KES IDT-IMSS 2013

Intelligent Decision Making in the Era of Semantic Web and Big Data

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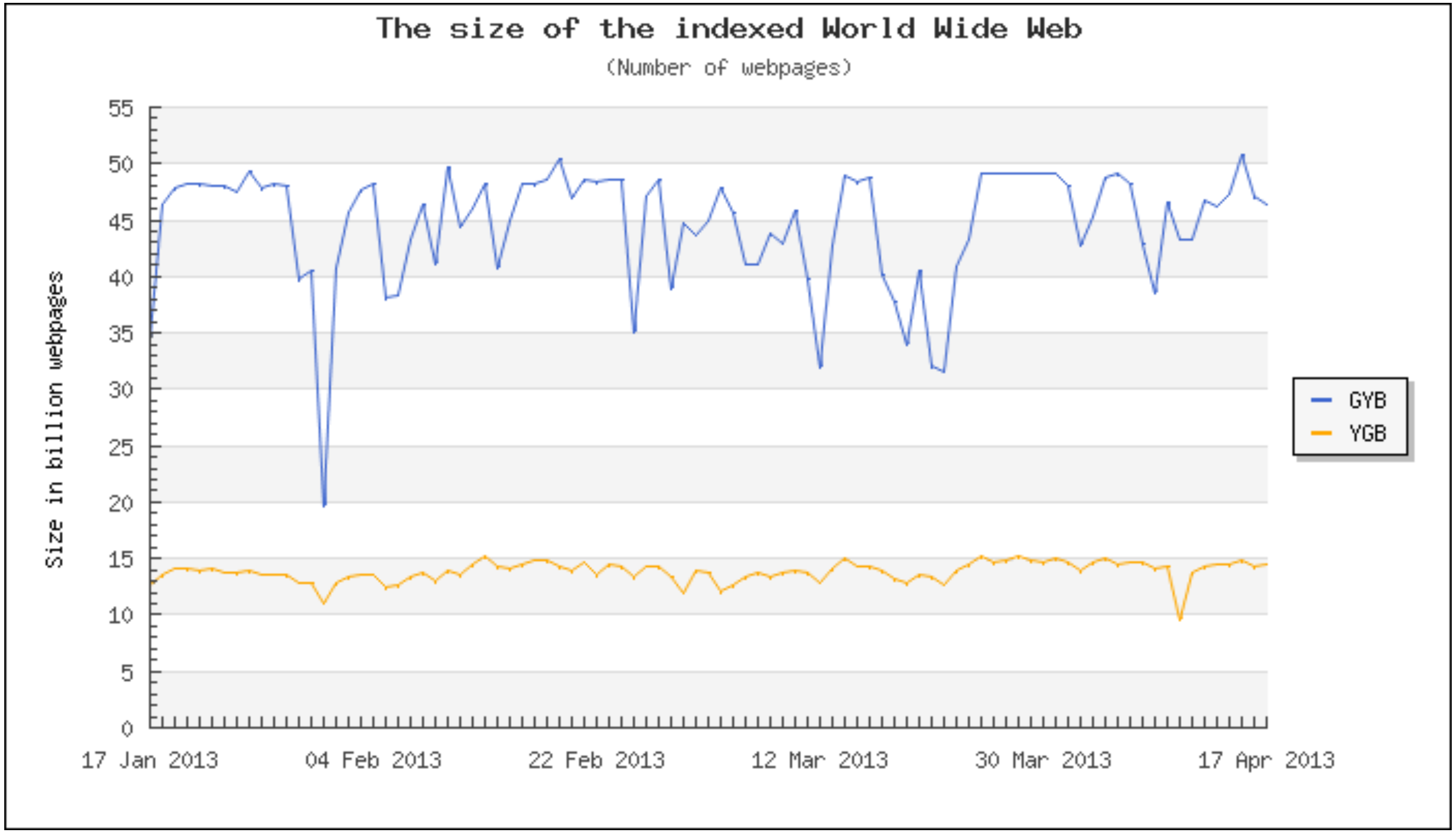
Agenda

- Living in the Era of Big Numbers

- The Concept: Web Competitive Intelligence

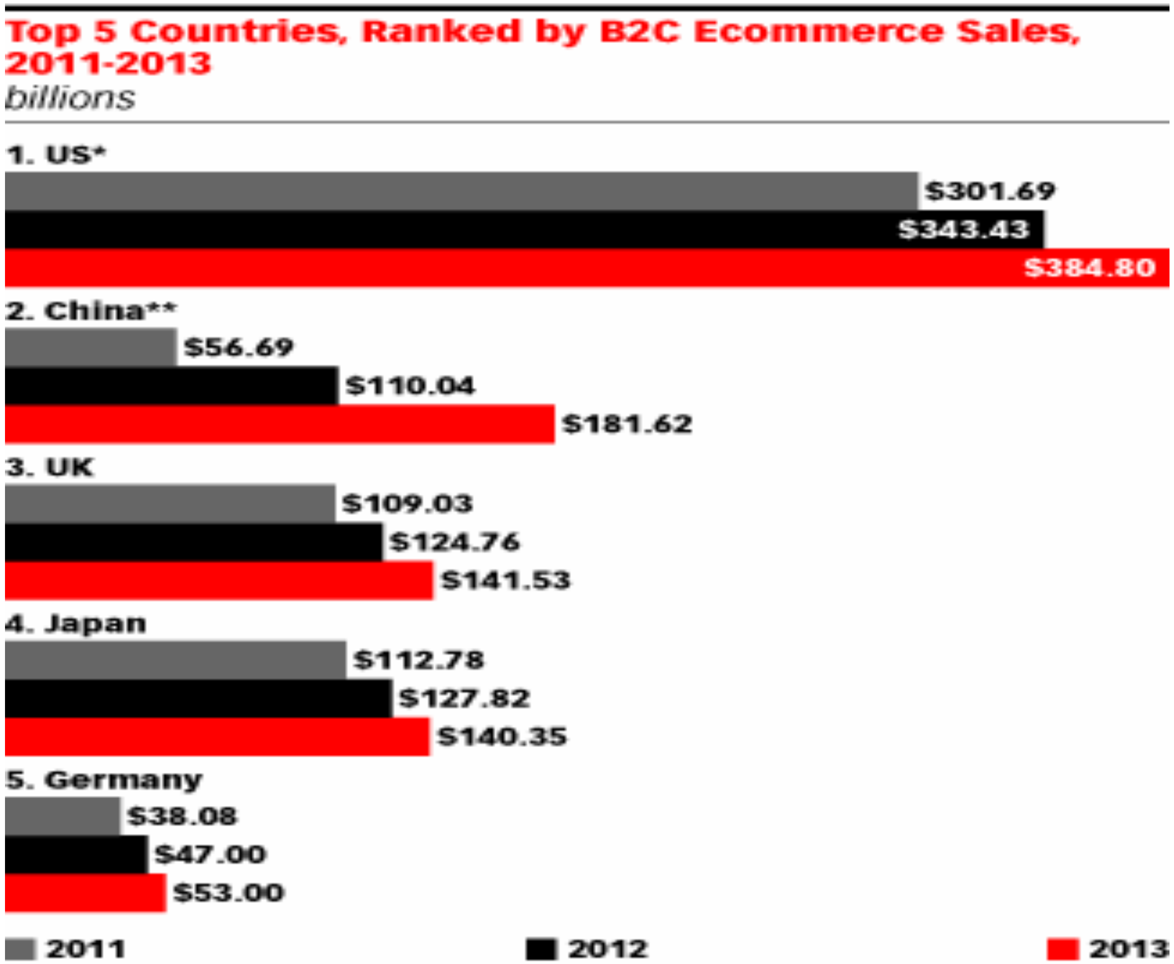
Living in the Era of Big Numbers

The Internet has 50 Billion Webpages



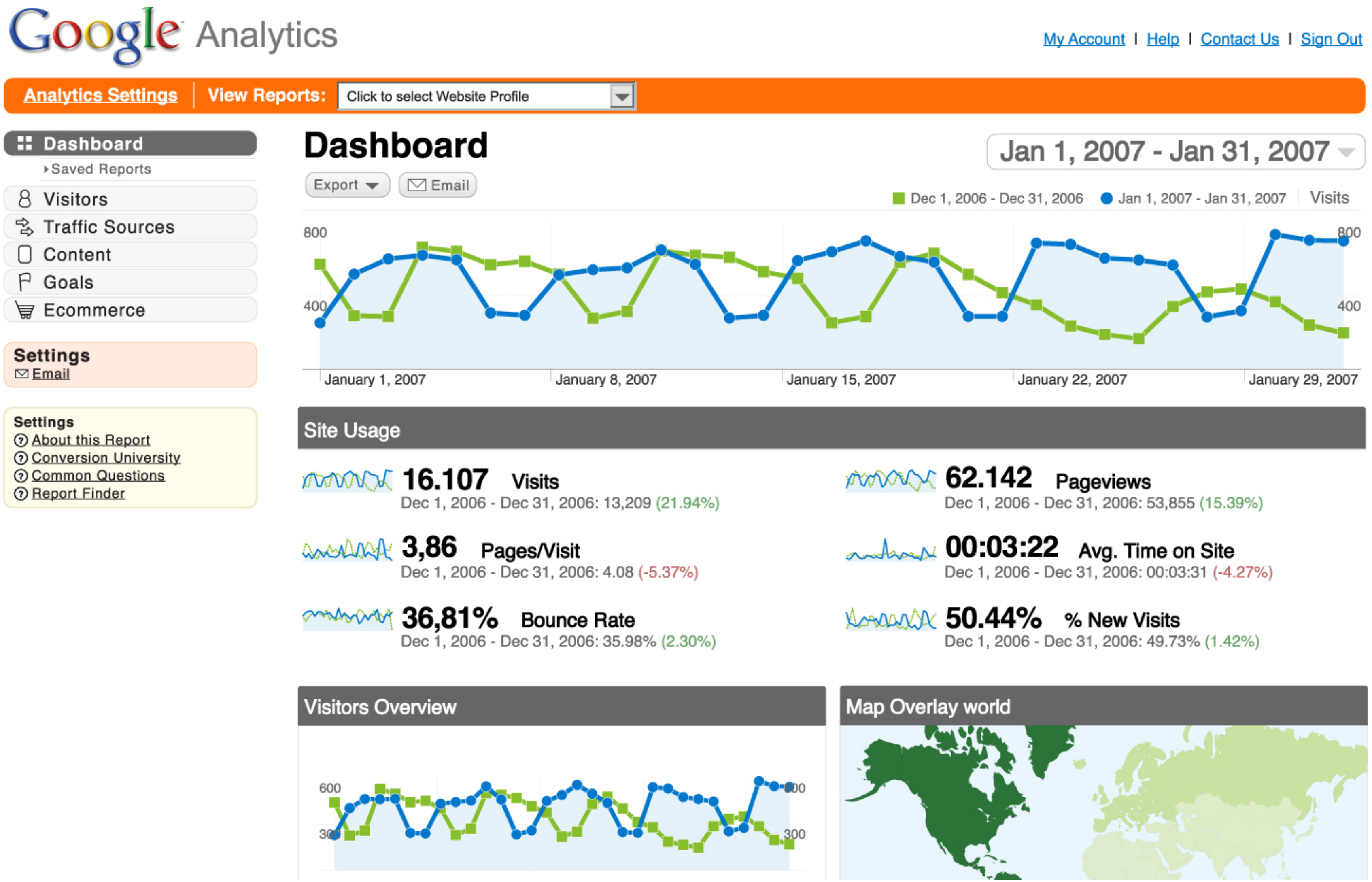
Source: http://www.worldwidewebsize.com/

B2C E-Commerce of 1 Trillion US Dollars

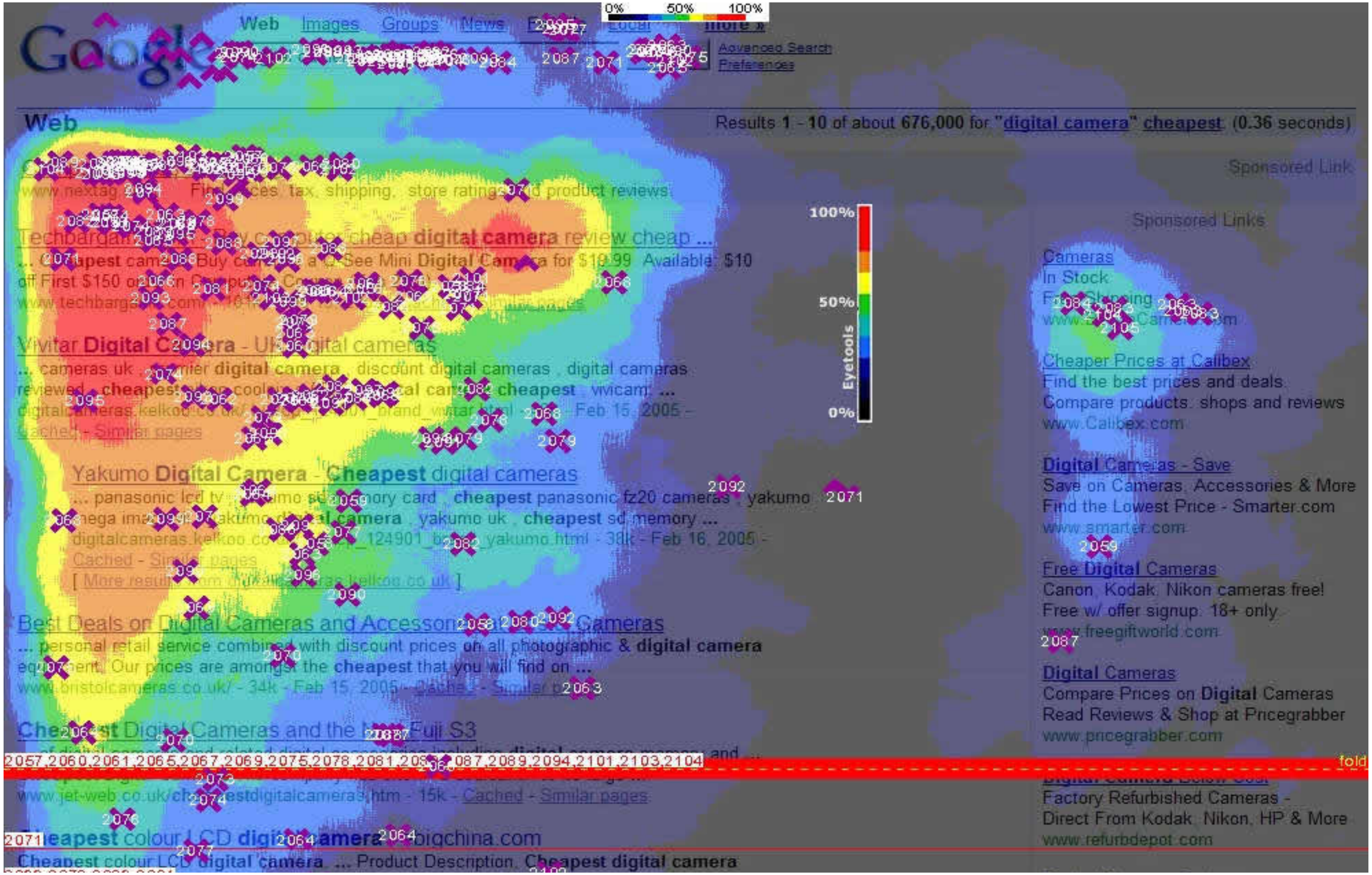


Source: www.emarketer.com - Ecommerce Sales Topped $1 Trillion for First Time in 2012

Web Analytics are Common



Sophisticated Web Analytics



The Emergence of Social Networks

*"**Social media is a group of platforms and tools** that users employ to share information, photos, videos, and other contents."*

(Turban and Lai, 2011)

*"Social technologies are products and services that enable **social interactions in the digital realm and provide distributed rights to communicate and add, modify, or consume content**. They include social media, Web 2.0, and enterprise collaboration technologies."*

(McKinsey Quarterly, November 2012)

Facebook Users in 2013

1.11 Billion people using the site each month (+23 % 2012)

665 million active users each day on average

751 million from a mobile device each month, (+54 % 2012).

(...)

1 million users by the end of 2004.

Facebook Users in 2013

There are more than 1.5 Billion social network users…

…which make up to 80% of total internet users.

