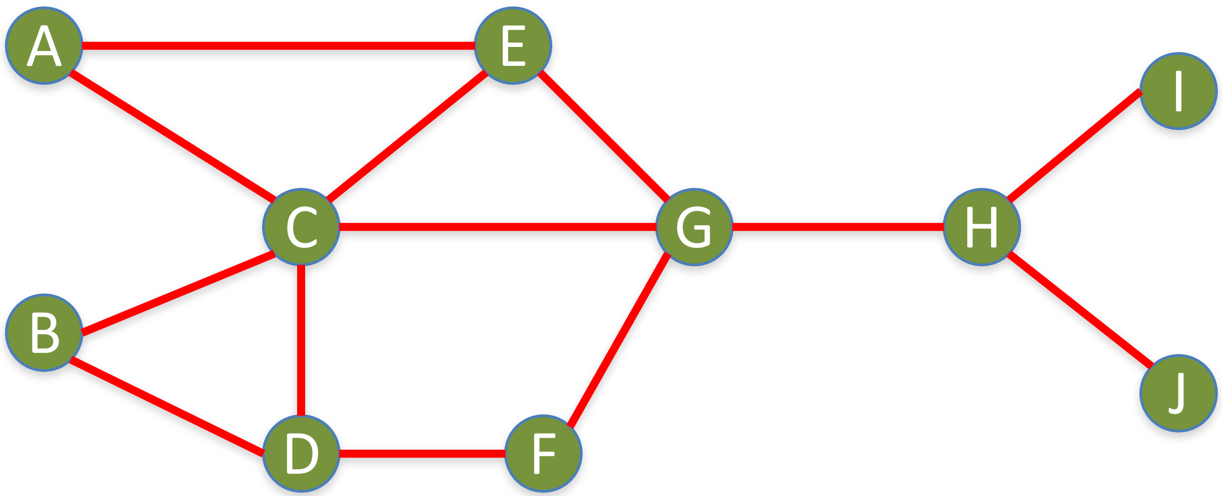
Total Possible Edges: 10

Density: 5/10 = 0.5



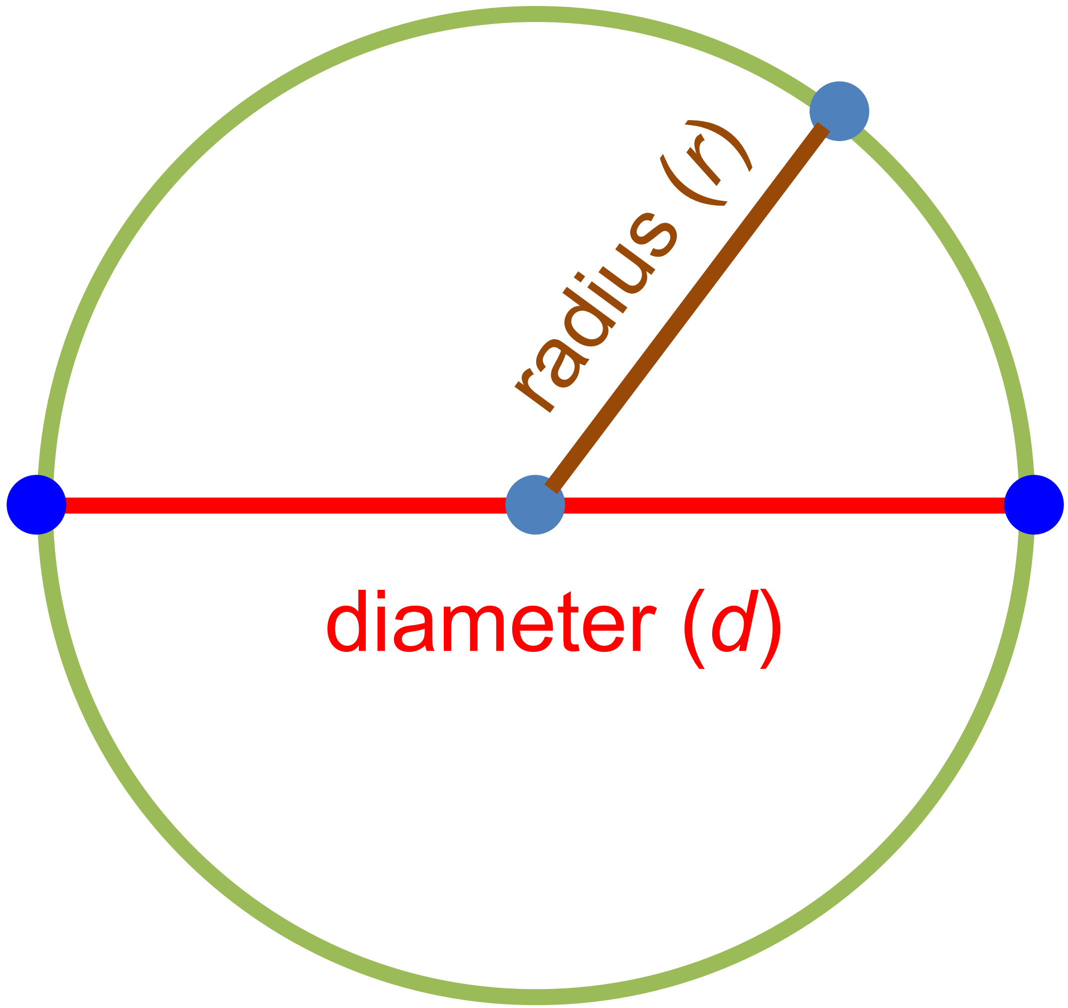
Source: https://www.youtube.com/watch?v=89mxOdwPfxA

Density

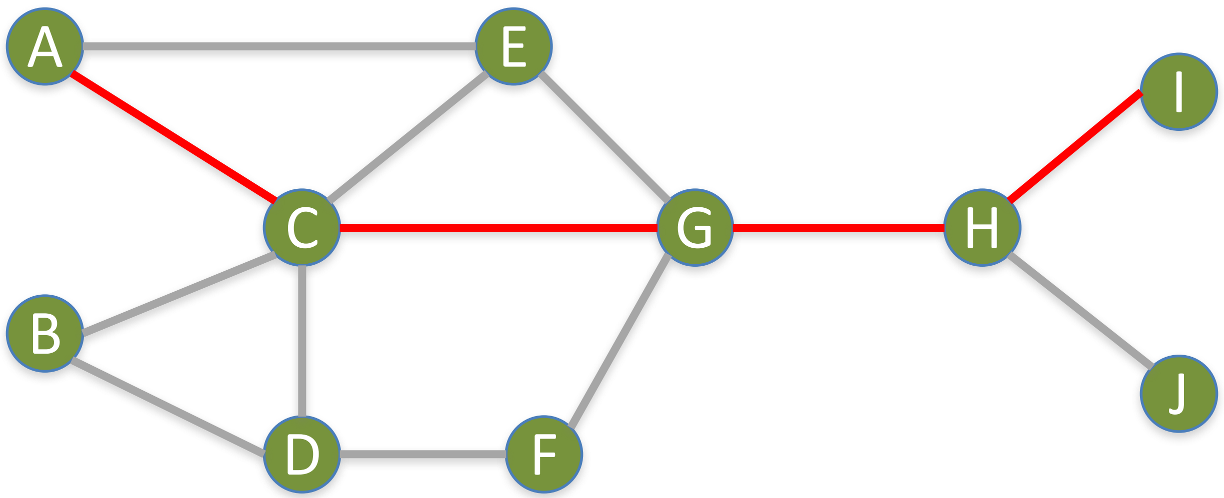


Nodes (n): 10
Edges (Links): 13
Total Possible Edges: (n * (n-1)) / 2 = (10 * 9) / 2 = 45
Density: 13/45 = 0.29

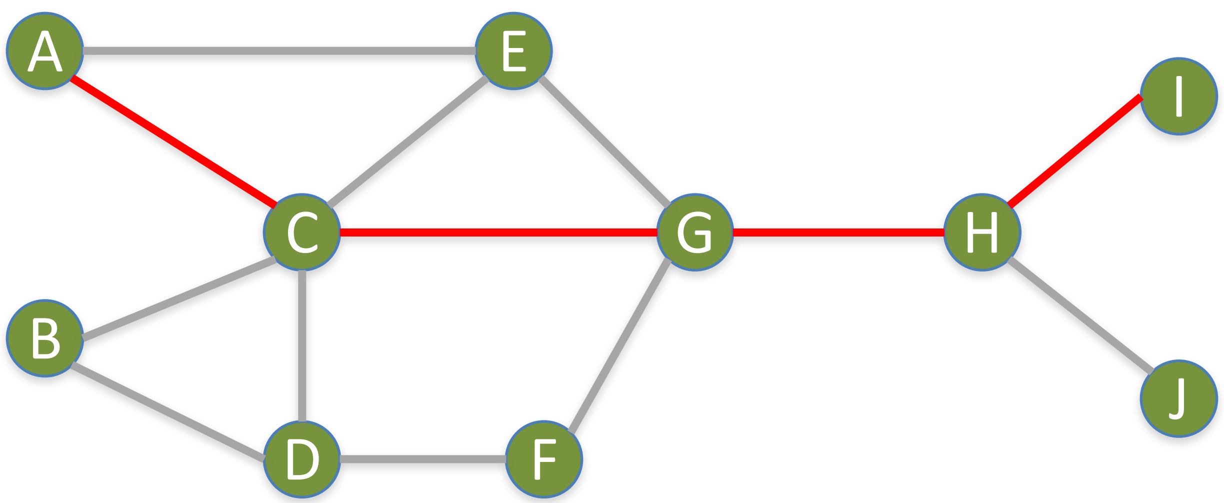
Diameter



Diameter

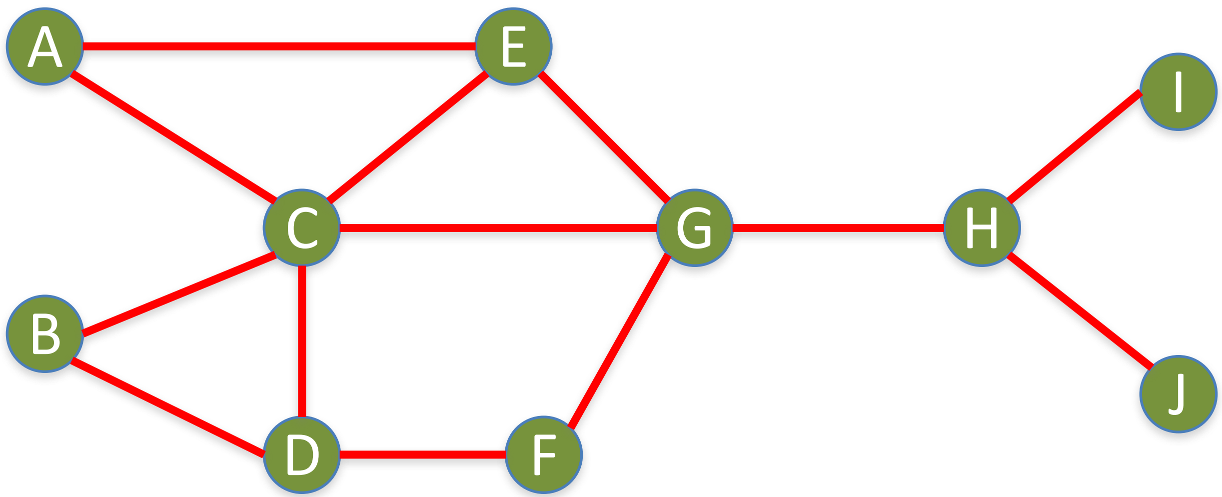


Diameter
Geodesic Path (Shortest Path)