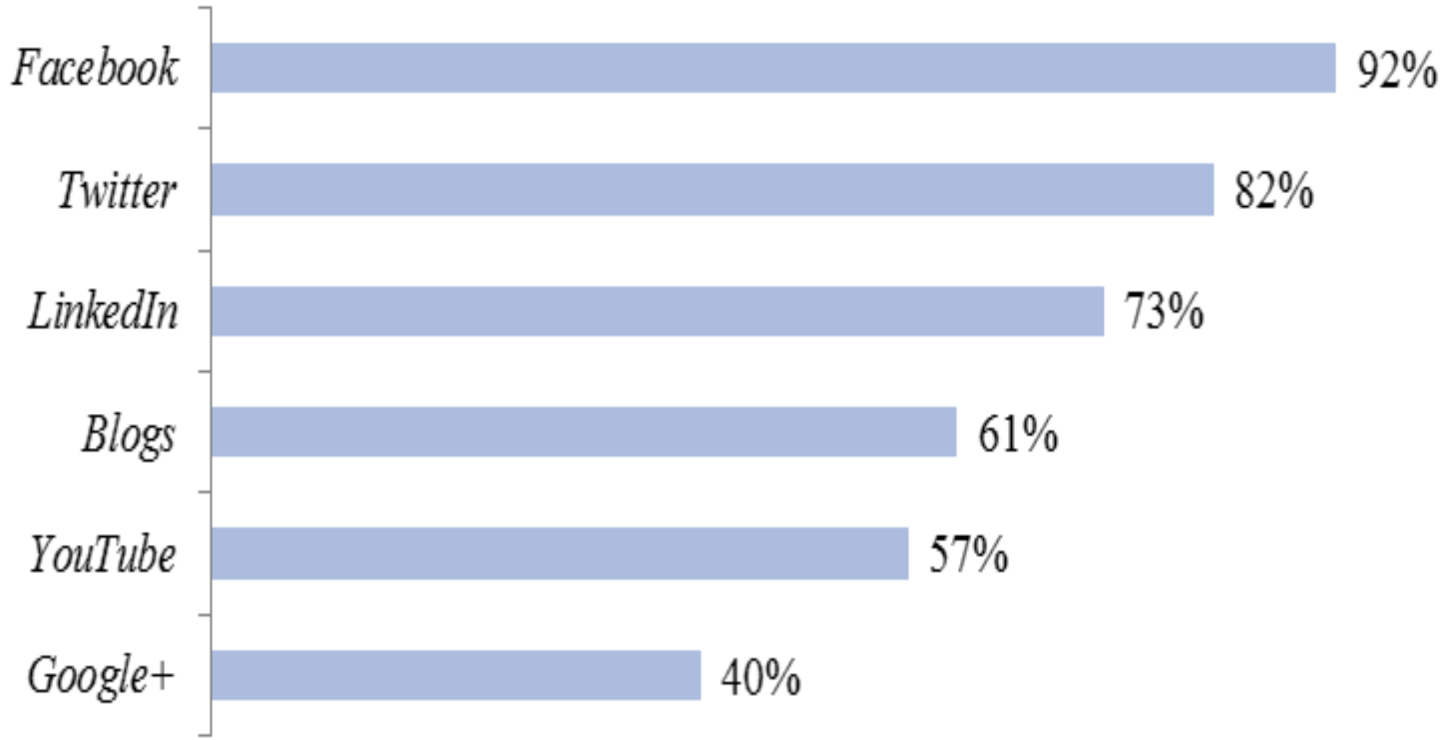
70% of companies use social networks

90% recognize the benefit

Workers spend 28 hours every week writing emails, searching information, and collaborating internally.

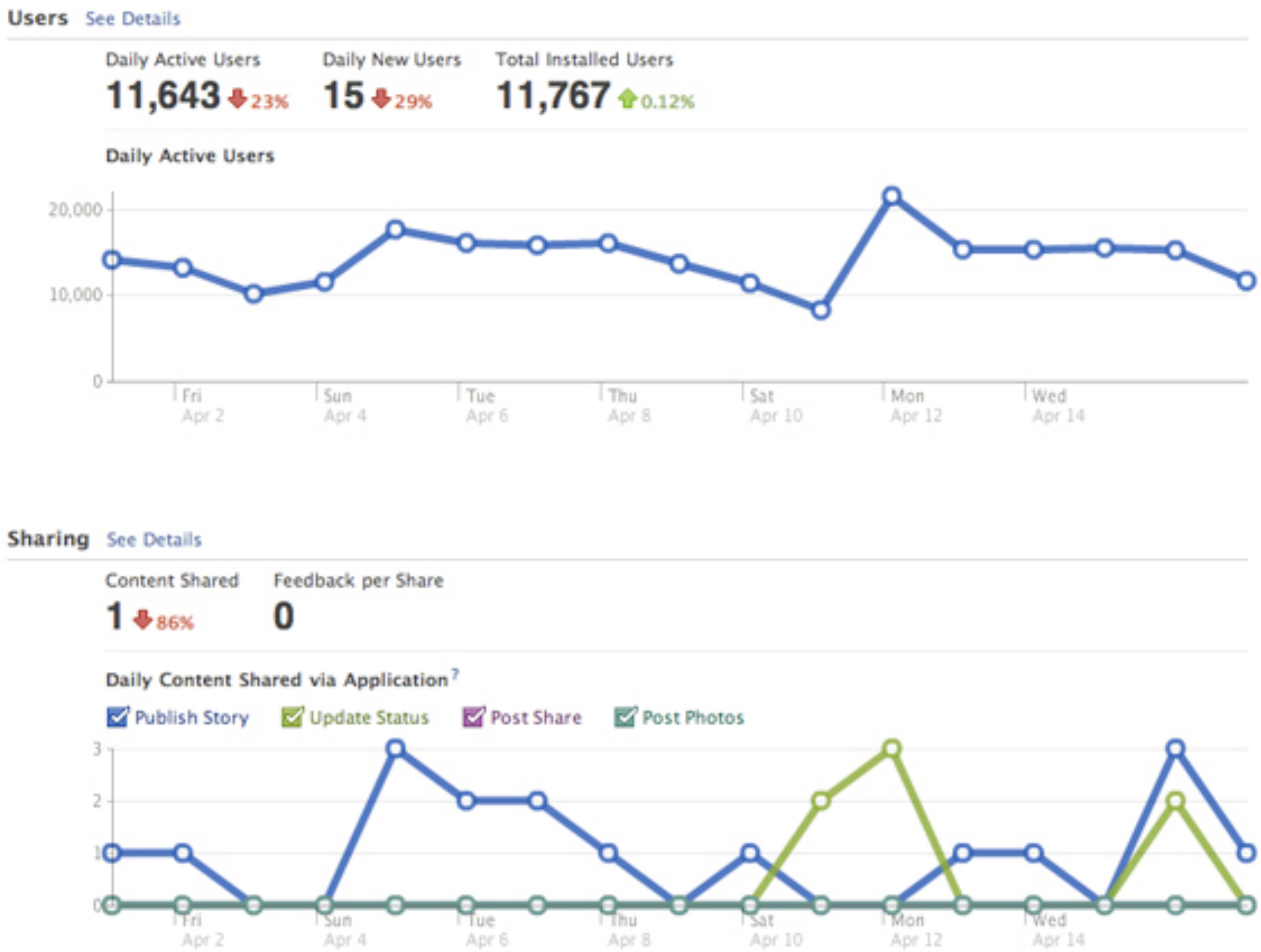
Source: The social economy: Unlocking value and productivity trough social networks, McKinsey July 2012

Social Network Platforms

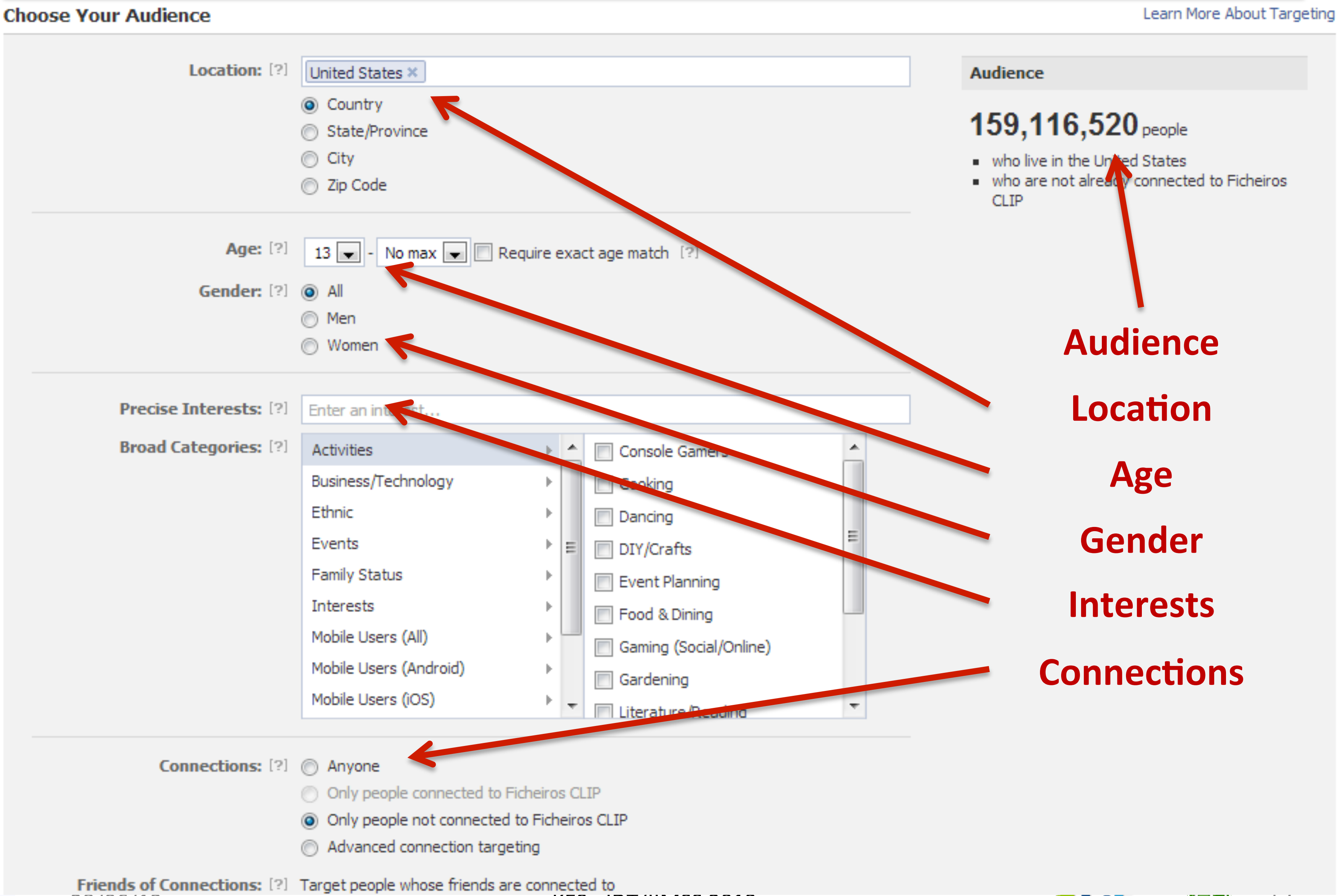


Source: Social marketing industry report: How marketers are using social to grow their business, Stelzner MA, 2012

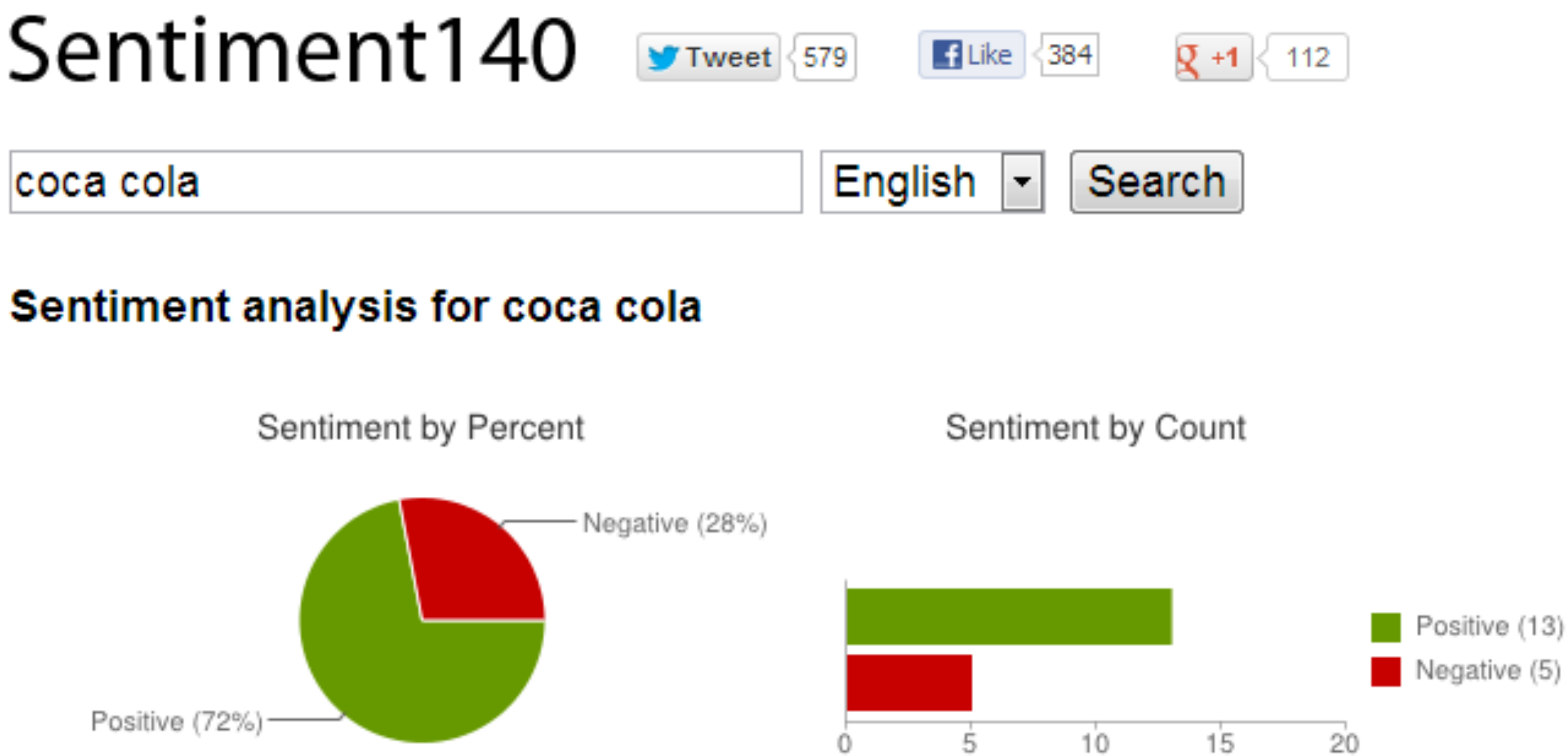
Social Media Analytics



Social Media Analytics - Targeting



Social Media Analytics – Sentiment Analysis



Social Media Analytics – Sentiment Analysis

Dionnova: @DJFreshSA I-phone; wen u type pepsi it corrects to capital letter P, but type coke or **coca cola** it d
Posted: 21 seconds ago

MaxaEnPointe: That unofficial **Coca Cola** Zim ad is soooo messed up it's funny. I wasn't offended though! http:/
Posted: 7 minutes ago

rimonator: @Econsultancy BRILLIANT how **coca cola** use their social media
Posted: 8 minutes ago

YetNaive: I love **coca cola** so much. It's like the only dark soda I actually enjoy.
Posted: 10 minutes ago

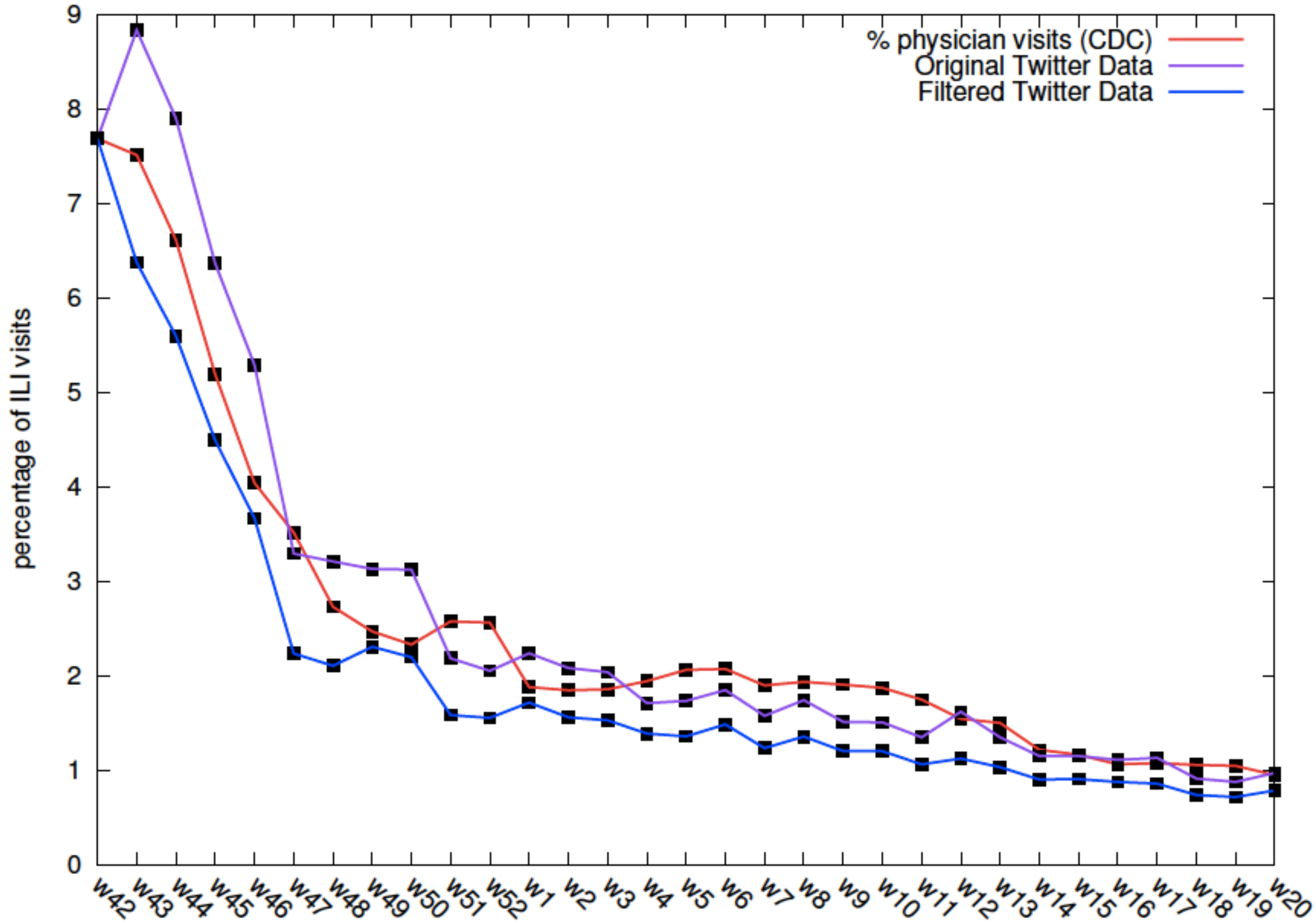
MarthaaMor_77: **Coca cola** cherry is a heavenly creation
Posted: 10 minutes ago

aiR_La: RT @khuul_khidd: ?@dRealest_felix: **Coca cola** RT @Questionnier: A drink you're addicted to? #QnA
Posted: 14 minutes ago

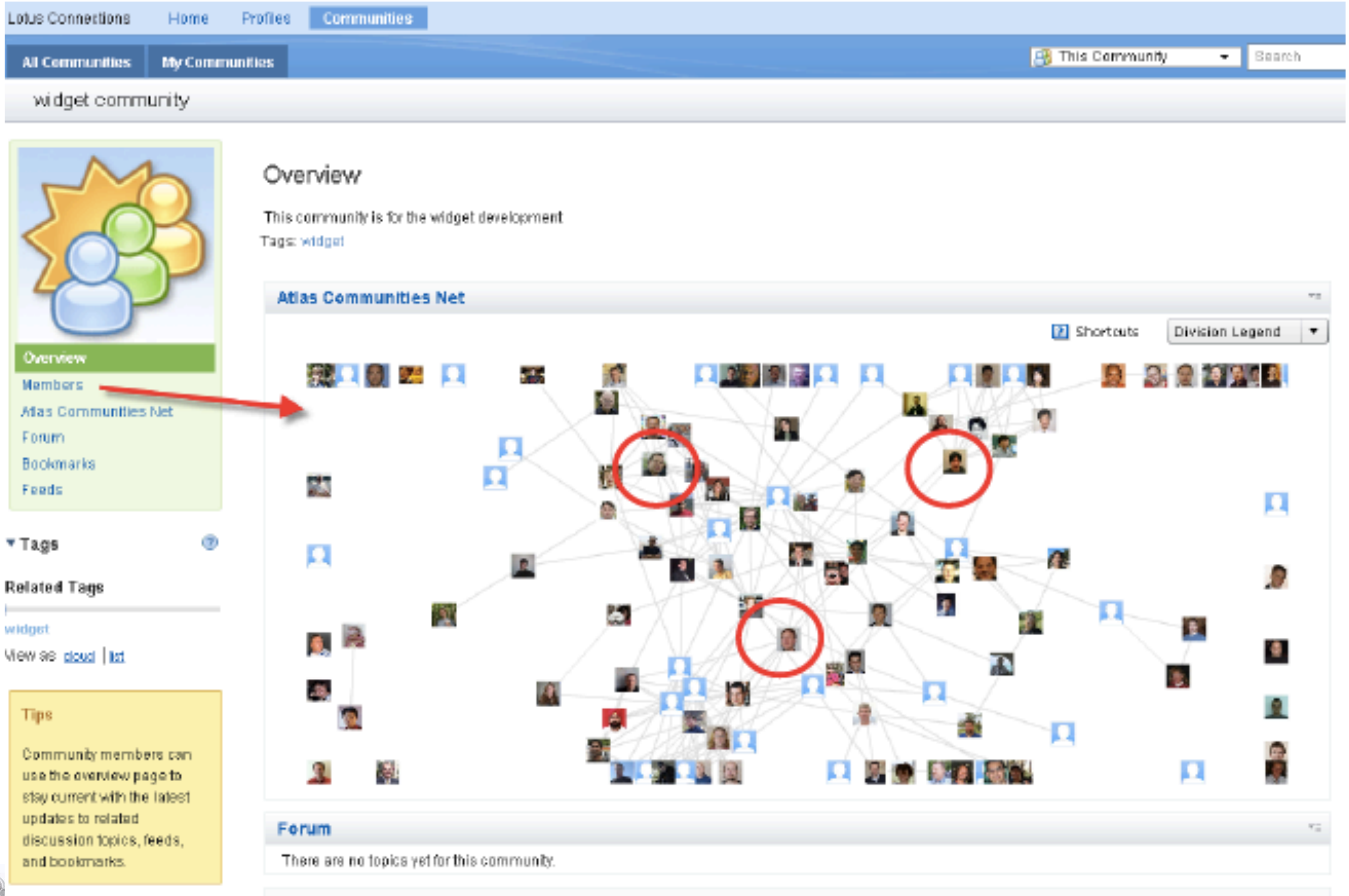
Nomusa_DM: **Coca cola** RT"@Questionnier: A drink you're addicted to? #QnA"
Posted: 16 minutes ago

coca_cola_fan: **#CocaCola** reveals plans to sell its drinks in "greener" plastic bottles in China. http://t.co/SSQh4
Posted: 19 minutes ago

Social Media Analytics – Flu & Twitter



Social Media Analytics – Who's Important



Semantic Web

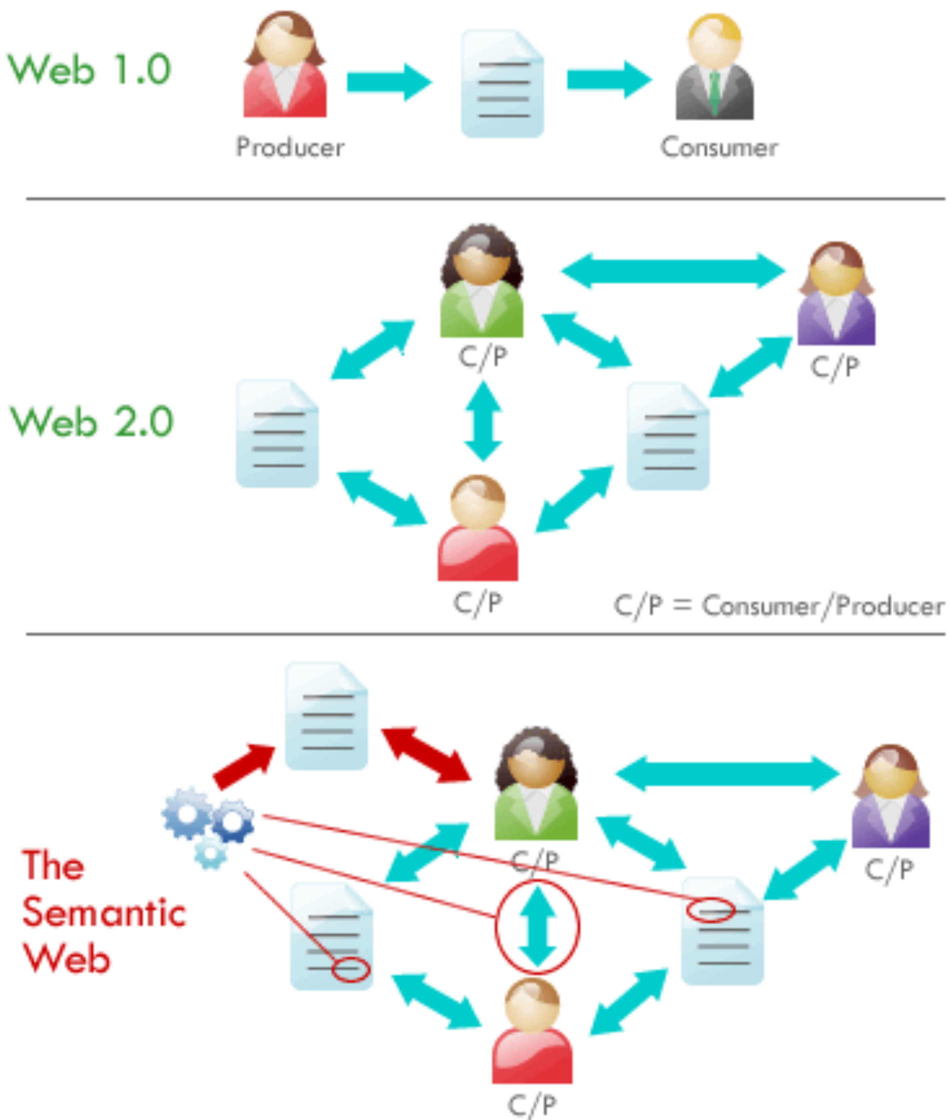
The Semantic Web is the extension of the World Wide Web that enables people to share content beyond the boundaries of applications and website. **Semantic Web is a web that is able to describe things in a way that computers applications can understand**.

The Semantic Web describes the **relationships between things** (like A is a part of B and Y is a member of Z) and the **properties of things** (like size, weight, age, and price)

"*If HTML and the Web made all the online documents look like one huge **book**, RDF, schema, and inference languages will make all the data in the world look like one huge **database***"

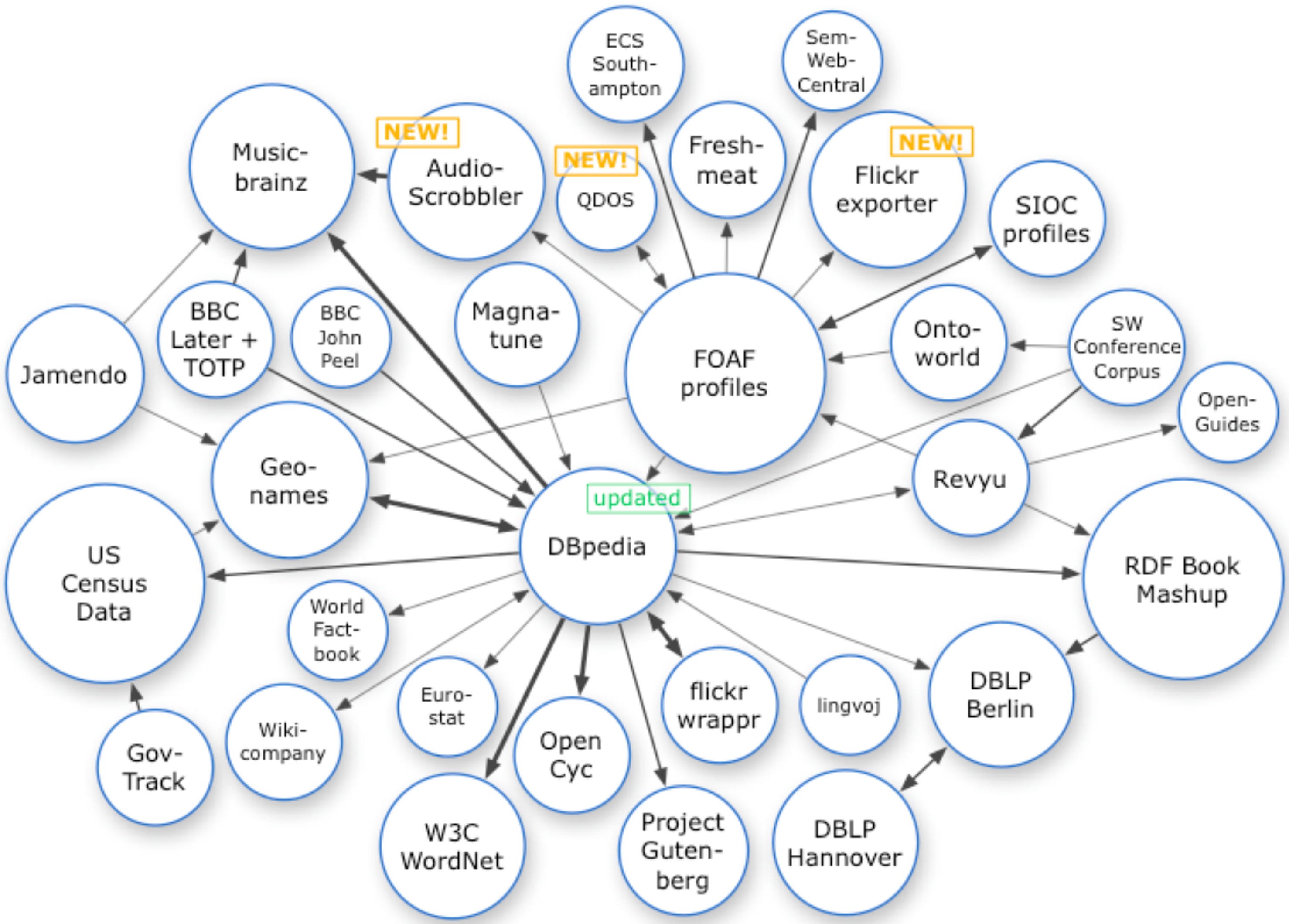
Tim Berners-Lee, Weaving the Web, 1999

Semantic Web for Dummies…



Source: www.semanticwebexplained.co.uk

Semantic Web: No Big Numbers Yet…



“Internet of Things” by 2020

50 Billion mobile wireless devices connected to the Internet across the globe

Total number of devices connected to the Internet in some way could reach 500 Billion.

Source: OECD (2012), “Machine-to-Machine Communications: Connecting Billions of Devices”, *OECD Digital Economy Papers*, No. 192,

"Internet of Things"

Internet of Things is mainly associated with applications that involve Radio Frequency Identification (RFID). These make use of so called tags, tiny chips with antennae that start to transmit data when they come in contact with an electromagnetic field.

Machine to Machine communication (M2M) describes devices that are connected to the Internet, using a variety of fixed and wireless networks and communicate with each other and the wider world.

Embedded Wireless has been coined, for a variety of applications where wireless cellular communication is used to connect any device that is not a phone

Smart is used in conjunction with various words such **as Living, Cities, Metering, Grids, Water Levy and Lighting** to describe a variety of applications that make use of inexpensive communication to improve the delivery of services.

Internet of Things Applications by Mobility and Dispersion

	Fixed	Mobile
Dispersed	**Smart Grid, Meter, City** **Remote monitoring**	**Car automation** **eHealth** **Logistics** **Portable consumer electronics**
Concentrated	**Smart Home** **Factory automation** **eHealth**	**On-site logistics**

Source: OECD (2012), "Machine-to-Machine Communications: Connecting Billions of Devices", *OECD Digital Economy Papers*, No. 192,

Big Data

Big data usually includes data sets with sizes beyond the ability of commonly used software tools to capture, curate, manage, and process the data within a tolerable elapsed time.