A→ I : Diameter = 4

Which Node is Most Important?



Centrality

- Important or prominent actors are those that are linked or involved with other actors extensively.
- A person with extensive contacts (links) or communications with many other people in the organization is considered more important than a person with relatively fewer contacts.
- The links can also be called **ties**.
  A central actor is one involved in many ties.

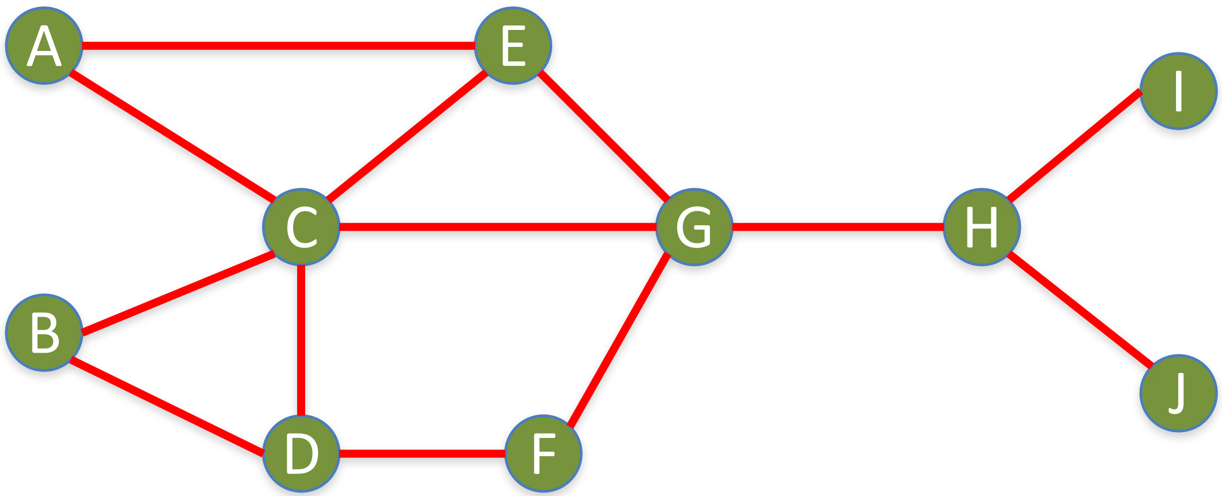
Source: Bing Liu (2011) , “Web Data Mining: Exploring Hyperlinks, Contents, and Usage Data”

Social Network Analysis (SNA)

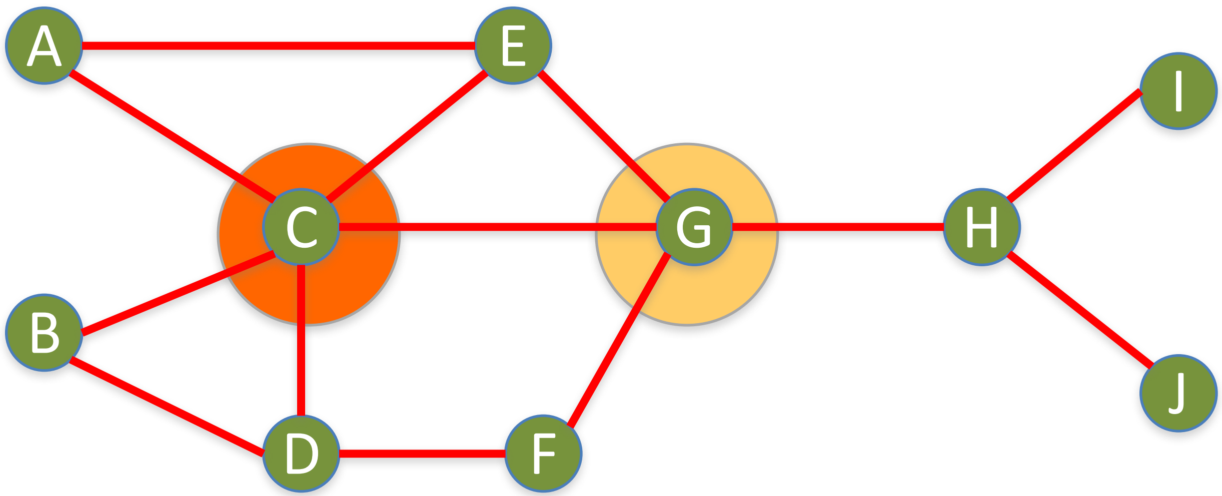
- Degree Centrality
- Betweenness Centrality
- Closeness Centrality

Degree Centrality

Social Network Analysis: Degree Centrality



Social Network Analysis: Degree Centrality



Node	Score	Standardized Score
A	2	2/10 = 0.2
B	2	2/10 = 0.2
C	**5**	**5/10 = 0.5**
D	3	3/10 = 0.3
E	3	3/10 = 0.3
F	2	2/10 = 0.2
G	**4**	**4/10 = 0.4**
H	3	3/10 = 0.3
I	1	1/10 = 0.1
J	1	1/10 = 0.1

Betweenness Centrality

Betweenness centrality:

Connectivity

Number of shortest paths going through the actor

Betweenness Centrality

$$C_B(i) = \sum_{j<k} g_{jk}(i) / g_{jk}$$

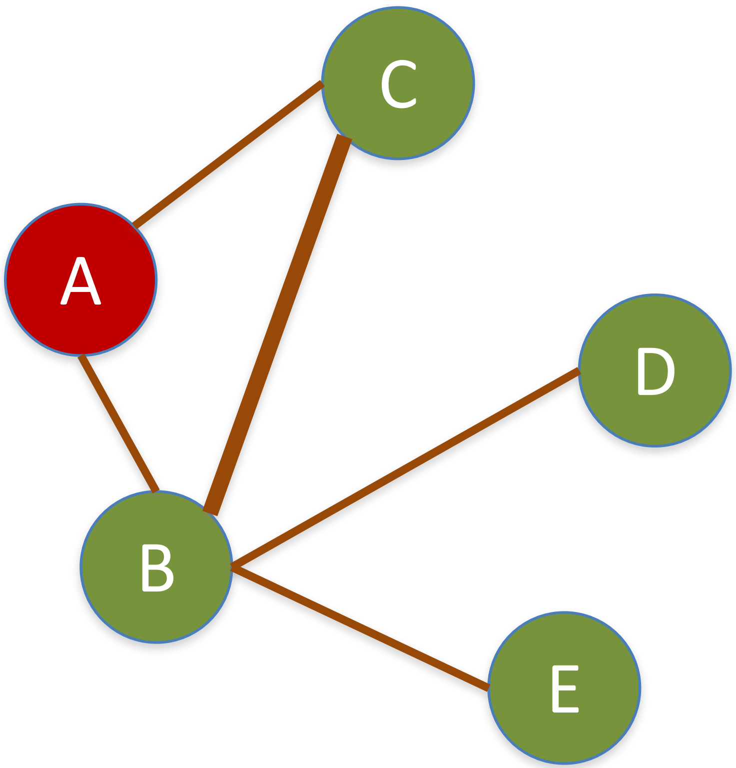
Where g_{jk} = the number of shortest paths connecting jk
$g_{jk}(i)$ = the number that actor i is on.

Normalized Betweenness Centrality

$$C'_B(i) = C_B(i) / \boxed{[(n-1)(n-2)/2]}$$

Number of pairs of vertices excluding the vertex itself

Betweenness Centrality



A:

B→C: 0/1 = 0

B→D: 0/1 = 0

B→E: 0/1 = 0

C→D: 0/1 = 0

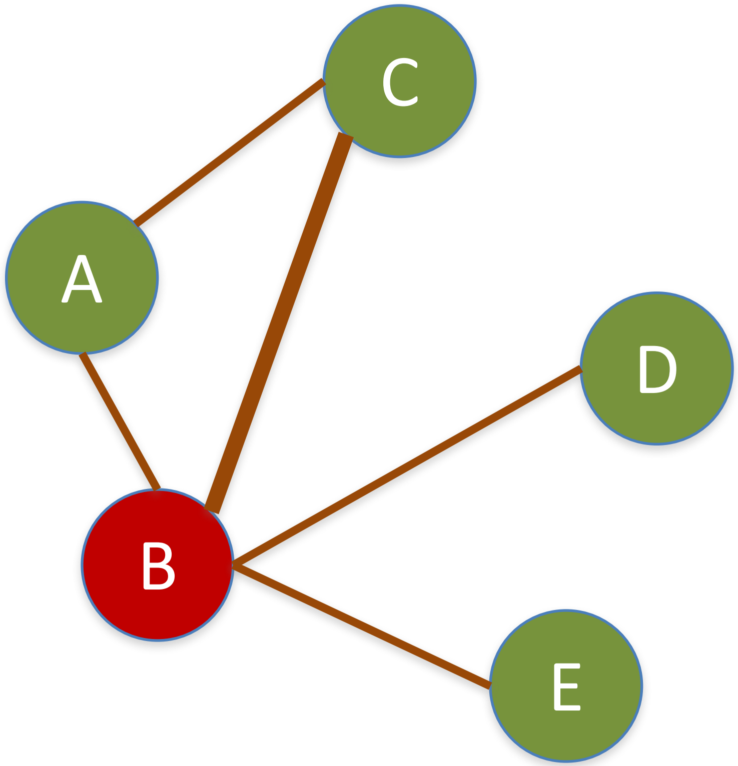
C→E: 0/1 = 0

D→E: 0/1 = 0

Total: 0

A: Betweenness Centrality = 0

Betweenness Centrality

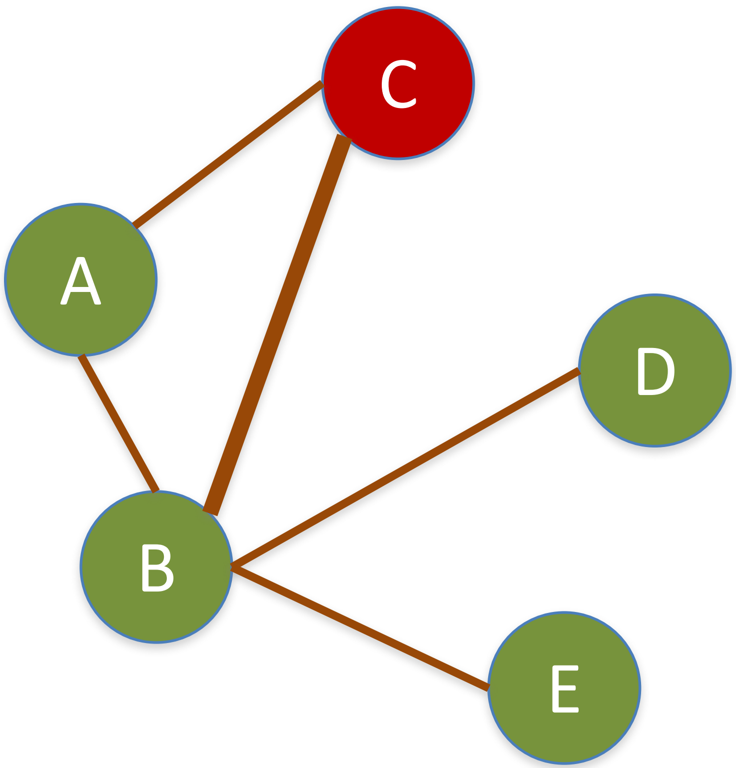


B:
A→C: 0/1 = 0
A→D: 1/1 = 1
A→E: 1/1 = 1
C→D: 1/1 = 1
C→E: 1/1 = 1
D→E: 1/1 = 1

Total: 5

B: Betweenness Centrality = 5

Betweenness Centrality

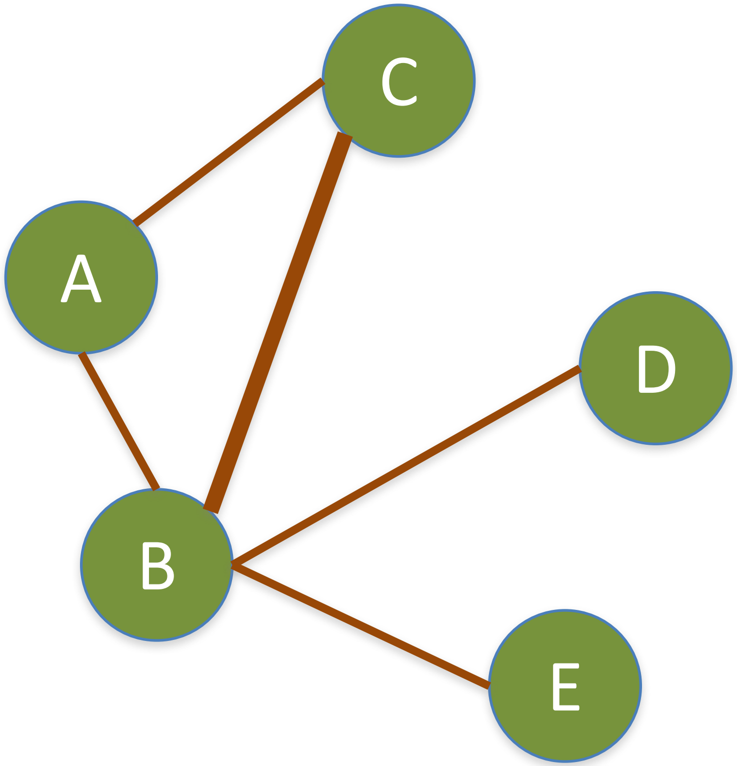


C:
A→B: 0/1 = 0
A→D: 0/1 = 0
A→E: 0/1 = 0
B→D: 0/1 = 0
B→E: 0/1 = 0
D→E: 0/1 = 0

Total: 0

C: Betweenness Centrality = 0

Betweenness Centrality



A: 0

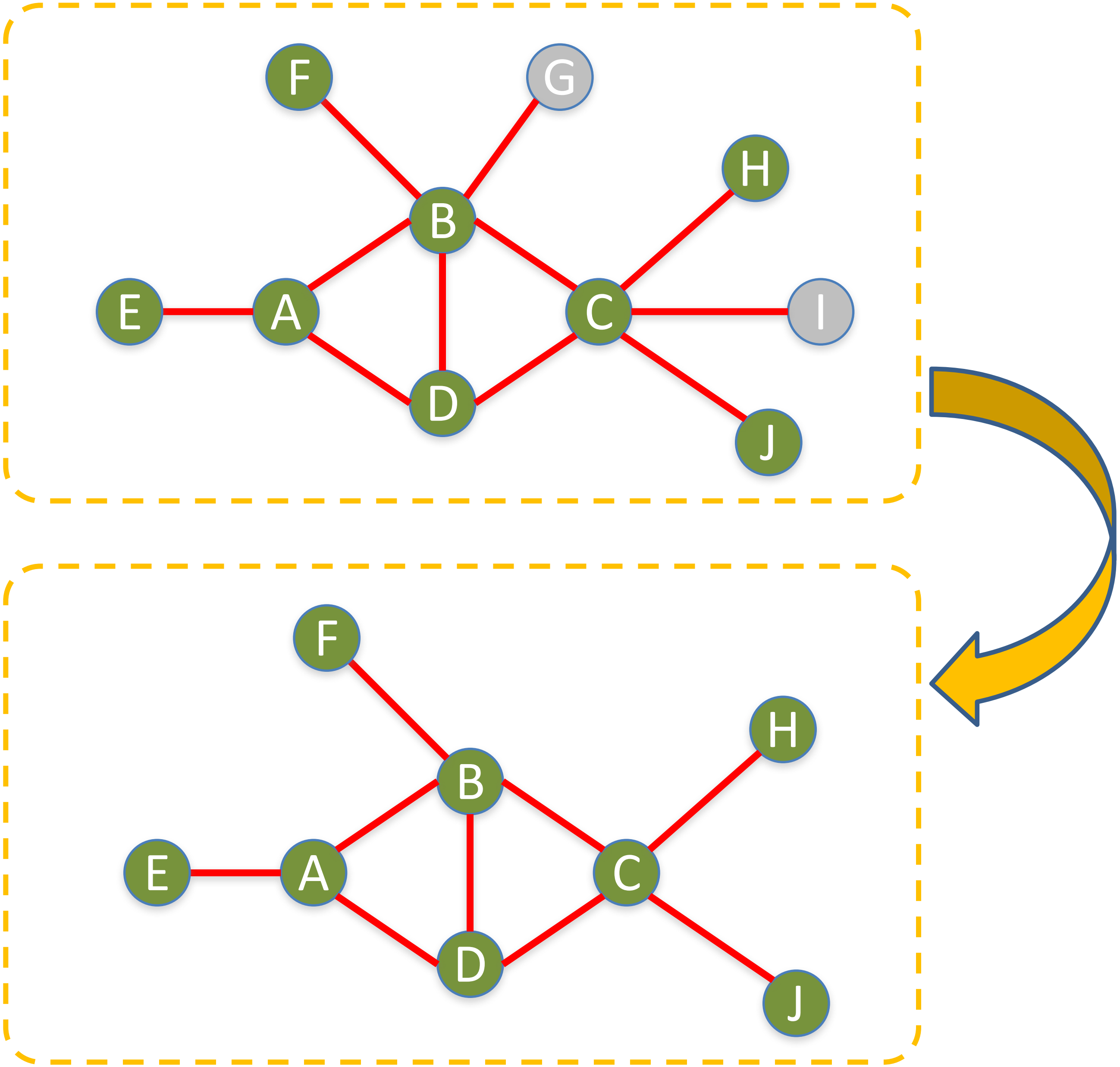
<u>B: 5</u>

C: 0

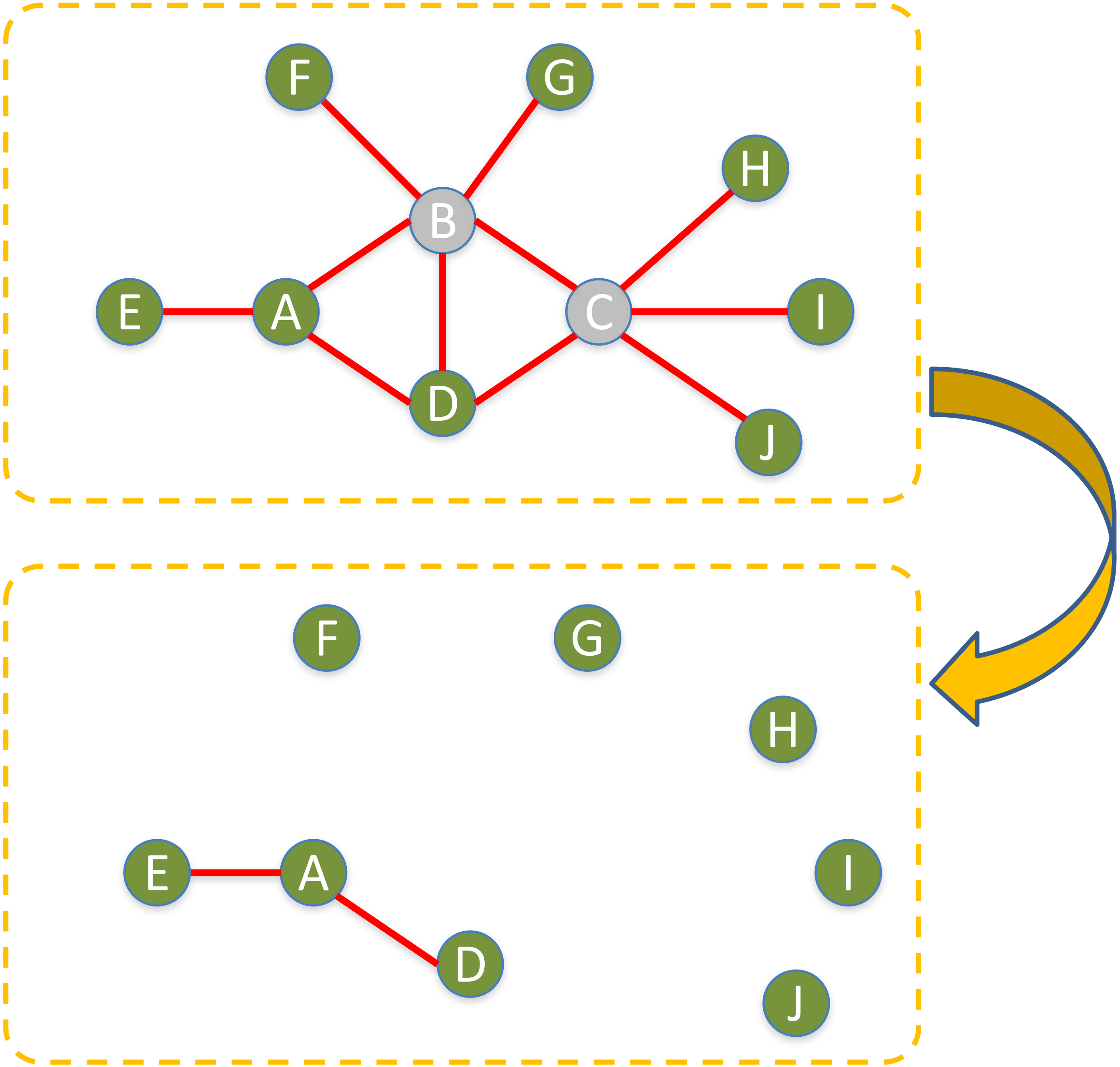
D: 0

E: 0

Which Node is Most Important?

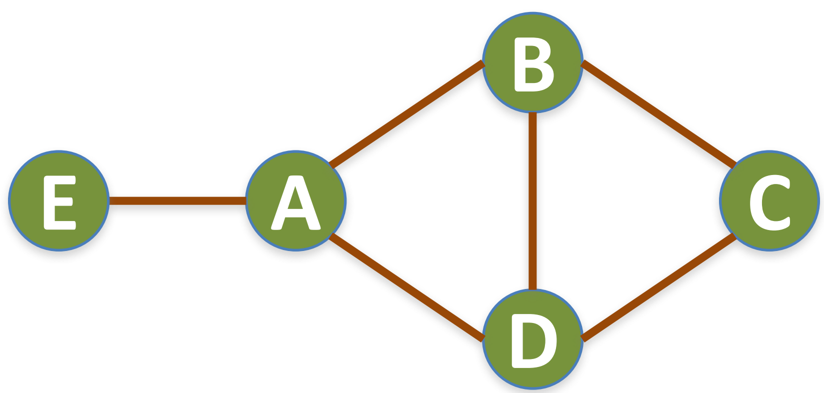


Which Node is Most **Important**?

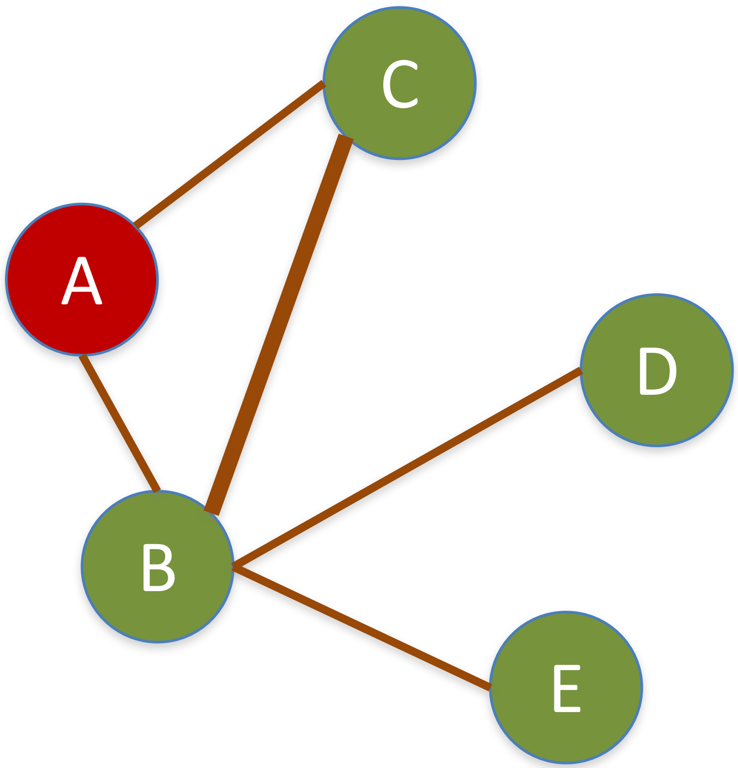


Betweenness Centrality

$$C_B(i) = \sum_{j<k} g_{jk}(i) / g_{jk}$$



Betweenness Centrality



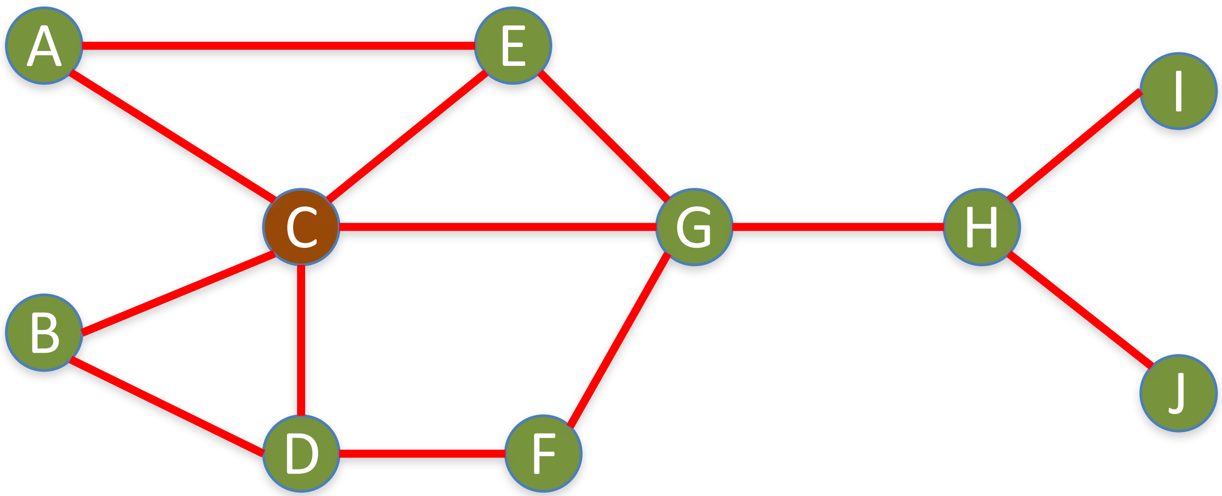
A:
B→C: 0/1 = 0
B→D: 0/1 = 0
B→E: 0/1 = 0
C→D: 0/1 = 0
C→E: 0/1 = 0
D→E: 0/1 = 0