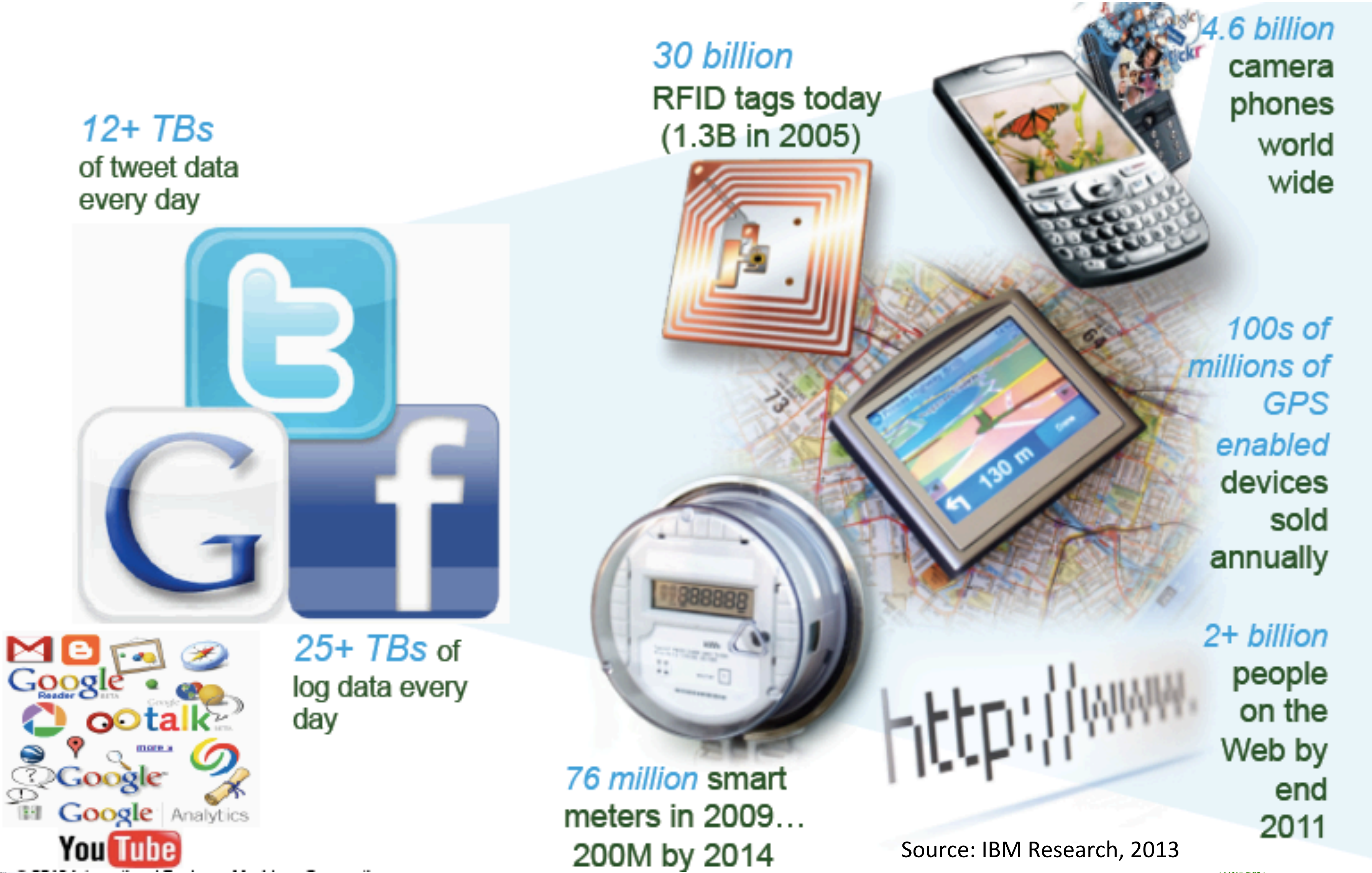
Source: Snijders, C., Matzat, U., & Reips, U.-D. (2012). ‘Big Data’: Big gaps of knowledge in the field of Internet science. *International Journal of Internet Science*

Big data are high **volume**, high **velocity**, and/or high **variety** information assets that require new forms of processing to enable enhanced decision making, insight discovery and process optimization.

Source: Douglas, Laney. "The Importance of 'Big Data': A Definition". Gartner, 2012

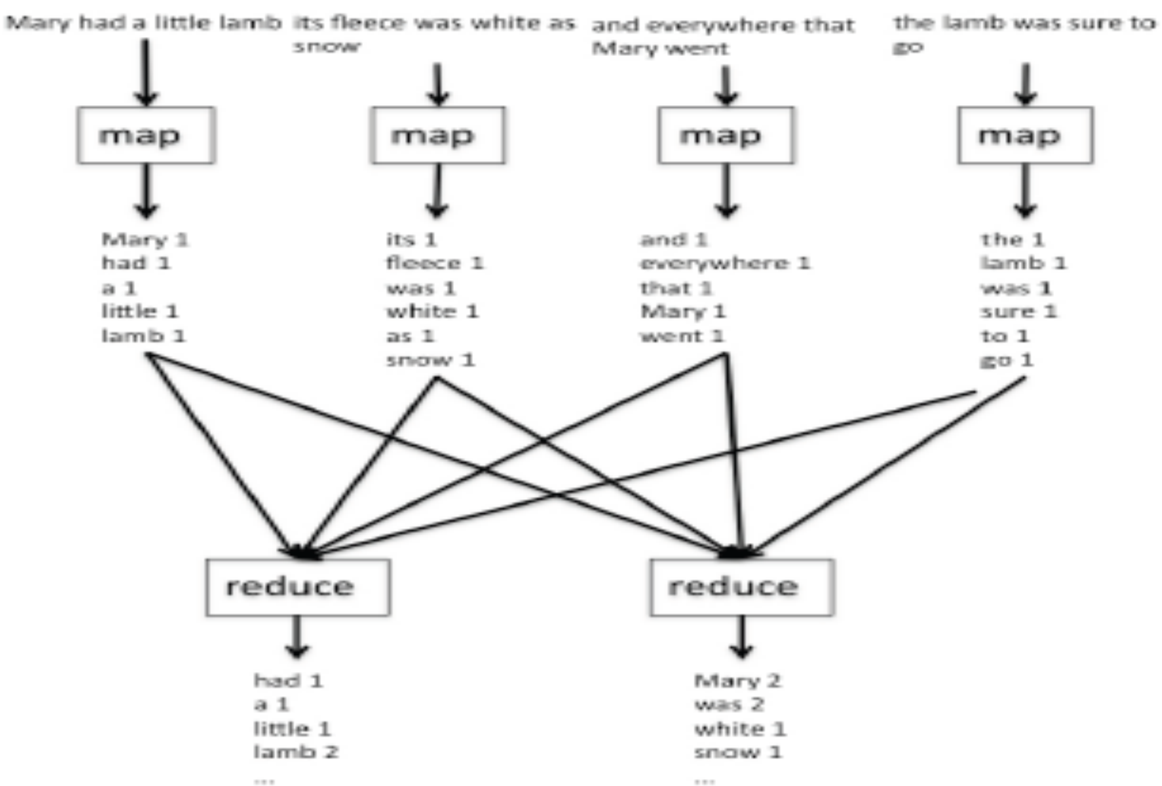
Big Data mostly uses **inductive statistics with data with low information density whose huge volume** allow to infer laws and thus giving (with the limits of inference reasoning) to Big Data some **predictive capabilities**.

Where does Big Data come from ?



Source: IBM Research, 2013

Big Data is Still Very Complex do Implement



Source: IBM Research, 2013

Data Analysis or Decision Models?

Alexa

socialbakers

quintly

Google Analytics

radian6

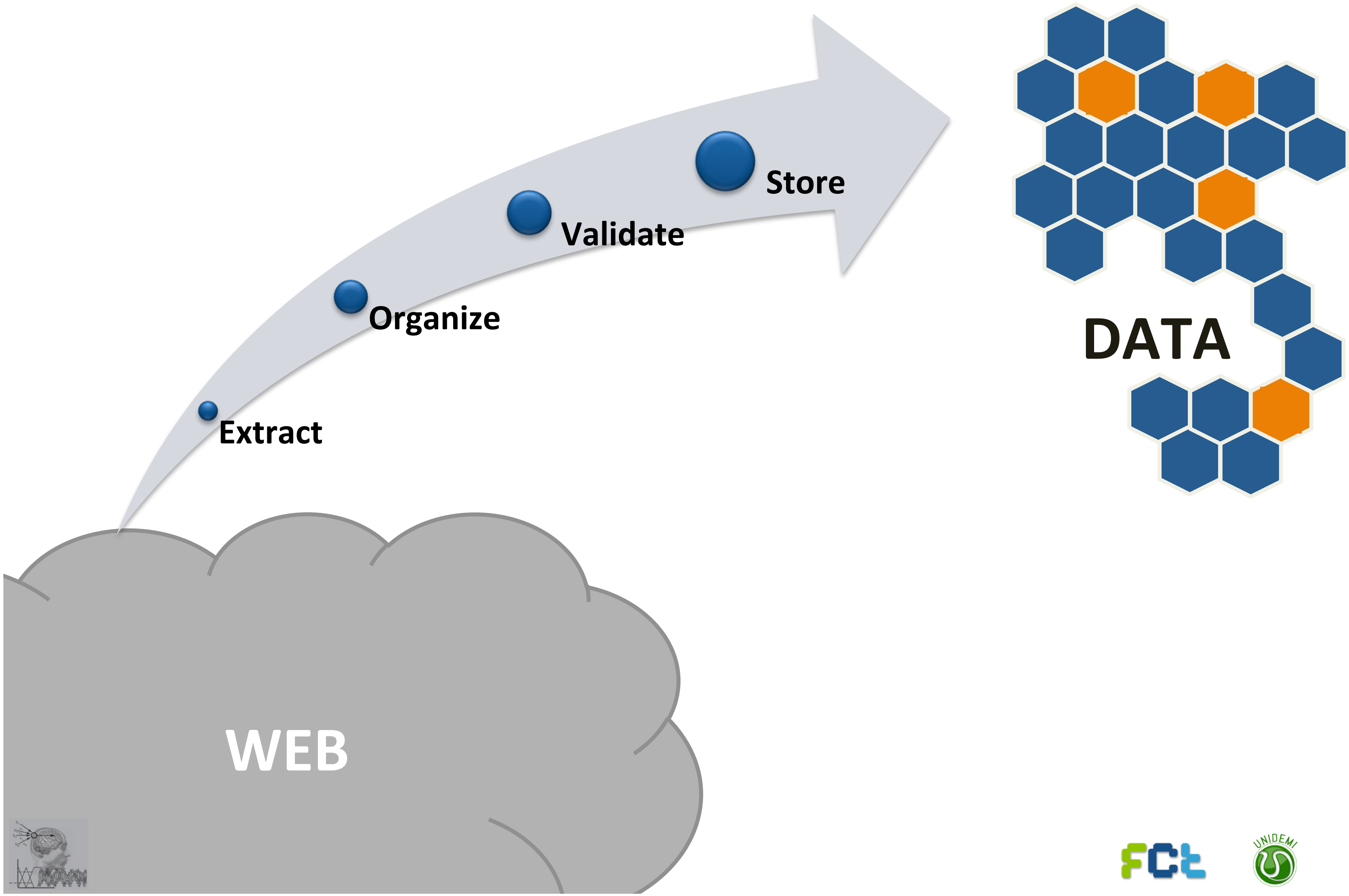
The Concept: Web Competitive Intelligence

Web Competitive Intelligence

The basic objective is the creation of a simple methodology to develop, implement and manage Competitive Intelligence tools based on information collected from the Web.

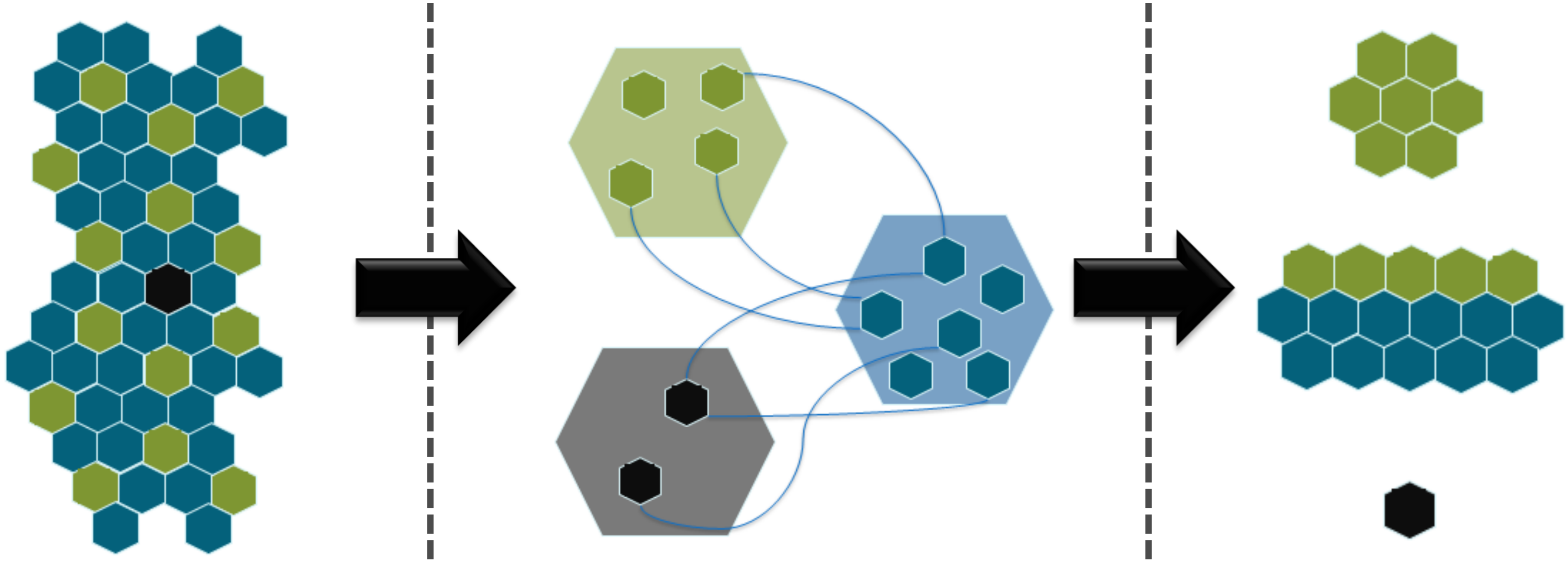
Web-based competitive intelligence information is based on **automatic gathering, filtering, search and transformation of information** in the Web using a combination **of crawlers, wrappers and ontologies.**

Data from the Web

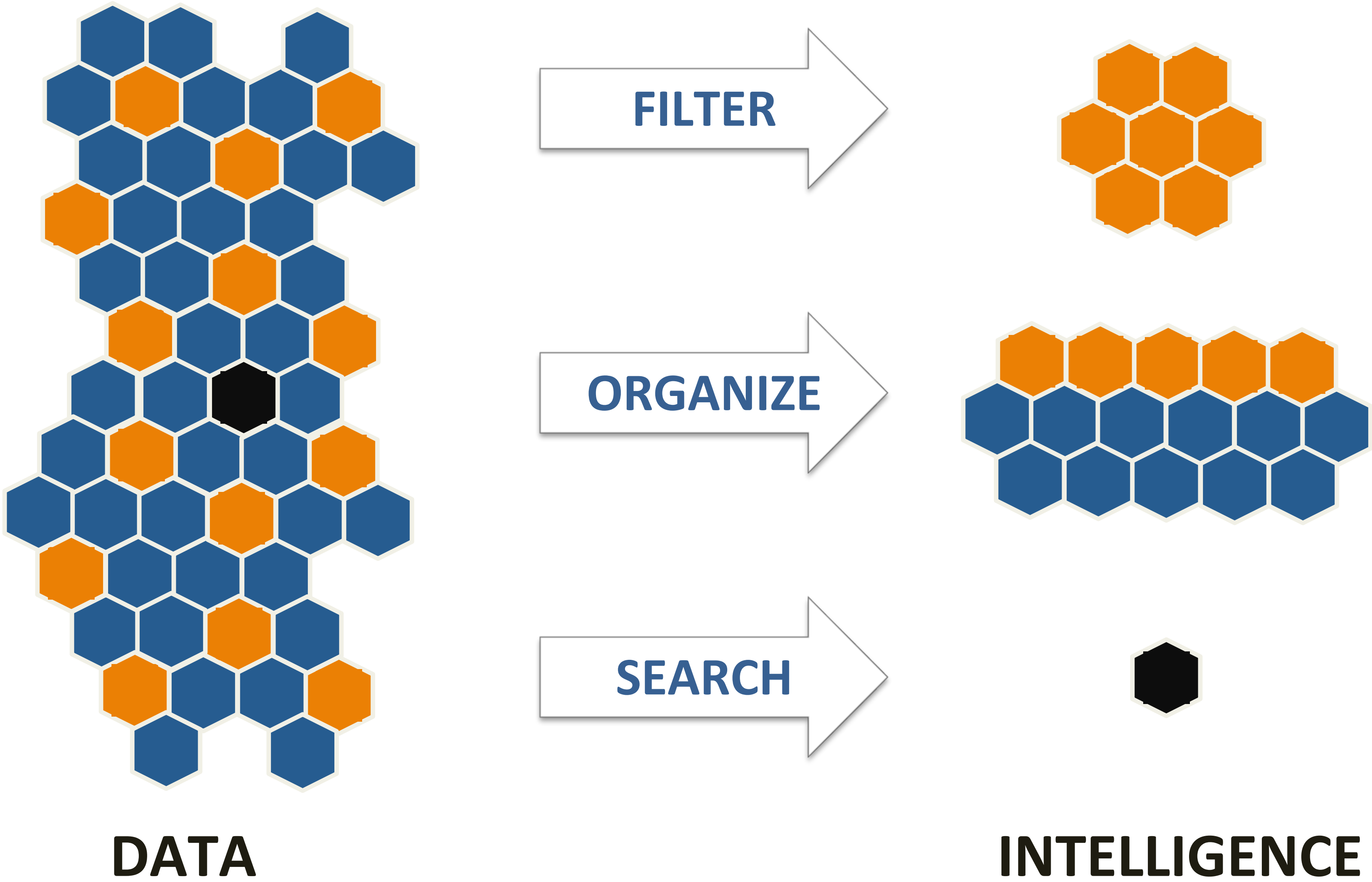


Proposed Framework

Crawler Wrapper	Ontology Storage	Data Analysis & Decision Models

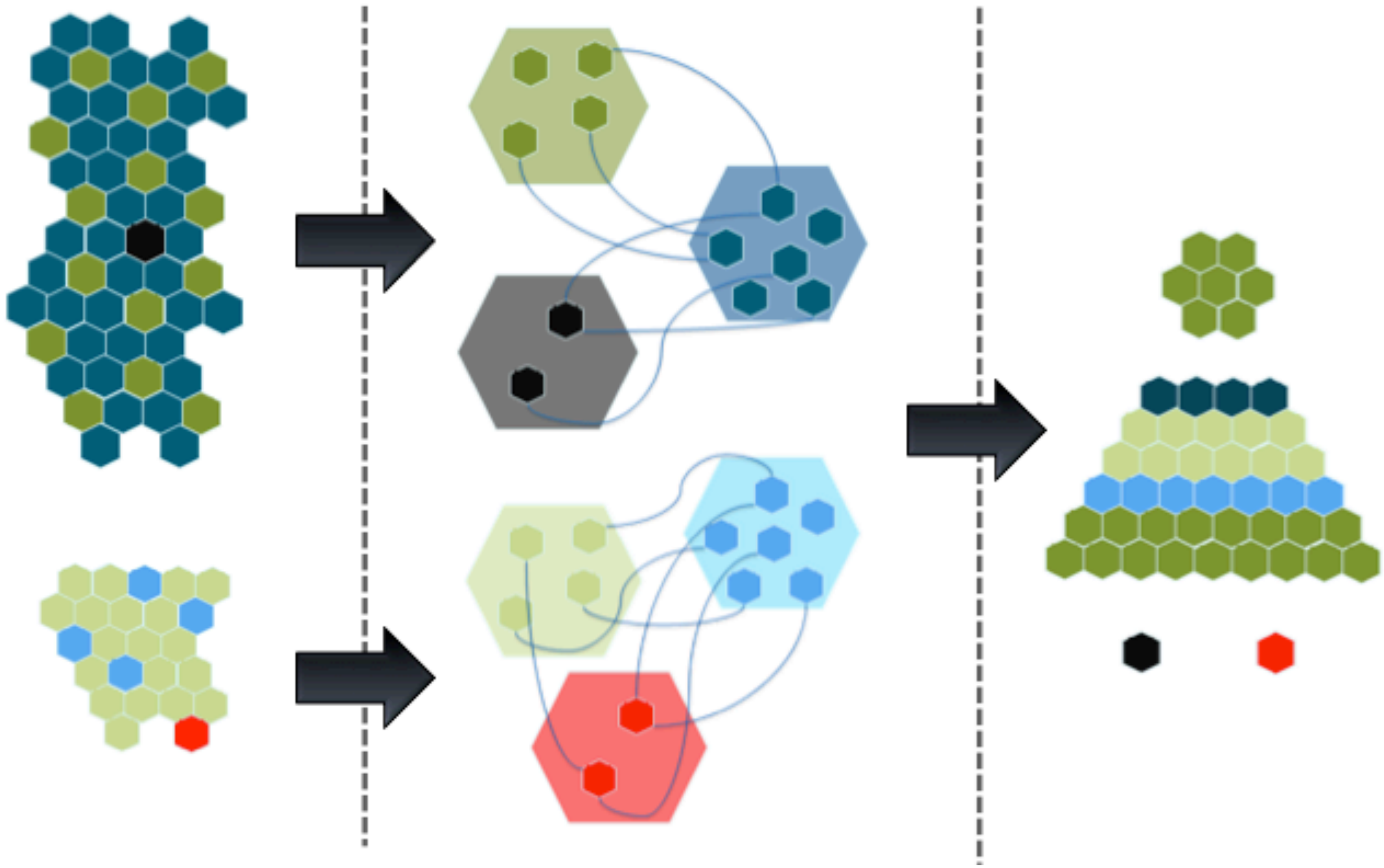


Proposed Framework



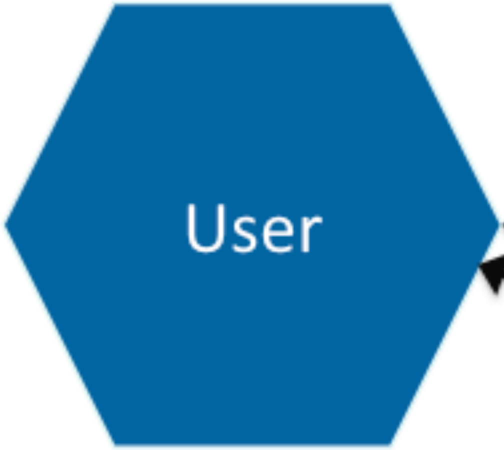
Proposed Framework

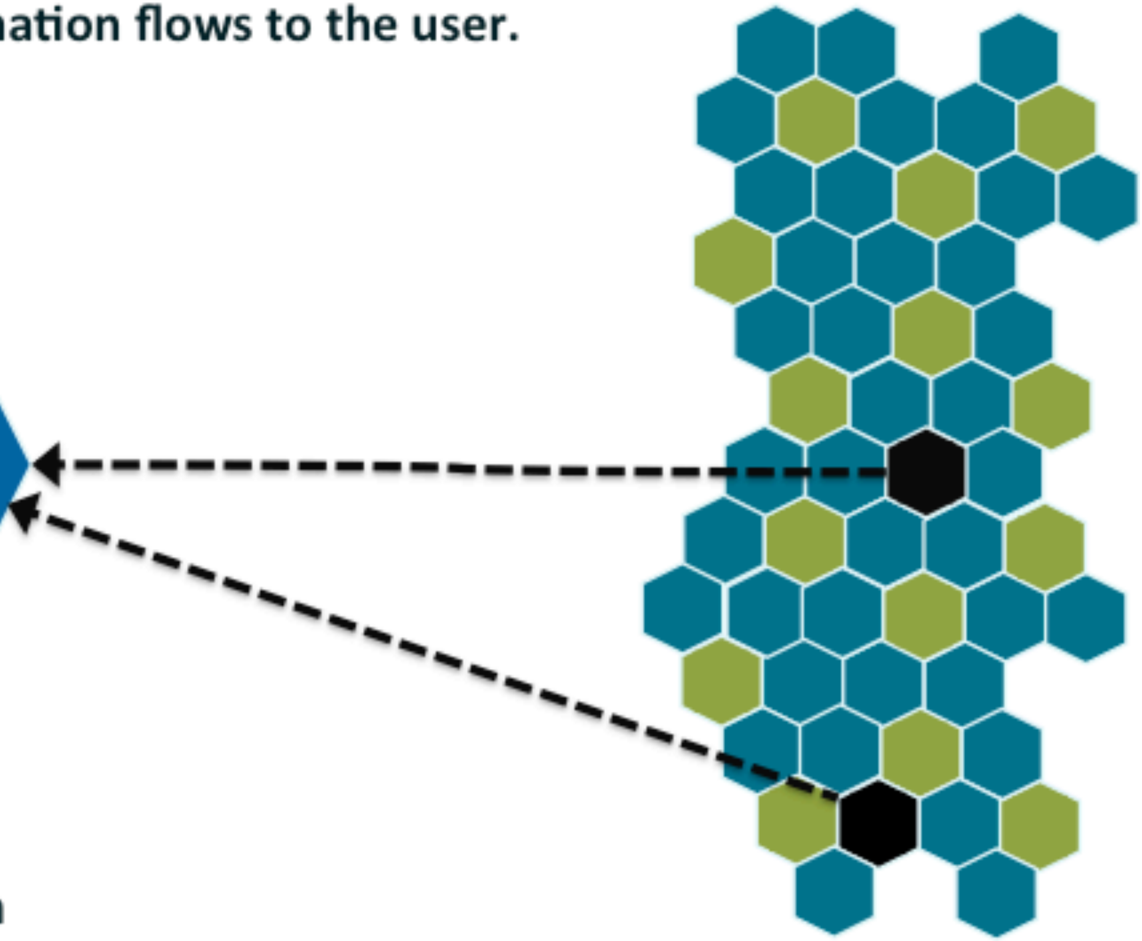
Multiple-Configuration:



Proposed Framework

New Paradigm: Information flows to the user.



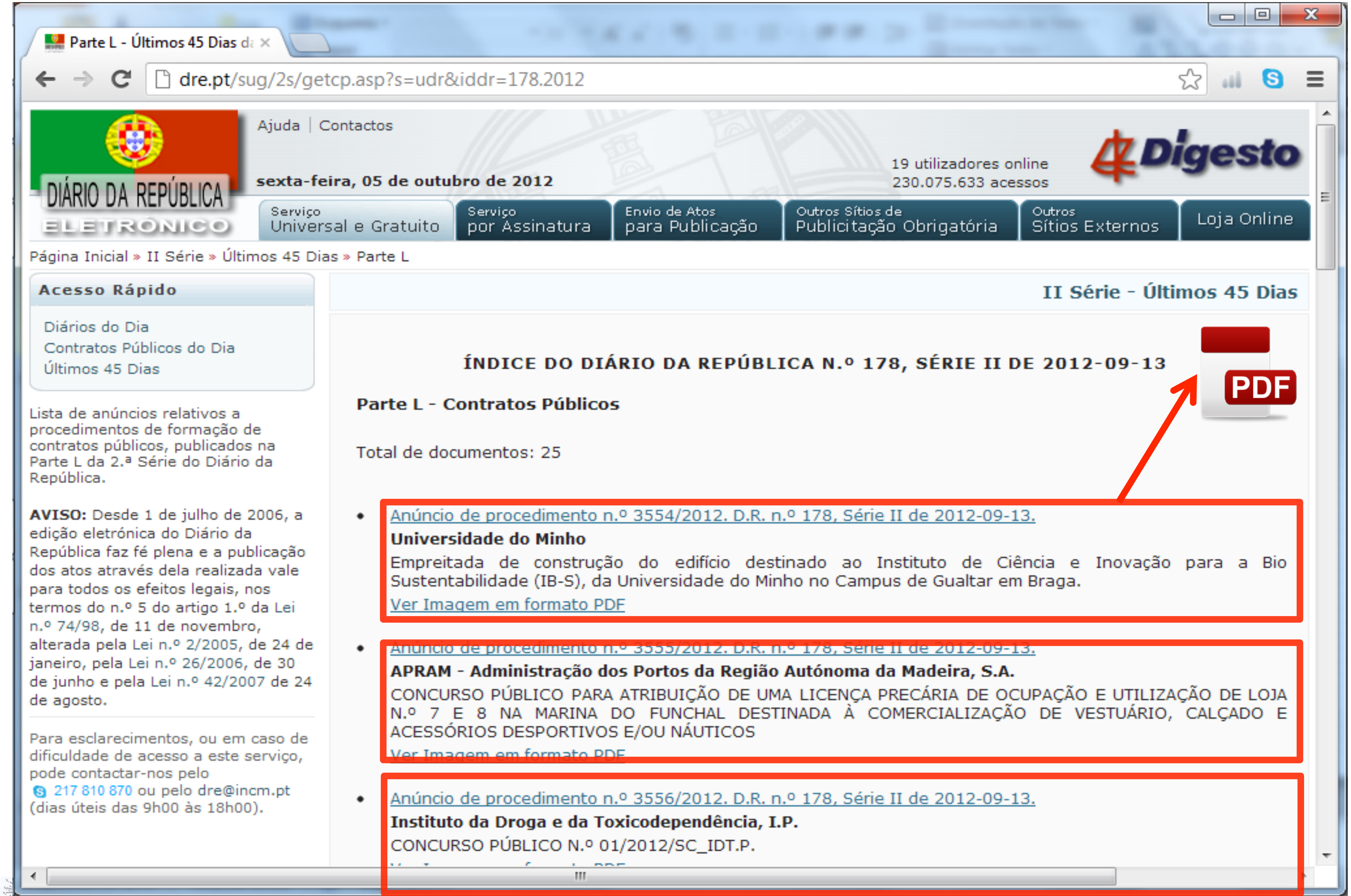


Notifications

- email
- web plataform
- instante messaging
- intranets

Case Study - Public Tender Calls

www.dre.pt


Parte L - Últimos 45 Dias d
dre.pt/sug/2s/getcp.asp?s=udr&iddr=178.2012
Ajuda | Contactos
DIÁRIO DA REPÚBLICA ELETRÓNICO
sexta-feira, 05 de outubro de 2012
19 utilizadores online
230.075.633 acessos
Digesto
Serviço Universal e Gratuito
Serviço por Assinatura
Envio de Atos para Publicação
Outros Sítios de Publicitação Obrigatória
Outros Sítios Externos
Loja Online
Página Inicial » II Série » Últimos 45 Dias » Parte L
Acesso Rápido
Diários do Dia
Contratos Públicos do Dia
Últimos 45 Dias
Lista de anúncios relativos a procedimentos de formação de contratos públicos, publicados na Parte L da 2.ª Série do Diário da República.
AVISO: Desde 1 de julho de 2006, a edição eletrónica do Diário da República faz fé plena e a publicação dos atos através dela realizada vale para todos os efeitos legais, nos termos do n.º 5 do artigo 1.º da Lei n.º 74/98, de 11 de novembro, alterada pela Lei n.º 2/2005, de 24 de janeiro, pela Lei n.º 26/2006, de 30 de junho e pela Lei n.º 42/2007 de 24 de agosto.
Para esclarecimentos, ou em caso de dificuldade de acesso a este serviço, pode contactar-nos pelo 217 810 870 ou pelo dre@incm.pt (dias úteis das 9h00 às 18h00).
II Série - Últimos 45 Dias
ÍNDICE DO DIÁRIO DA REPÚBLICA N.º 178, SÉRIE II DE 2012-09-13
PDF
Parte L - Contratos Públicos
Total de documentos: 25
Anúncio de procedimento n.º 3554/2012. D.R. n.º 178, Série II de 2012-09-13.
Universidade do Minho
Empreitada de construção do edifício destinado ao Instituto de Ciência e Inovação para a Bio Sustentabilidade (IB-S), da Universidade do Minho no Campus de Gualtar em Braga.
Ver Imagem em formato PDF
APRAM - Administração dos Portos da Região Autónoma da Madeira, S.A.
CONCURSO PÚBLICO PARA ATRIBUIÇÃO DE UMA LICENÇA PRECÁRIA DE OCUPAÇÃO E UTILIZAÇÃO DE LOJA N.º 7 E 8 NA MARINA DO FUNCHAL DESTINADA À COMERCIALIZAÇÃO DE VESTUÁRIO, CALÇADO E ACESSÓRIOS DESPORTIVOS E/OU NÁUTICOS
Anúncio de procedimento n.º 3556/2012. D.R. n.º 178, Série II de 2012-09-13.
Instituto da Droga e da Toxicodependência, I.P.
CONCURSO PÚBLICO N.º 01/2012/SC_IDT.P.

PDFs contain information to populate the ontology.

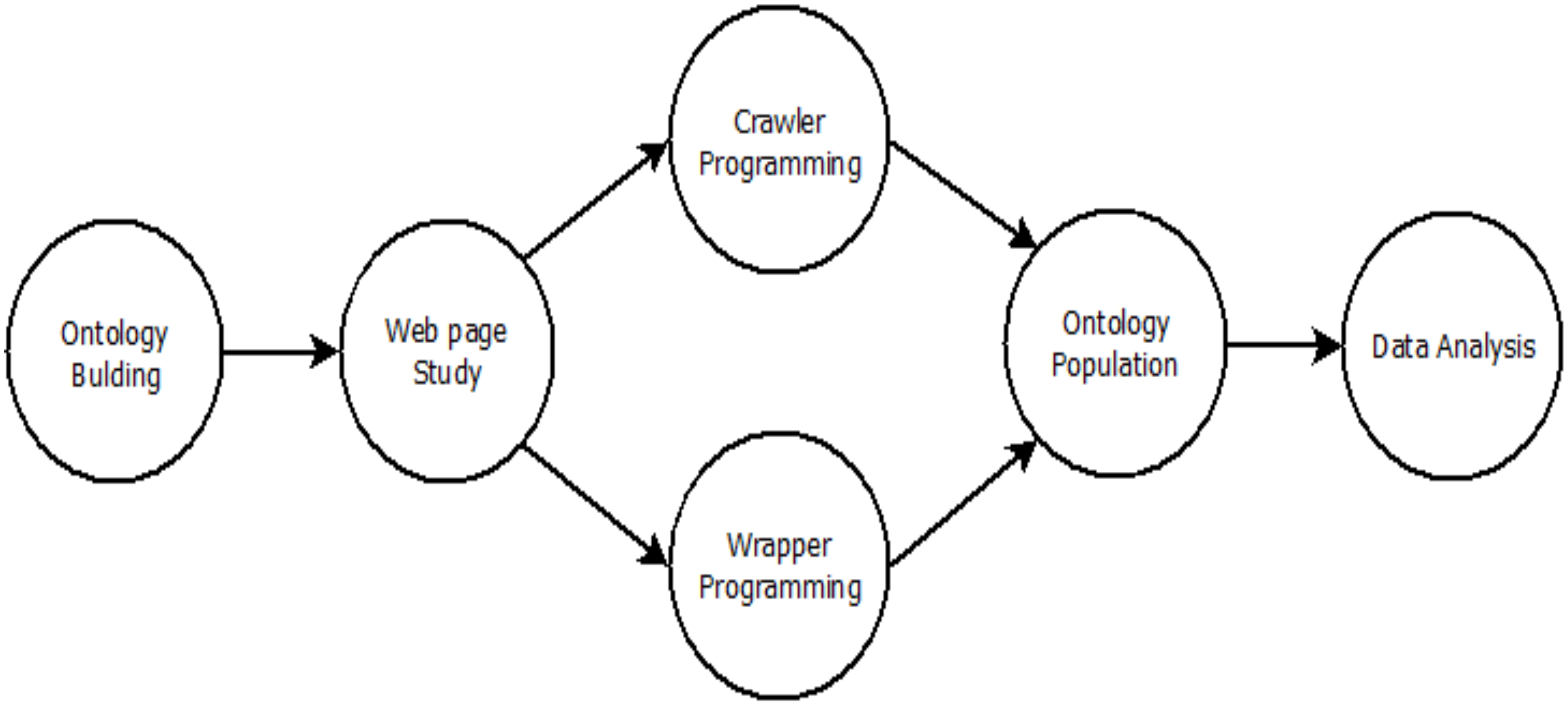
MODELO DE ANÚNCIO DO CONCURSO PÚBLICO

1 - IDENTIFICAÇÃO E CONTACTOS DA ENTIDADE ADJUDICANTE
NIF e designação da entidade adjudicante:
505456010 - Município da Amadora
Serviço/Órgão/Pessoa de contacto: Departamento de Obras Municipais
Endereço: Travessa Vasco da Gama, nº 7
Código postal: 2701 833
Localidade: Amadora
Telefone: 00351 214369000
Fax: 00351 214927837
Endereço Eletrónico: obras.municipais@cm-amadora.pt