Total: 0

A: Betweenness Centrality = 0

Closeness Centrality

Social Network Analysis: Closeness Centrality

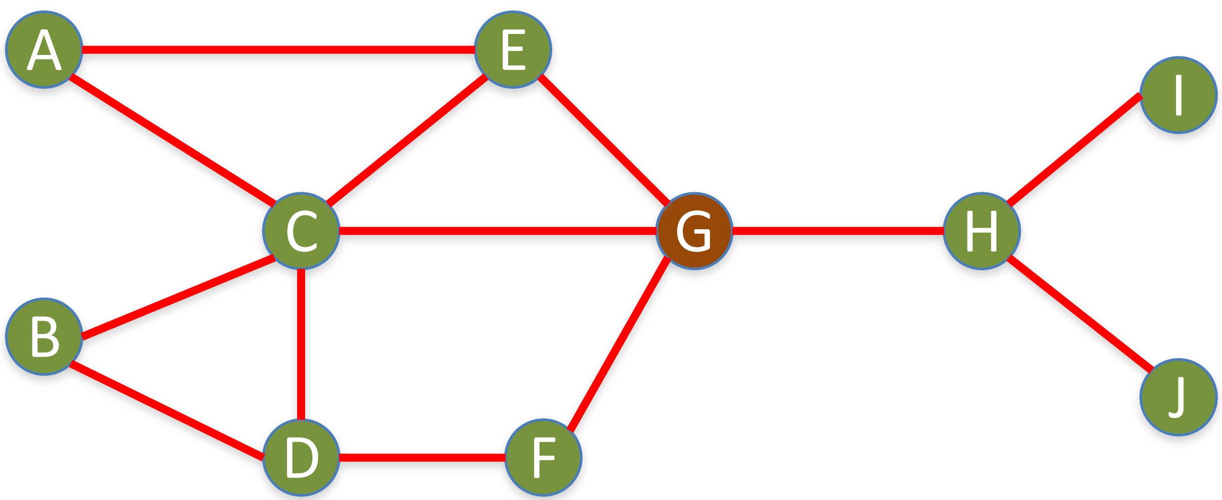


C→A: 1
C→B: 1
C→D: 1
C→E: 1
C→F: 2
C→G: 1
C→H: 2
C→I: 3
C→J: 3

Total=15

C: Closeness Centrality = 15/9 = 1.67

Social Network Analysis: Closeness Centrality

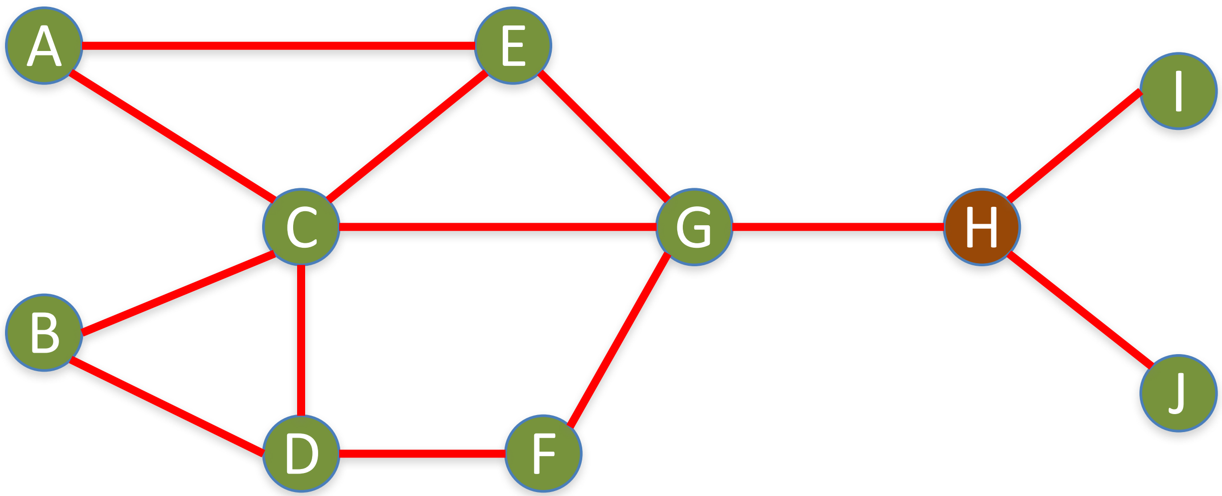


G→A: 2
G→B: 2
G→C: 1
G→D: 2
G→E: 1
G→F: 1
G→H: 1
G→I: 2
G→J: 2

Total=14

G: Closeness Centrality = 14/9 = 1.56

Social Network Analysis: Closeness Centrality

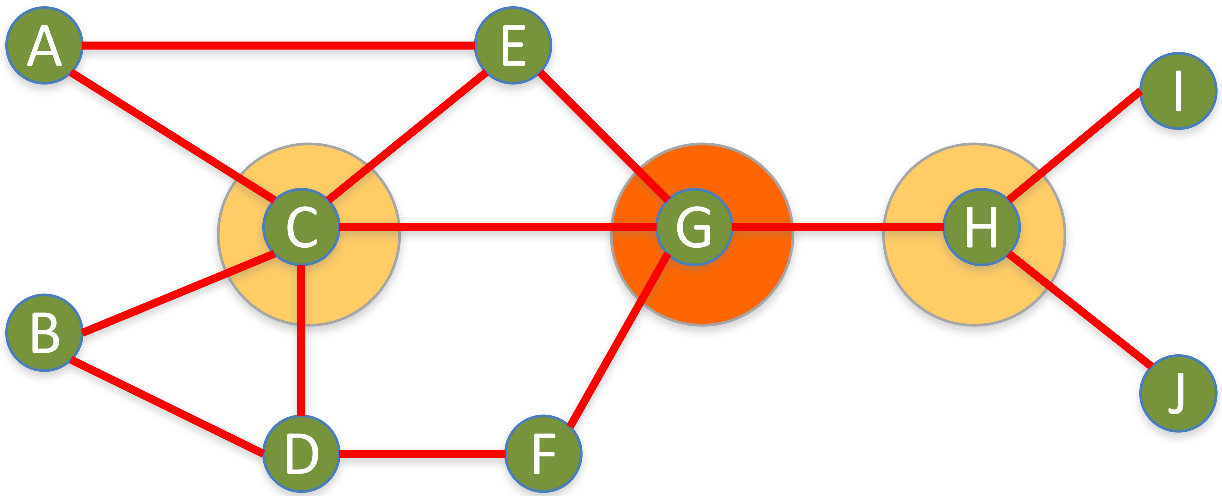


H→A: 3
H→B: 3
H→C: 2
H→D: 2
H→E: 2
H→F: 2
H→G: 1
H→I: 1
H→J: 1

Total=17

H: Closeness Centrality = 17/9 = 1.89

Social Network Analysis: Closeness Centrality



G: Closeness Centrality = 14/9 = 1.56 1

C: Closeness Centrality = 15/9 = 1.67 2

H: Closeness Centrality = 17/9 = 1.89 3

International Research Collaboration and Mobility

Application of SNA

Social Network Analysis
of
Research Collaboration
in
Information Reuse and Integration

Source: Min-Yuh Day, Sheng-Pao Shih, Weide Chang (2011),
"Social Network Analysis of Research Collaboration in Information Reuse and Integration"

Example of SNA Data Source

home | browse | search | about

dblp
computer science bibliography

IRI 2010: Las Vegas, NV, USA

- **Proceedings of the IEEE International Conference on Information Reuse and Integration, IRI 2010, 4-6 August 2010, Las Vegas, Nevada, USA.** IEEE Systems, Man, and Cybernetics Society 2010
- Reda Alhajj, James B. D. Joshi, Mei-Ling Shyu: **Message from Program Co-Chairs.** 1
- Stuart Harvey Rubin, Shu-Ching Chen: **Forward.** 1
- Lotfi A. Zadeh: **Precisiation of meaning - toward computation with natural language.** 1-4
- Reda Alhajj, Shu-Ching Chen, Gongzhu Hu, James B. D. Joshi, Gordon K. Lee, Stuart Harvey Rubin, Mei-Ling Shyu, Lotfi A. Zadeh: **Panel title: Critical need for funding of basic and applied research in large-scale computing.** 1

Automation, Integration and Reuse across Various Apps

- László István Etesi, André Csillaghy, Lin-Ching Chang: **A message-based interoperability framework with application to astrophysics.** 1-6
- Awny Alnusair, Tian Zhao, Eric Bodden: **Effective API navigation and reuse.** 7-12
- Manabu Ohta, Ryohei Inoue, Atsuhiro Takasu: **Empirical evaluation of active sampling for CRF-based analysis of pages.** 13-18
- Qunzhi Zhou, Viktor K. Prasanna: **Workflow management of simulation based computation processes in transportation domain.** 19-24

Source: http://www.informatik.uni-trier.de/~ley/db/conf/iri/iri2010.html

Research Question

- RQ1: What are the scientific collaboration patterns in the IRI research community?

- RQ2: Who are the prominent researchers in the IRI community?

Source: Min-Yuh Day, Sheng-Pao Shih, Weide Chang (2011), "Social Network Analysis of Research Collaboration in Information Reuse and Integration"

Methodology

- Developed a simple web focused crawler program to download literature information about all IRI papers published between 2003 and 2010 from IEEE Xplore and DBLP.
  - 767 paper
  - 1599 distinct author
- Developed a program to convert the list of coauthors into the format of a network file which can be readable by social network analysis software.
- *UCINet* and *Pajek* were used in this study for the social network analysis.

Source: Min-Yuh Day, Sheng-Pao Shih, Weide Chang (2011), "Social Network Analysis of Research Collaboration in Information Reuse and Integration"

Top10 prolific authors (IRI 2003-2010)

1. Stuart Harvey Rubin
2. Taghi M. Khoshgoftaar
3. Shu-Ching Chen
4. Mei-Ling Shyu
5. Mohamed E. Fayad
6. Reda Alhajj
7. Du Zhang
8. Wen-Lian Hsu
9. Jason Van Hulse
10. Min-Yuh Day

Source: Min-Yuh Day, Sheng-Pao Shih, Weide Chang (2011), "Social Network Analysis of Research Collaboration in Information Reuse and Integration"

Data Analysis and Discussion

- **Closeness Centrality**
  - Collaborated widely
- **Betweenness Centrality**
  - Collaborated diversely
- **Degree Centrality**
  - Collaborated frequently
- **Visualization of Social Network Analysis**
  - Insight into the structural characteristics of research collaboration networks

Source: Min-Yuh Day, Sheng-Pao Shih, Weide Chang (2011), "Social Network Analysis of Research Collaboration in Information Reuse and Integration"

Top 20 authors with the highest closeness scores

Rank	ID	Closeness	Author
1	3	0.024675	Shu-Ching Chen
2	1	0.022830	Stuart Harvey Rubin
3	4	0.022207	Mei-Ling Shyu
4	6	0.020013	Reda Alhajj
5	61	0.019700	Na Zhao
6	260	0.018936	Min Chen
7	151	0.018230	Gordon K. Lee
8	19	0.017962	Chengcui Zhang
9	1043	0.017962	Isai Michel Lombera
10	1027	0.017962	Michael Armella
11	443	0.017448	James B. Law
12	157	0.017082	Keqi Zhang
13	253	0.016731	Shahid Hamid
14	1038	0.016618	Walter Z. Tang
15	959	0.016285	Chengjun Zhan
16	957	0.016285	Lin Luo
17	956	0.016285	Guo Chen
18	955	0.016285	Xin Huang
19	943	0.016285	Sneh Gulati
20	960	0.016071	Sheng-Tun Li

Source: Min-Yuh Day, Sheng-Pao Shih, Weide Chang (2011),
"Social Network Analysis of Research Collaboration in Information Reuse and Integration"

Top 20 authors with the highest betweeness scores

Rank	ID	Betweenness	Author
1	1	0.000752	Stuart Harvey Rubin
2	3	0.000741	Shu-Ching Chen
3	2	0.000406	Taghi M. Khoshgoftaar
4	66	0.000385	Xingquan Zhu
5	4	0.000376	Mei-Ling Shyu
6	6	0.000296	Reda Alhajj
7	65	0.000256	Xindong Wu
8	19	0.000194	Chengcui Zhang
9	39	0.000185	Wei Dai
10	15	0.000107	Narayan C. Debnath
11	31	0.000094	Qianhui Althea Liang
12	151	0.000094	Gordon K. Lee
13	7	0.000085	Du Zhang
14	30	0.000072	Baowen Xu
15	41	0.000067	Hongji Yang
16	270	0.000060	Zhiwei Xu
17	5	0.000043	Mohamed E. Fayad
18	110	0.000042	Abhijit S. Pandya
19	106	0.000042	Sam Hsu
20	8	0.000042	Wen-Lian Hsu