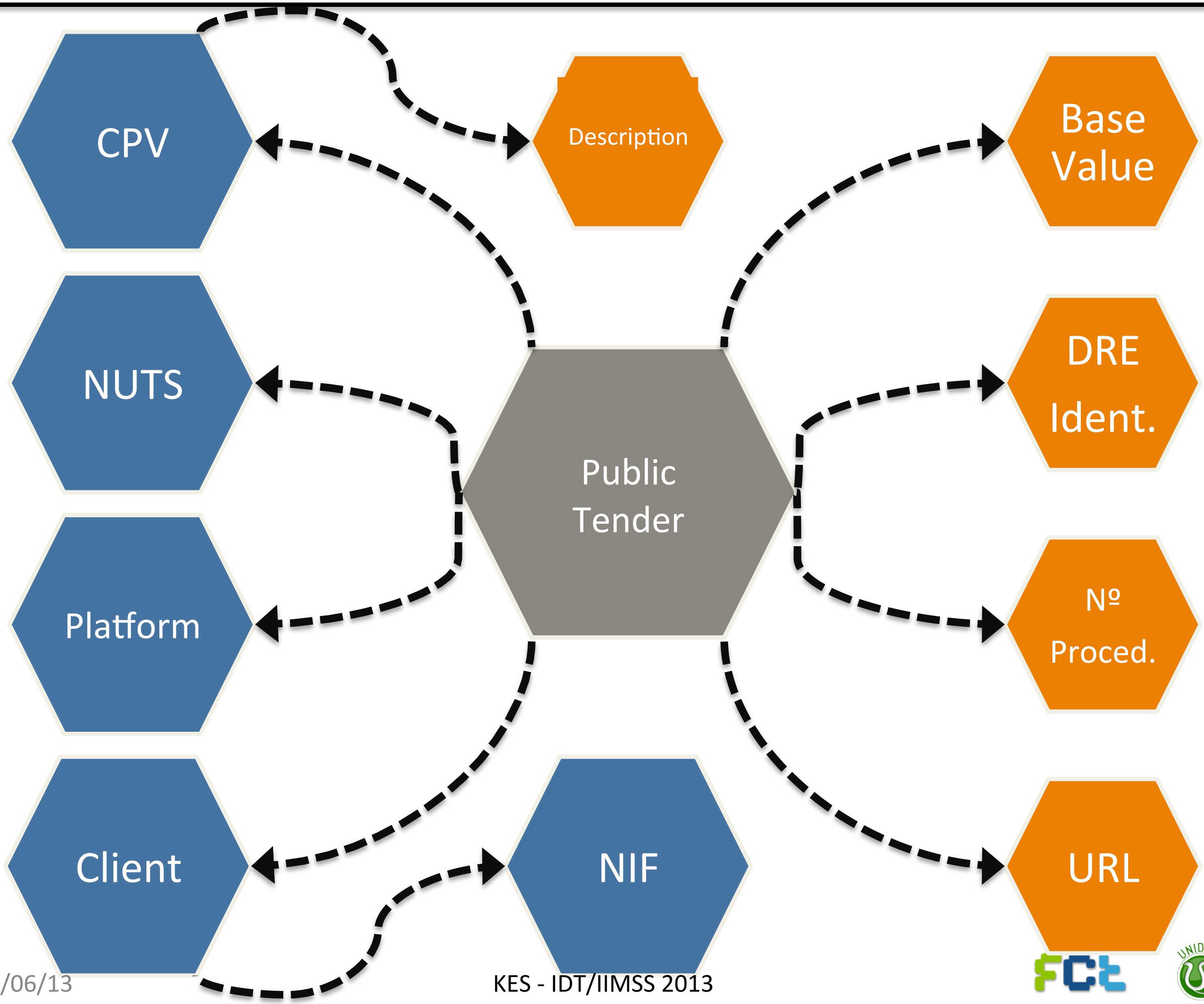
2 - OBJETO DO CONTRATO
Designação do contrato: Empreitada nº 9/12 - "Escola EB1/JI Moinhos da Funcheira (ex-Mina 9) - Execução de Obras de Beneficiação"
Descrição sucinta do objeto do contrato: A empreitada consiste na conservação e impermeabilização da Escola EB1/JI Moinhos da Funcheira
Tipo de Contrato: Empreitada de Obras Públicas
Valor do preço base do procedimento 331182.35 EUR
Classificação CPV (Vocabulário Comum para os Contratos Públicos)
Objeto principal
Vocabulário principal: 45214200

6 - LOCAL DA EXECUÇÃO DO CONTRATO
Escola EB1/JI Moinhos da Funcheira, freguesia de S. Brás
País: PORTUGAL
Distrito: Lisboa
Concelho: Amadora
Código NUTS: PT171

Method


Ontology
Bulding
Web page
Study
Crawler
Programming
Wrapper
Programming
Ontology
Population
Data Analysis

Public Tender Ontology



Data Reasoning and Querying

Past data and autonomous collection of current instances results in all data related to public tender markets.

Ontologies query and reasoning engines results in a “smart” data base able to answer questions in line with the conceptual knowledge.

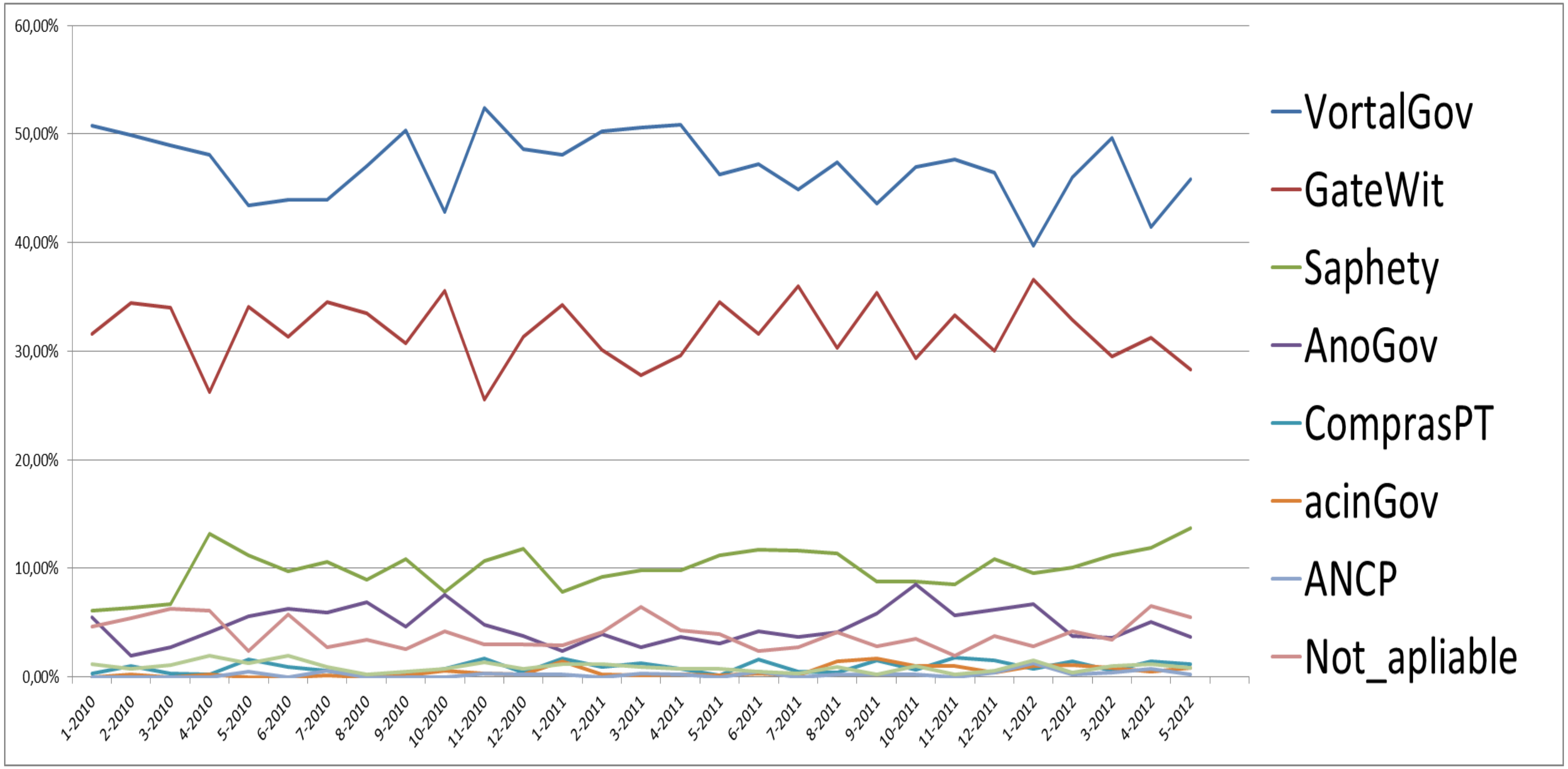
REASONING: given axioms and restrictions, the engine is able to compute conclusions. Ex.: given the notion the NIF is unique per entity, all entity with NIF X are the same. No need to inject more data then the NIF to identify the public tender publisher.

QUERY: given the axioms and restrictions, the engine can compute query without the prior concept of data tables structures and relations. Ex.: Entities that have published PT from cpv 45xxxxxx, in Lisbon, in the last month. All PTs in Porto, above 1.000.000 Euros celling value, with CPV 33xxxxxx.

Caracterization of the Data

- Developed in Visual Basic.
- Ontology building supported in Protégé.
- Data collected from 2010, 2011 and until 2012.
- 20.000 (aprox.) gathered documents.
- Continuous and autonomous functioning.

Example of Data Analysis on Public Tenders



Public Tenders in Portuguese E-Procurement Platforms

Example of Data Analysis on Public Tenders

Select client. Only clients with more than 20 PT available.

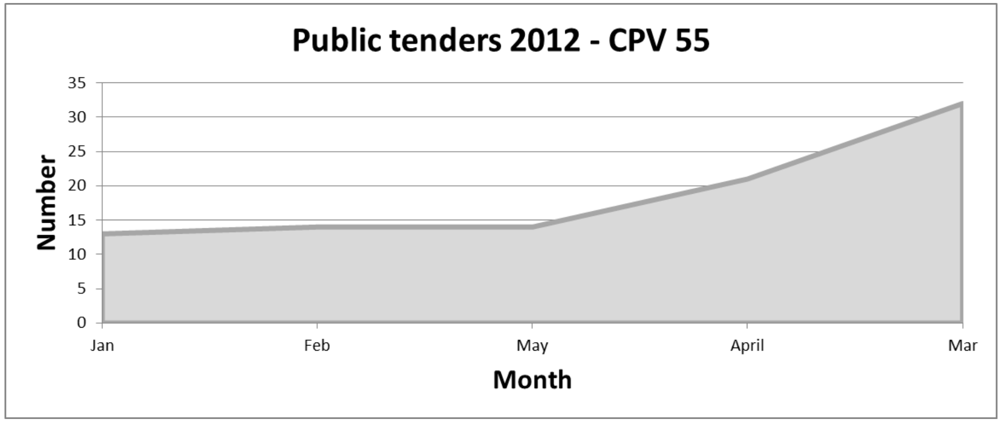
INSTITUTO NACIONAL DE SAUDE DR. RICARDO JORGE I.P.

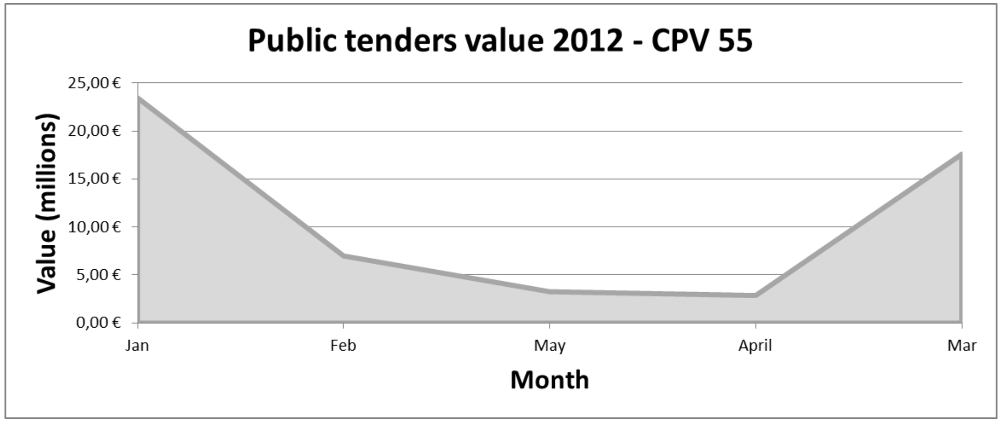
	Total	2010	2011	2012
PT (#)	87	10	50	27
PT (%)	0,56%	0,15%	0,75%	1,19%
∑ BV	8.768.560,67 €	649.737,47 €	5.376.845,98 €	2.741.977,22 €
∑ BV (%)	0,08%	0,01%	0,11%	0,22%
Average BV	100.788,05 €	64.973,75 €	107.536,92 €	101.554,71 €

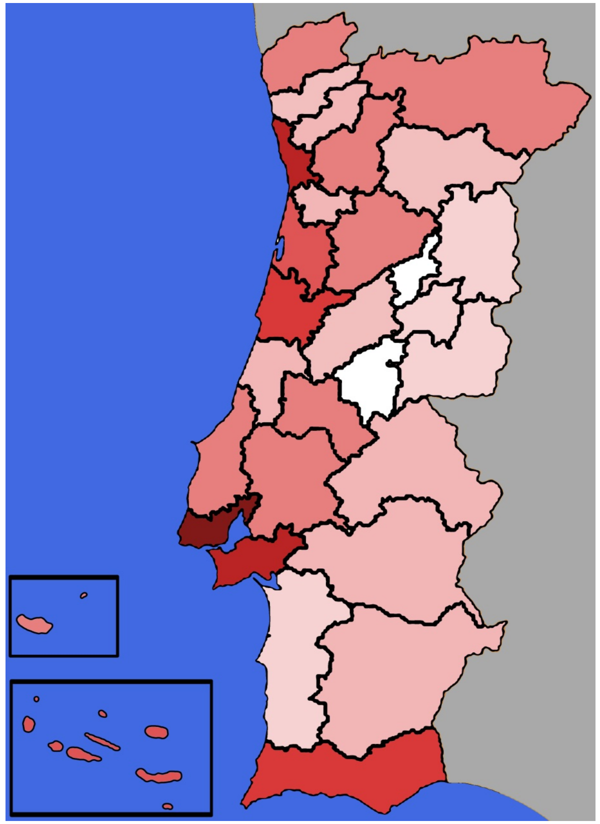
	Preferred CPV		
	PT (#)	Main Cat.	Description
1º	55	33	Equipamento médico, medicamentos e produtos para cuidados pessoais
2º	17	24	Produtos químicos
3º	7	31	Maquinaria, aparelhagem, equipamento e consumíveis eléctricos; iluminação

	Preferred NUT codes	
	PT (#)	Main Cat.
1º	87	PT171
2º	-	-
3º	-	-

Example of Data Analysis on Public Tenders





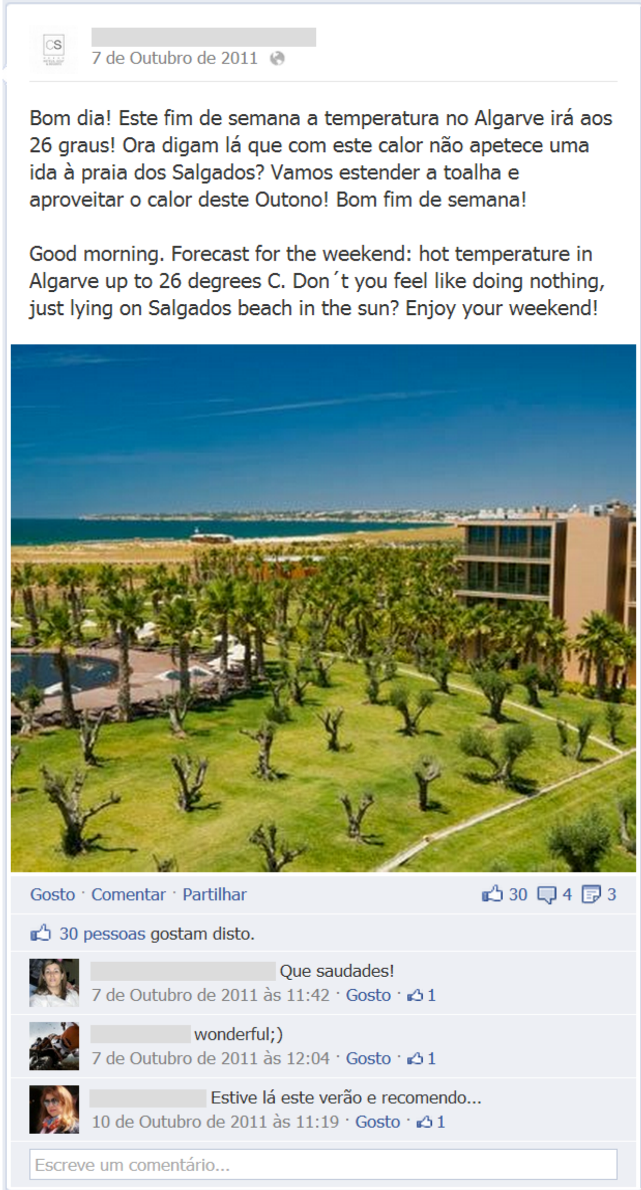


Location of Tenders

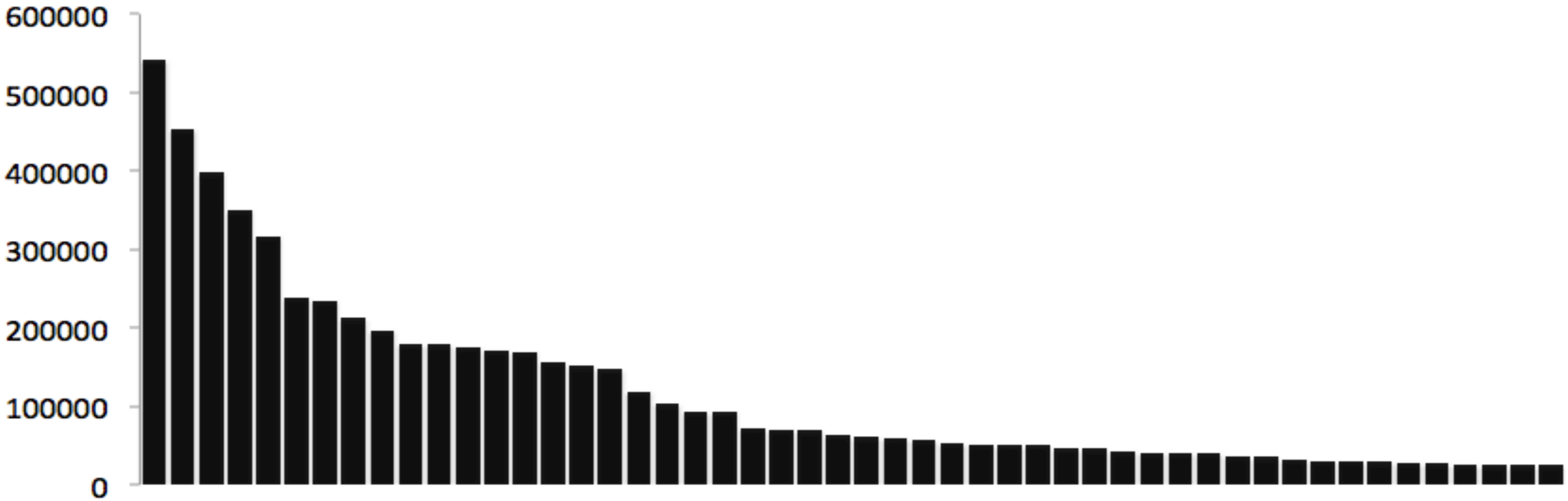
Case Study – Eficiency of Facebook Posts in Hotels Using DEA

Facebook public data was collected. Characterizes the publishing behavior of Facebook pages marked as "Hotel".

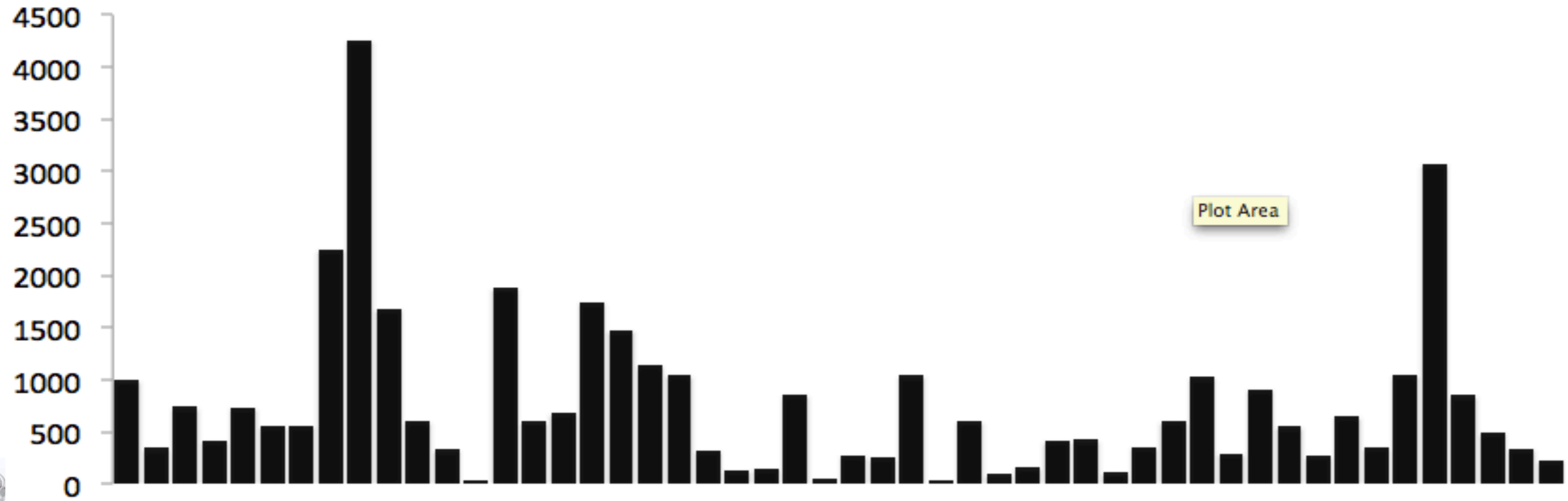
- Sample includes 50 most popular "Hotel" pages in Facebook (by Fans number)
- Fans range between 540.000 and 25.000
- All post history, from each page was collected.
- Each post is defined by its type and total number of shares, likes, and comments.
- 78,000 were collected.
- In 2012 all page were active. Hence 38,000 post were used to comparison analysis.



Page fans (descending)

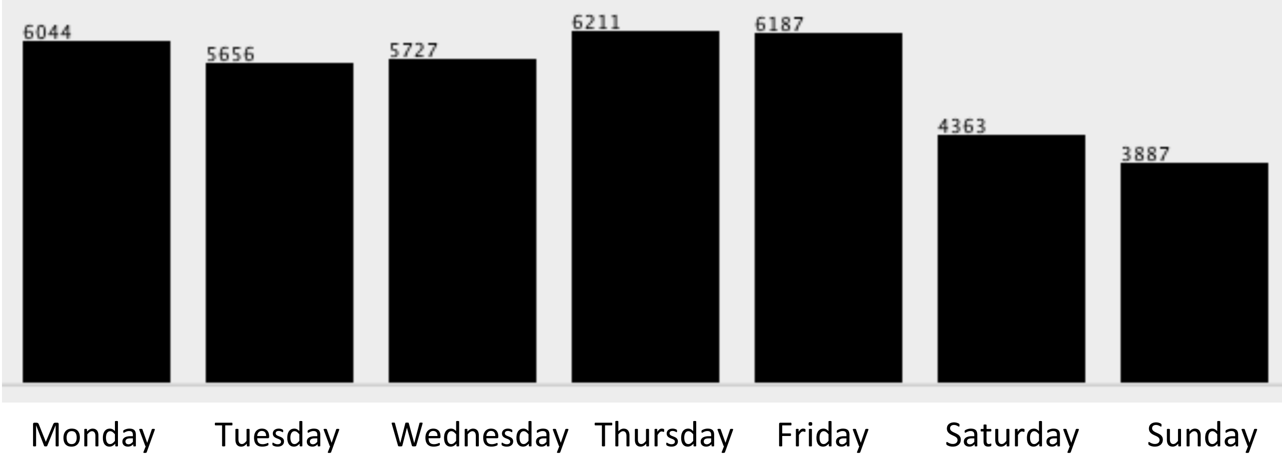


Posts per page: same order (random posting strategies)

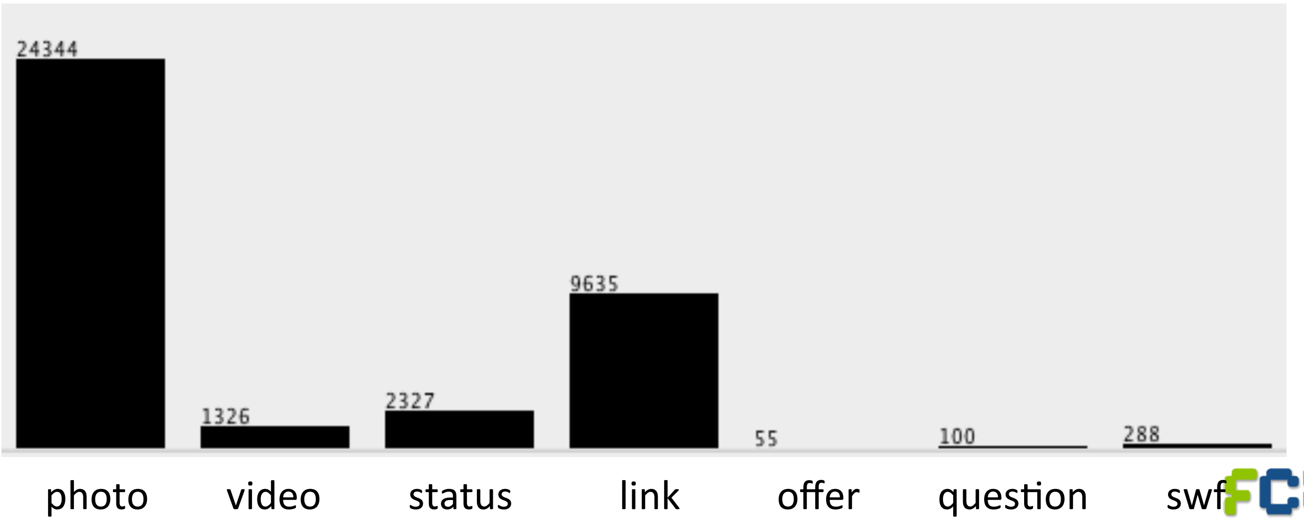


Posts Activity by Week day and Type

Posts per weekday: Publishing activity drops on weekends.



Posts per type: Photo leads



Models that Classify the Page Efficiency Considering that High Interaction Levels Represent Good Output of Marketing Strategy.

Inputs:

- Number of photo posts done in 2012
- Number of status posts done in 2012
- Number of link posts done in 2012
- Number of video posts done in 2012

DEA models 1.X:

Outputs:

- Total number of shares of all posts
- Total number of likes of all posts
- Total number of comments of all posts

DEA models 2.X:

Outputs:

- Ratio of total number of shares of all posts over page fans.
- Ratio of total number of likes of all posts over page fans.
- Ratio of total number of comments of all posts over page fans.

DEA Models

Four BCC DEA models where design for each output type 1.X and 2.x
They matchup different BCC parameterizations.

DEA INPUTS (Ex: 15 from the 50 pages)

#	Hotel	INPUTS				Outputs 1.X			Outputs 2.X		
		Photos	Status	Links	Videos	Shares	Likes	Comm.	Shares	Likes	Comm.
1	AO Hostels	115	82	25	8	483	8496	4363	1.95%	34.37%	17.65%
2	ARIA Resort & Casino	572	89	301	13	35818	681219	24712	6.61%	125.80%	4.56%
3	Atlantis The Palm Dubai	448	12	62	35	45173	336411	16855	19.23%	143.22%	7.18%
4	Bellagio Las Vegas	337	23	53	5	26998	271123	13449	7.71%	77.45%	3.84%
5	Big Cedar Lodge Official Page	300	38	151	8	2472	32638	3481	9.90%	130.67%	13.94%
6	Caesars Palace	455	53	171	40	19796	228561	13265	6.25%	72.11%	4.19%
7	Casa Andina Hotels	360	14	25	19	9308	58605	4471	20.17%	126.97%	9.69%
8	Courtyard by Marriott Aguadilla	73	16	4	1	1703	22029	643	3.36%	43.49%	1.27%
9	Cove Haven Entertainment Reso	412	267	143	20	1425	39564	7317	5.54%	153.89%	28.46%
10	Danubius Hotels Group	196	2	144	10	3972	38097	2190	9.58%	91.92%	5.28%
11	El Conquistador Resort	647	117	94	31	3686	72452	3820	10.38%	204.02%	10.76%
12	French Lick Resort	132	70	128	22	2183	20206	2592	7.43%	68.76%	8.82%
13	Grand Sierra Resort and Casino	393	28	128	40	3958	48728	6030	9.57%	117.82%	14.58%
14	Great Wolf Lodge	388	51	217	61	7440	103926	9963	1.87%	26.12%	2.50%
15	Hard Rock Hotel and Casino Las	1052	148	335	23	14101	158669	9982	9.57%	107.63%	6.77%
…	…	…	…	…	…	…	…	…	…	…	…

Example of DEA Models Results: Model 1.1

#	Hotels	Efficiency	SLACKS Photos	Status	Links	Videos	Shares	Likes	Comm.
1	AO Hostels	**1.000**	0	0	0	0	0	0	0
2	ARIA Resort & Casino	**1.000**	0	0	0	0	0	0	0
3	Atlantis The Palm Dubai	**1.000**	0	0	0	0	0	0	0
4	Bellagio Las Vegas	**1.000**	0	0	0	0	0	0	0
5	Big Cedar Lodge Official Page	**0.342**	8	0	24	2	829	30950	561
6	Caesars Palace	**0.741**	0	16	74	25	7202	42562	184
7	Casa Andina Hotels	**1.000**	0	0	0	0	0	0	0
8	Courtyard by Marriott Aguadilla Hotel & Casino	**1.000**	0	0	0	0	0	0	0
9	Cove Haven Entertainment Resorts	**0.818**	0	195	64	11	25573	231559	6132
10	Danubius Hotels Group	**1.000**	0	0	0	0	0	0	0
11	El Conquistador Resort	**0.564**	28	43	0	12	23312	198671	9629
12	French Lick Resort	**0.720**	0	37	64	15	1118	43382	1450
13	Grand Sierra Resort and Casino	**0.858**	0	1	57	29	23040	222395	7419
14	Great Wolf Lodge	**0.869**	0	21	135	48	19558	167197	3486
15	Hard Rock Hotel and Casino Las Vegas	**0.320**	0	24	54	2	12897	112454	3467
...	...	...	...	...	...	...	...	...	...

Slacks can be interpret as: the over investment in publishing (inputs) or the lack of results (output) in order to achieve equivalent efficiency compared to best practices.

DEA Models Result: All models. Combined Analysis Sustain Consistent Conclusions.

- 13 and 18 are consistent efficient Facebook pages.
- Ratio interactions demonstrates that large pages are in fact inefficient.
- Model 1.1 and 2,1 are very “forgiving”.

#	Fans	Hotels	Absolute Interations				Relative Interaction			
			1.1	1.2	1.3	1.4	2.1	2.2	2.3	2.4
1	541492	ARIA Resort & Casino	1.000	1.000	1.000	1.000	0.444	0.255	0.255	0.211
2	453806	Holiday Inn	1.000	0.380	0.297	0.297	0.333	0.172	0.054	0.054
3	397837	Great Wolf Lodge	0.869	0.516	0.516	0.442	0.255	0.104	0.100	0.100
4	350056	Bellagio Las Vegas	1.000	1.000	1.000	1.000	1.000	0.411	0.397	0.397
5	316960	Caesars Palace	0.741	0.633	0.633	0.593	0.558	0.160	0.160	0.160
6	238724	Mandalay Bay Resort and Casino	1.000	0.752	0.741	0.741	1.000	0.315	0.315	0.305
7	234883	Atlantis The Palm Dubai	1.000	1.000	1.000	1.000	1.000	0.784	0.784	0.724
8	212354	Ushua\u00efa Ibiza Beach Hotel (C	1.000	1.000	1.000	0.868	0.886	0.614	0.614	0.338
9	197343	Sakura Hotel & Hostel in Tokyo Jap	1.000	0.705	0.705	0.651	0.513	0.292	0.292	0.245
10	179008	Resorts World Genting	0.349	0.155	0.150	0.150	0.118	0.052	0.052	0.052
11	178922	Planet Hollywood Resort & Casino	0.789	0.259	0.241	0.241	0.286	0.116	0.104	0.104
12	176212	Mazagan Beach Resort	1.000	0.186	0.173	0.173	0.139	0.112	0.094	0.094
13	**171890**	**Vital Hotel Westfalen Therme Spa**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**
14	169475	Pearl Continental Karachi	1.000	1.000	1.000	1.000	1.000	0.634	0.634	0.551
15	156678	Palms Casino Resort	0.955	0.237	0.235	0.235	0.269	0.126	0.119	0.119
16	151413	The Cosmopolitan of Las Vegas	1.000	1.000	1.000	1.000	1.000	0.527	0.527	0.488
17	147419	Hard Rock Hotel and Casino Las Ve	0.320	0.200	0.200	0.199	0.241	0.117	0.117	0.115
18	**119188**	**Horta da Moura**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**

Case Study – Facebook Ontology for Post Life Cycle Analysis

Objective:

- Gather Facebook data
- Model Post Life Cycle (LC)
- Design intelligent algorithms to detect behavior outliers.