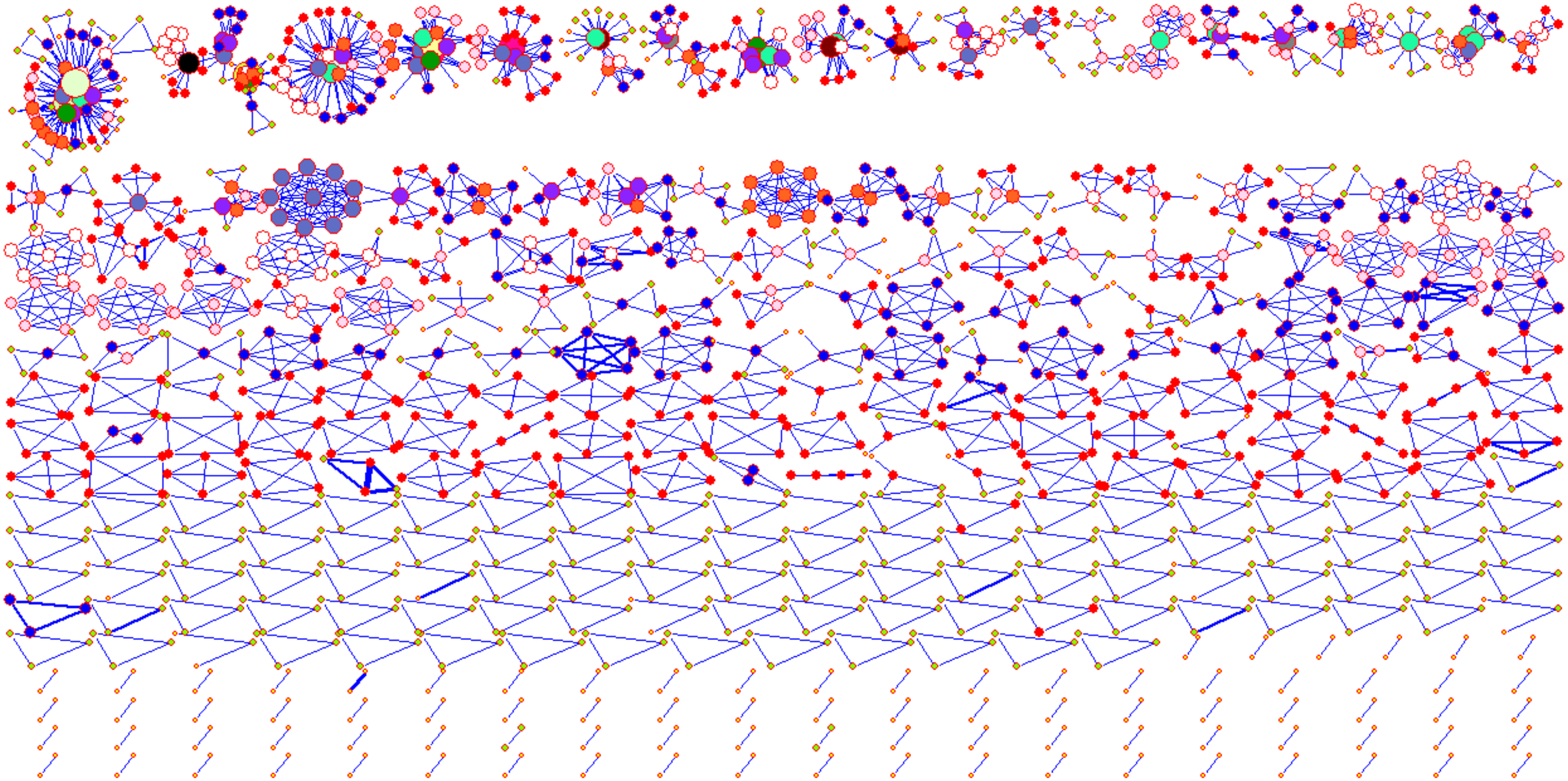
Source: Min-Yuh Day, Sheng-Pao Shih, Weide Chang (2011),
"Social Network Analysis of Research Collaboration in Information Reuse and Integration"

Top 20 authors with the highest degree scores

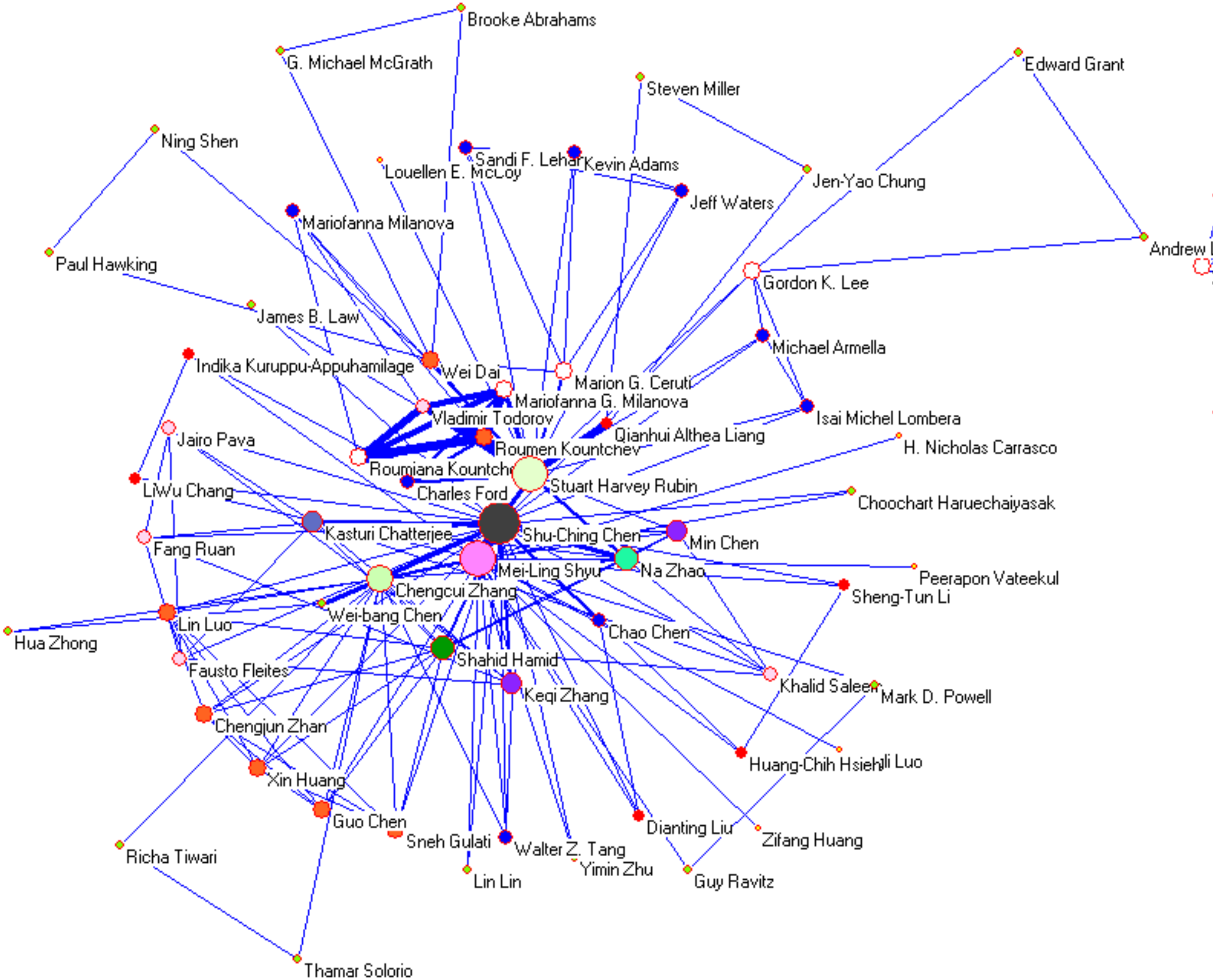
Rank	ID	Degree	Author
1	3	0.035044	Shu-Ching Chen
2	1	0.034418	Stuart Harvey Rubin
3	2	0.030663	Taghi M. Khoshgoftaar
4	6	0.028786	Reda Alhajj
5	8	0.028786	Wen-Lian Hsu
6	10	0.024406	Min-Yuh Day
7	4	0.022528	Mei-Ling Shyu
8	17	0.021277	Richard Tzong-Han Tsai
9	14	0.017522	Eduardo Santana de Almeida
10	16	0.017522	Roumen Kountchev
11	40	0.016896	Hong-Jie Dai
12	15	0.015645	Narayan C. Debnath
13	9	0.015019	Jason Van Hulse
14	25	0.013767	Roumiana Kountcheva
15	28	0.013141	Silvio Romero de Lemos Meira
16	24	0.013141	Vladimir Todorov
17	23	0.013141	Mariofanna G. Milanova
18	5	0.013141	Mohamed E. Fayad
19	19	0.012516	Chengcui Zhang
20	18	0.011890	Waleed W. Smari

Source: Min-Yuh Day, Sheng-Pao Shih, Weide Chang (2011),
"Social Network Analysis of Research Collaboration in Information Reuse and Integration"

Visualization of IRI (IEEE IRI 2003-2010) co-authorship network (global view)