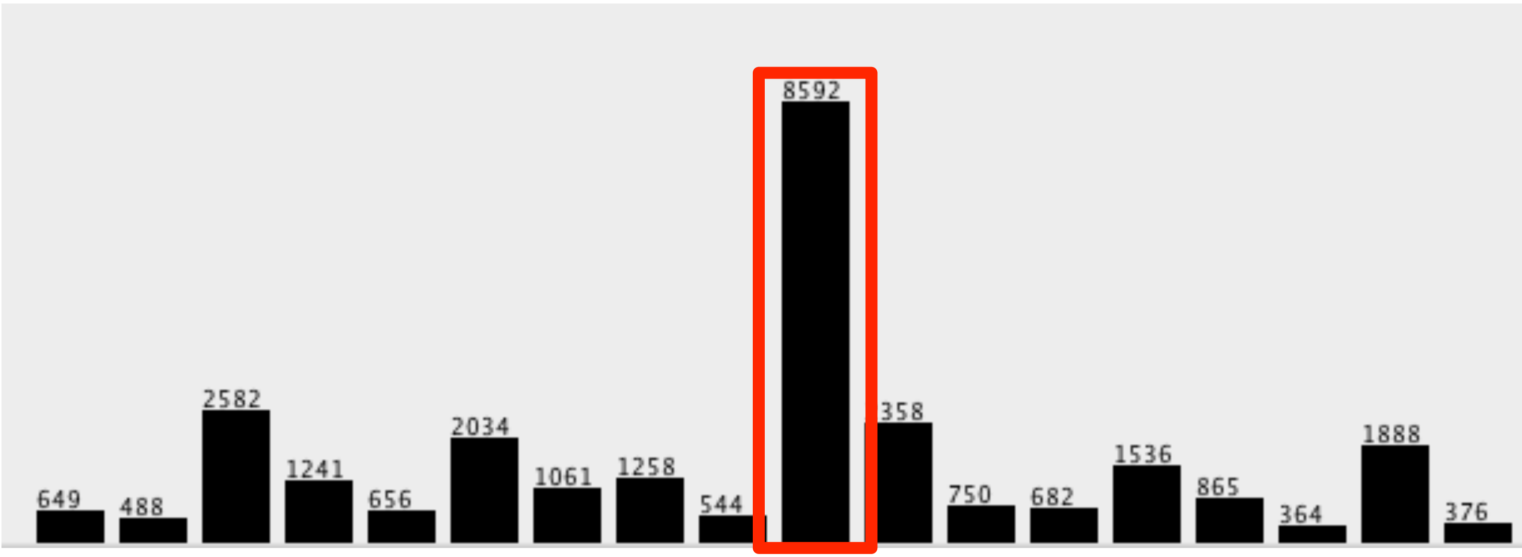
Development:

- Large data set collection.
- Model design
- Operationalize algorithm
    - Design ontology system
    - Populate
    - Let program infer when posts have uncommon behavior

Facebook public data was collected. Its characterizes the publishing behavior of Facebook pages from 18 categories.

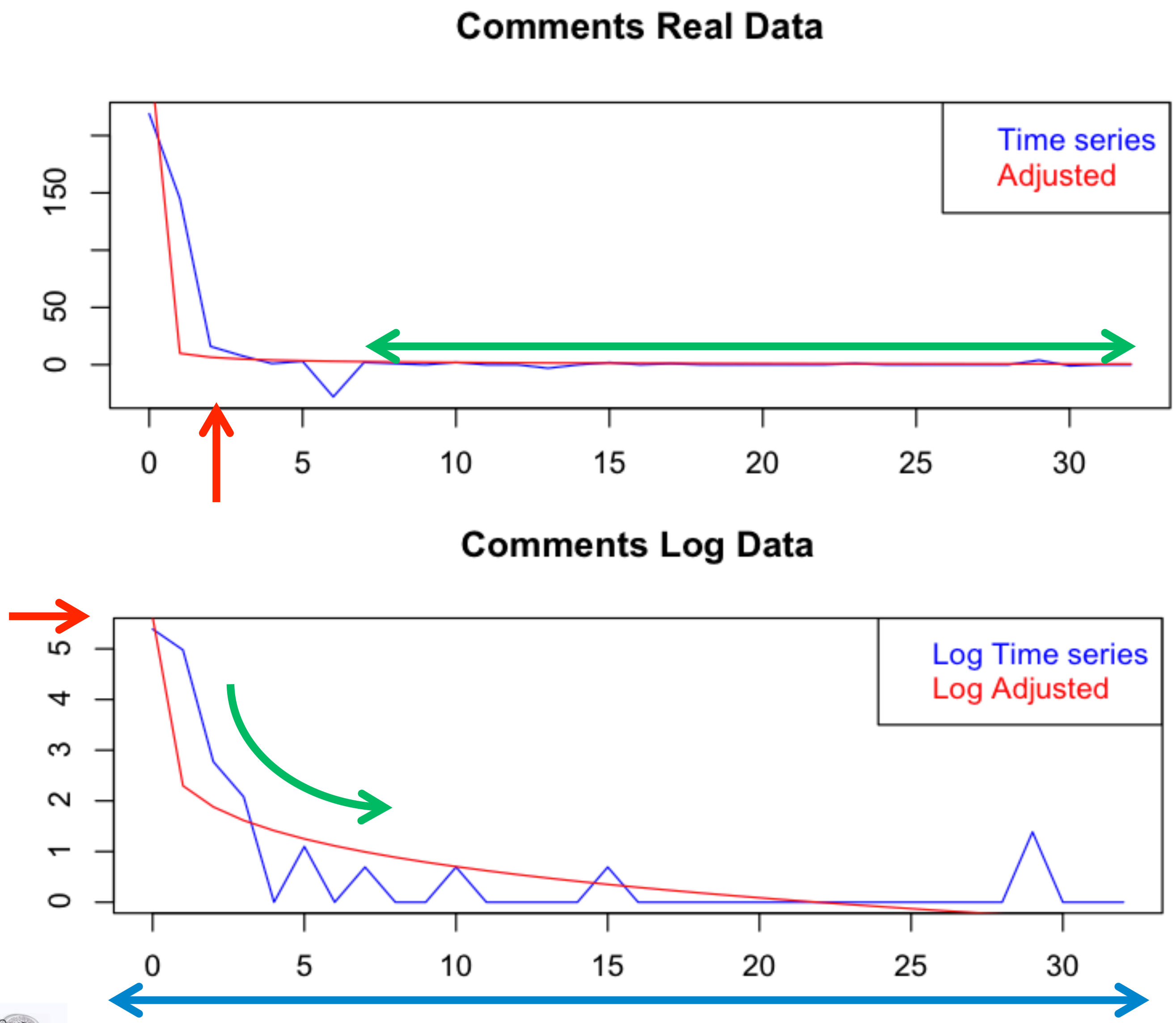
- Sample includes 560 most popular pages.
- Fans range between 189.660 and 450 thousand fans.
- Posts publish between 21st December 2012 and 21st January 2013.
- Collection gather post history, i.e., time series data of each one.
- 680.000 lines data set.
- 25.450 valid posts (deleted posts by page administrators were excluded).

Posts per category.



Media pages are the most active.

Typical post life cycle (95%).
Negative exponential fitting with logarithmic time transformation.



Real data

One to two days fierce activity

Flat (no activity) after initial days.

LC Model

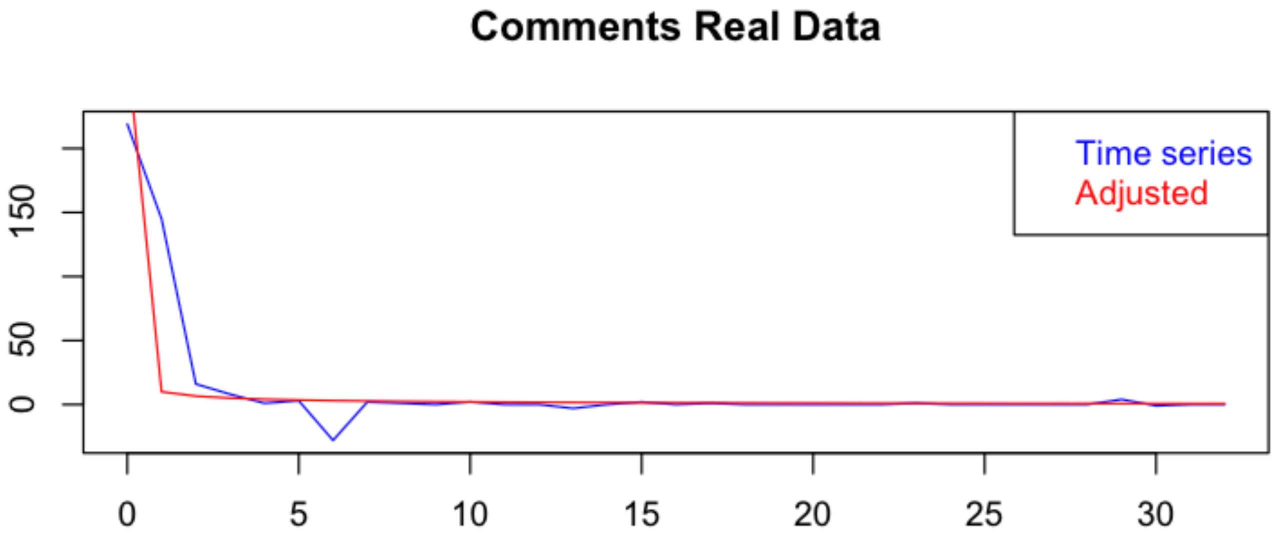
α : how high it starts.

β: how fast it decays in time.

R: Time transformation for fitting purposes.

Adjst: how well the model predicts LC.

Typical vs. outlier post life cycle.



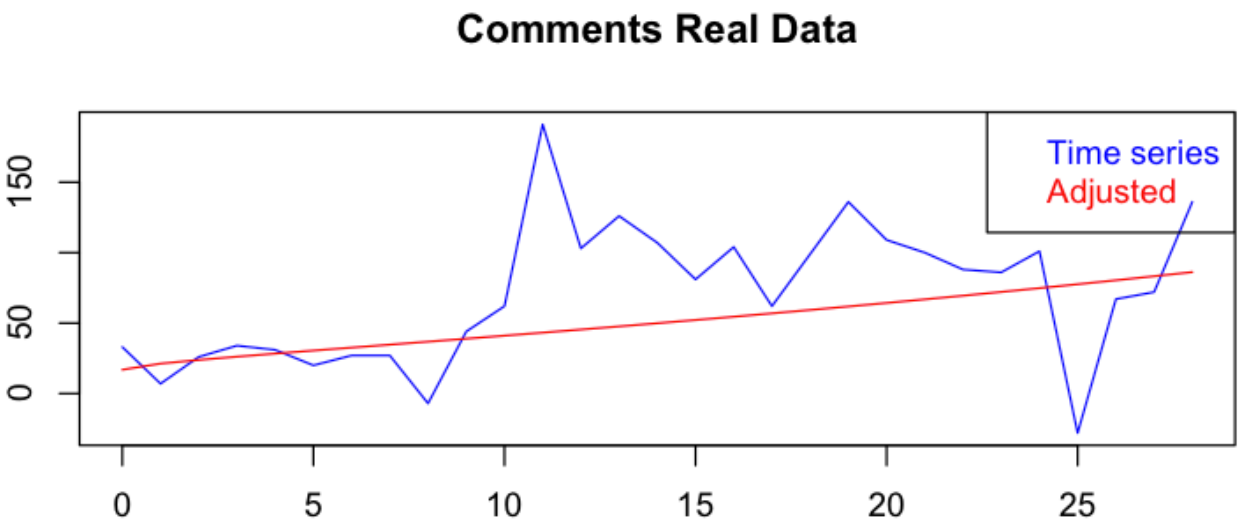
TYPICAL LC

α: can be high or low.

β: highly negative constant.

R: can be high or low

Adjst: adjust well (> 0.75)



OUTLIER LC

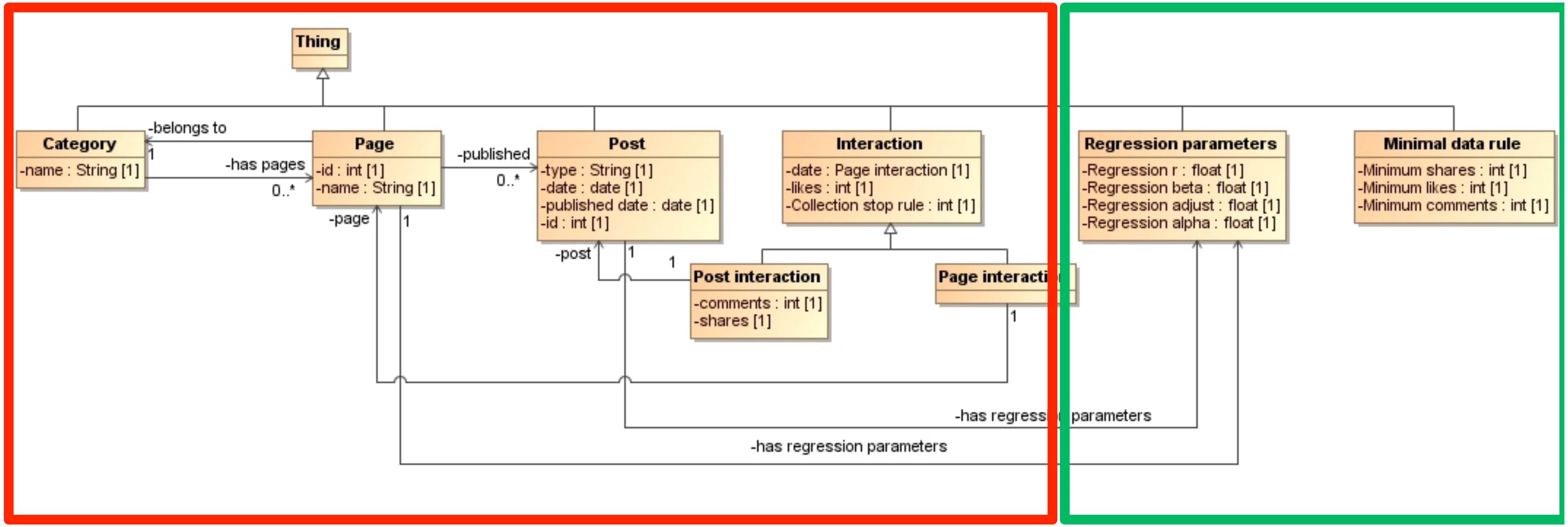
α: can be high or low

β: negative near zero or positive.

R: can be high or low.

Adjst: does not adjust well (< 0.75)

Facebook Post Life Cycle Intelligent Algorithm – The Ontology



It represents knowledge about Facebook pages:

- Pages have fans, belong to categories and publish posts.
- Posts are categorized by types, have like, shares, and comments responses.
- Page fans and posts interactions are recorded each day.
- Given a minimum post life time (ex.: 3 days) the regression model calculates regression models indicators.
- Regression indicators are then related to a post like, share or comment time series.

Facebook Post Life Cycle Intelligent Algorithm – The Ontology

A collection algorithm is responsible for instantiating the ontology.

Given the regression indicators described before is possible to detect posts that had unusual behaviors. In other words by representing a knowledge concept of a unusual post, is possible to ask the ontology to detect all behavior outliers. The rules by which a post is considered and outlier can be parameterized and improved over time. Examples of outlier post knowledge concept:

1. Post interaction that: has **beta > 0** ***AND*** **adjustment < 0.7**
2. Post interaction that: has **adjustment < 0.5**
3. Post interaction that: has **beta > 0** ***OR*** **adjustment < 0.6**
4. Post interaction that: [**has beta > 0** ***AND*** **adjustment < 0.8**] ***OR*** [**has adjustment < 0.5**]
5. Etc…

Posts are classified has having a typical or outlier behavior. Outliers should be analyzed and requires special attention. They may represent controversial content, interactive features, have viral nature, generated contestation, etc…

Conclusions

- We are living in the Era of Big numbers
- We must learn how to converge Data, Analysis and Decision Making