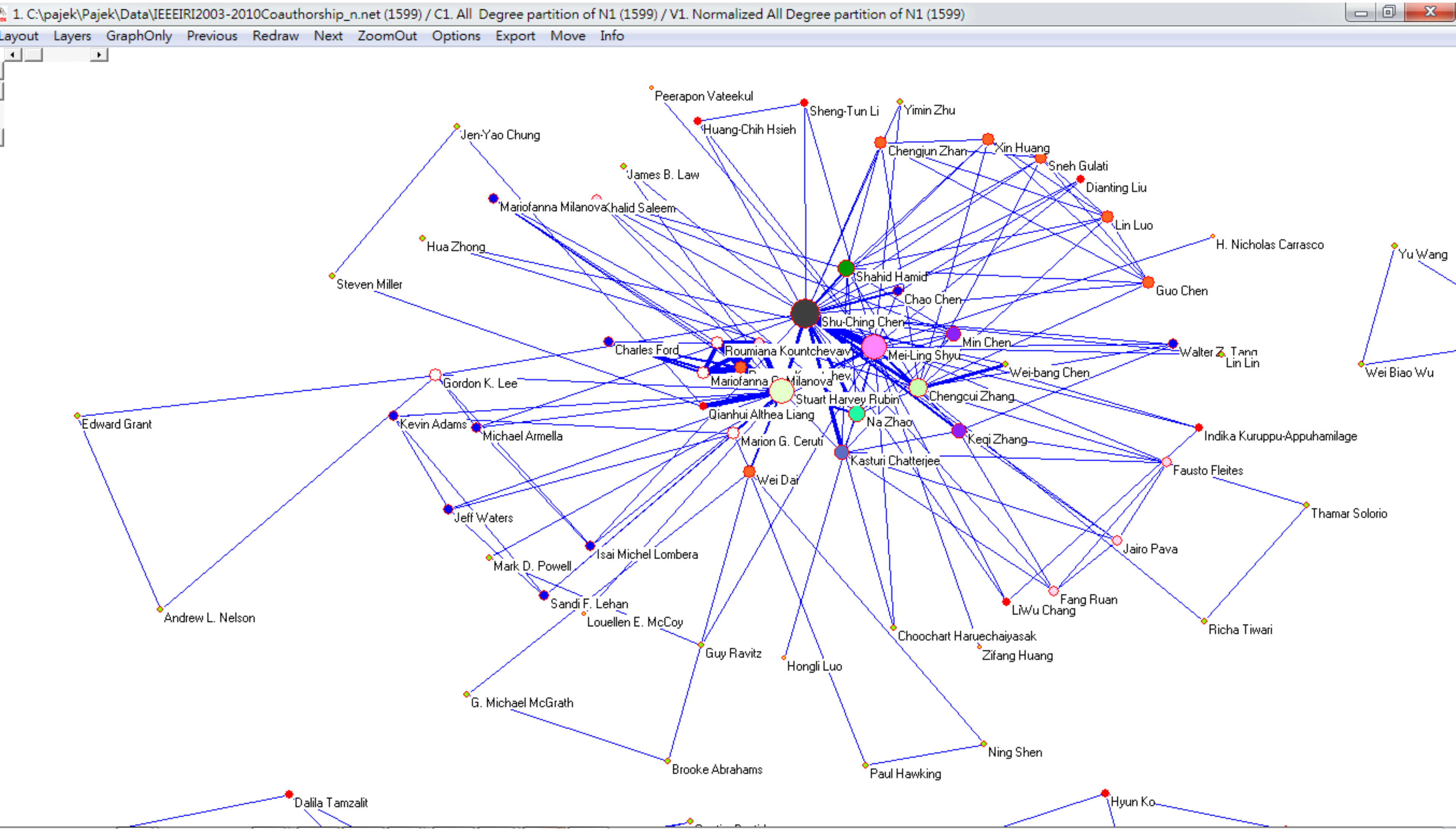


Source: Min-Yuh Day, Sheng-Pao Shih, Weide Chang (2011),
"Social Network Analysis of Research Collaboration in Information Reuse and Integration"



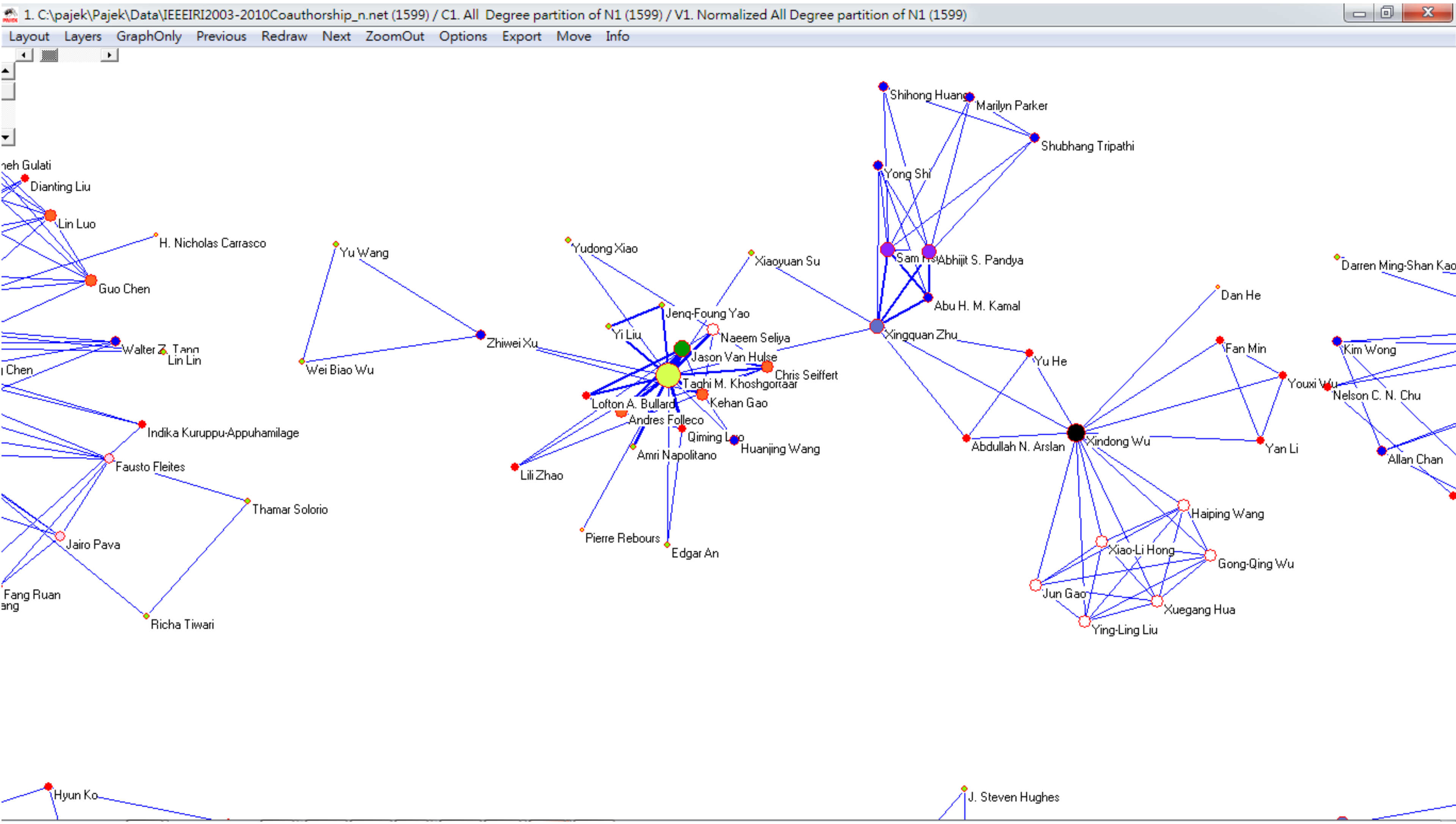
Source: Min-Yuh Day, Sheng-Pao Shih, Weide Chang (2011),
"Social Network Analysis of Research Collaboration in Information Reuse and Integration"

Visualization of Social Network Analysis



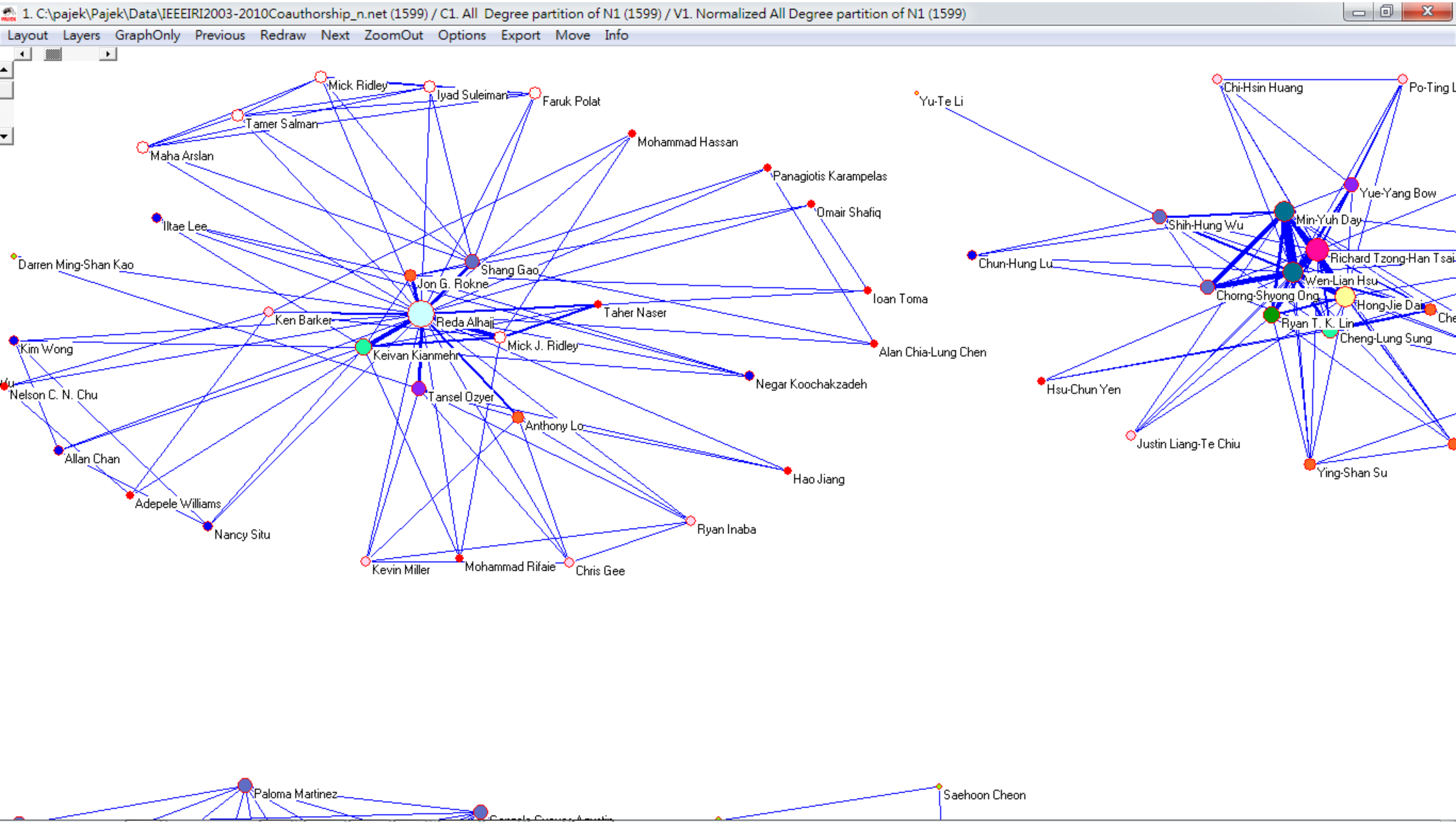
Source: Min-Yuh Day, Sheng-Pao Shih, Weide Chang (2011), "Social Network Analysis of Research Collaboration in Information Reuse and Integration"

Visualization of Social Network Analysis



Source: Min-Yuh Day, Sheng-Pao Shih, Weide Chang (2011),
"Social Network Analysis of Research Collaboration in Information Reuse and Integration"

Visualization of Social Network Analysis



Source: Min-Yuh Day, Sheng-Pao Shih, Weide Chang (2011),
"Social Network Analysis of Research Collaboration in Information Reuse and Integration"

Tamkang University

淡江大學

NTCIR-12, 2016
NTCIR-11, 2014
NTCIR-10, 2013
NTCIR-9, 2011

Tamkang University
淡江大學

Tamkang University

2011

IMTKU Textual Entailment System for Recognizing Inference in Text at NTCIR-9 RITE

NTCIR

Department of Information Management
Tamkang University, Taiwan

Min-Yuh Day Chun Tu

myday@mail.tku.edu.tw

NTCIR-9 Workshop, December 6-9, 2011, Tokyo, Japan

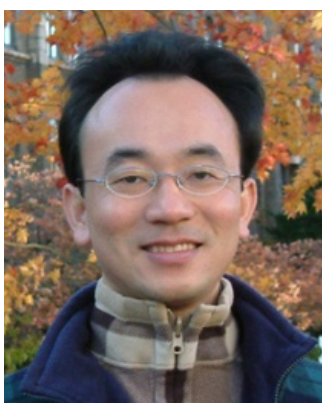
Tamkang University
淡江大學

2013

Tamkang University

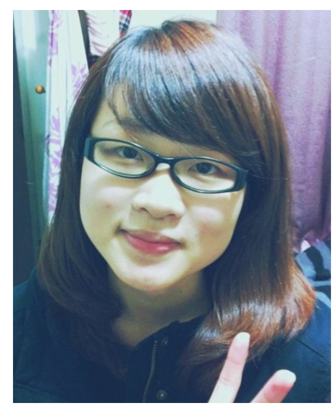
IMTKU Textual Entailment System for Recognizing Inference in Text at NTCIR-10 RITE-2

Department of Information Management
Tamkang University, Taiwan


Min-Yuh Day


Chun Tu


Hou-Cheng Vong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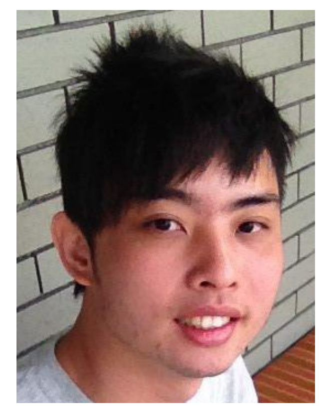

Shih-Jhen Huang

myday@mail.tku.edu.tw

NTCIR-10 Conference, June 18-21, 2013, Tokyo, Japan

IMTKU Textual Entailment System for Recognizing Inference in Text at NTCIR-11 RITE-VAL

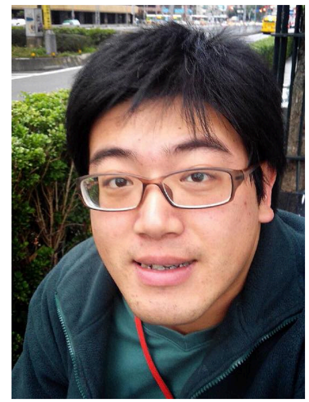
Tamkang University

淡江大學

2014

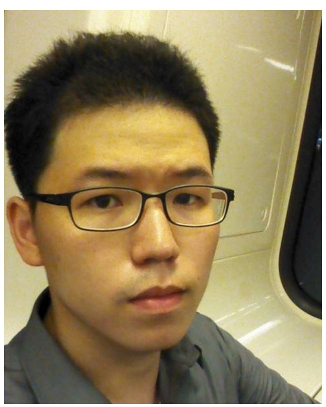
Min-Yuh Day

Ya-Jung Wang



Che-Wei Hsu

En-Chun Tu



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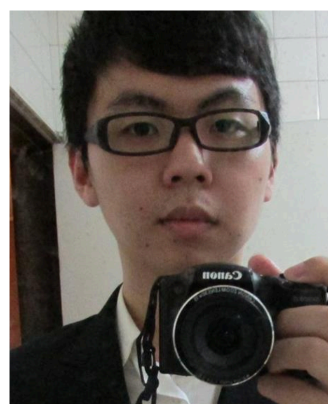
Yu-An Lin



Shang-Yu Wu

Yu-Hsuan Tai

Cheng-Chia Tsai

NTCIR

Tamkang University

淡江大學

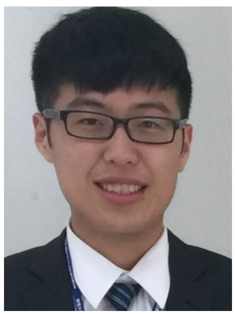
2016

IMTKU Question Answering System for World History Exams at NTCIR-12 QA Lab2

Department of Information Management
Tamkang University, Taiwan

Sagacity Technolog


Min-Yuh Day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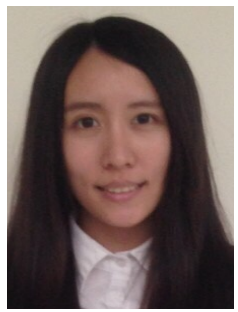
Wei-Chun Chung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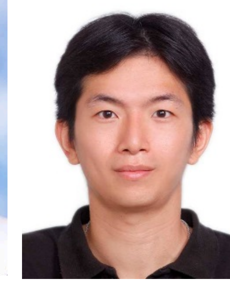
Tzu-Jui Sun


Yuan-Jie Tsai


Jin-Kun Lin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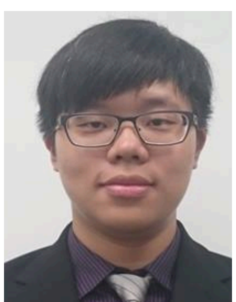
Yu-Ming Guo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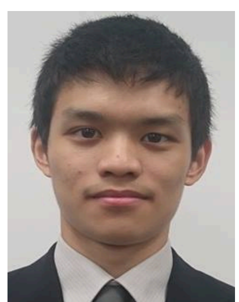
Wei-Ming Chen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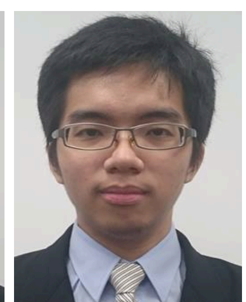
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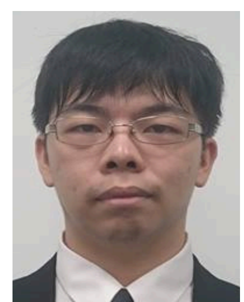
Yi-Jing Lin


Yi-Heng Chiang


Ching-Yuan Chien

myday@mail.tku.edu.tw

NTCIR-12 Conference, June 7-10, 2016, Tokyo, Japan

教育部資通人才培育計畫
社群運算與巨量資料
課程四大模組

(1)「社群媒體」(Social Media)
(政治大學)

(2)「資料科學」 (Data Science)
(政治大學)

(3)「分析技術」(Analytics Technology)
(高雄大學) (淡江大學)

(4)「領域應用」(Domain Application)
(淡江大學) (政治大學)

1.「社群媒體」(Social Media)(政治大學)

- 探討 社群媒體和資料分析的概念，以個案方式教學

2.「資料科學」(Data Science) (政治大學)

- 探討 Data Thinking 和 EDA 等，與DSP或痞客邦合作

3.「分析技術」(Analytics Technology) (高雄大學) (淡江大學)

- 列舉重要的分析方法，包括社會網絡分析，文字探勘分析技術簡介。
  - * 社會網絡分析 (高雄大學)
  - * 社會網絡量測 (高雄大學)
  - * 社會網絡分析工具 (高雄大學)
  - * 文字探勘分析技術簡介 (淡江大學)

4. 「領域應用」(Domain Application) (淡江大學) (政治大學)

- 區分 Domain Knowledge ，聚焦探討各種商業行銷和輿情分析等
  - * 社群媒體行銷分析 (淡江大學)
  - * 社群媒體情感分析 (淡江大學)

Summary

- Big Data Sentiment Analysis
- Social Computing
- International Research Collaboration and Mobility

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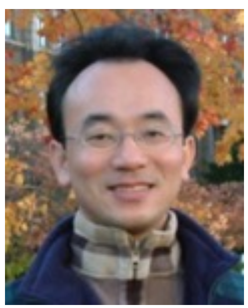
- Bing Liu (2015), Sentiment Analysis: Mining Opinions, Sentiments, and Emotions, Cambridge University Press

Q & A

Research on Social Computing and Big Data Analytics (社群運算與大數據分析研究)

Time: 2016/11/17 (Thu) (15:30-17:30)
Place: 東吳大學資管研究所 <城中校區 教室：4303>
Host: 鄭麗珍 教授 (Prof. Li-chen Cheng)



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專任助理教授
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2016-11-17