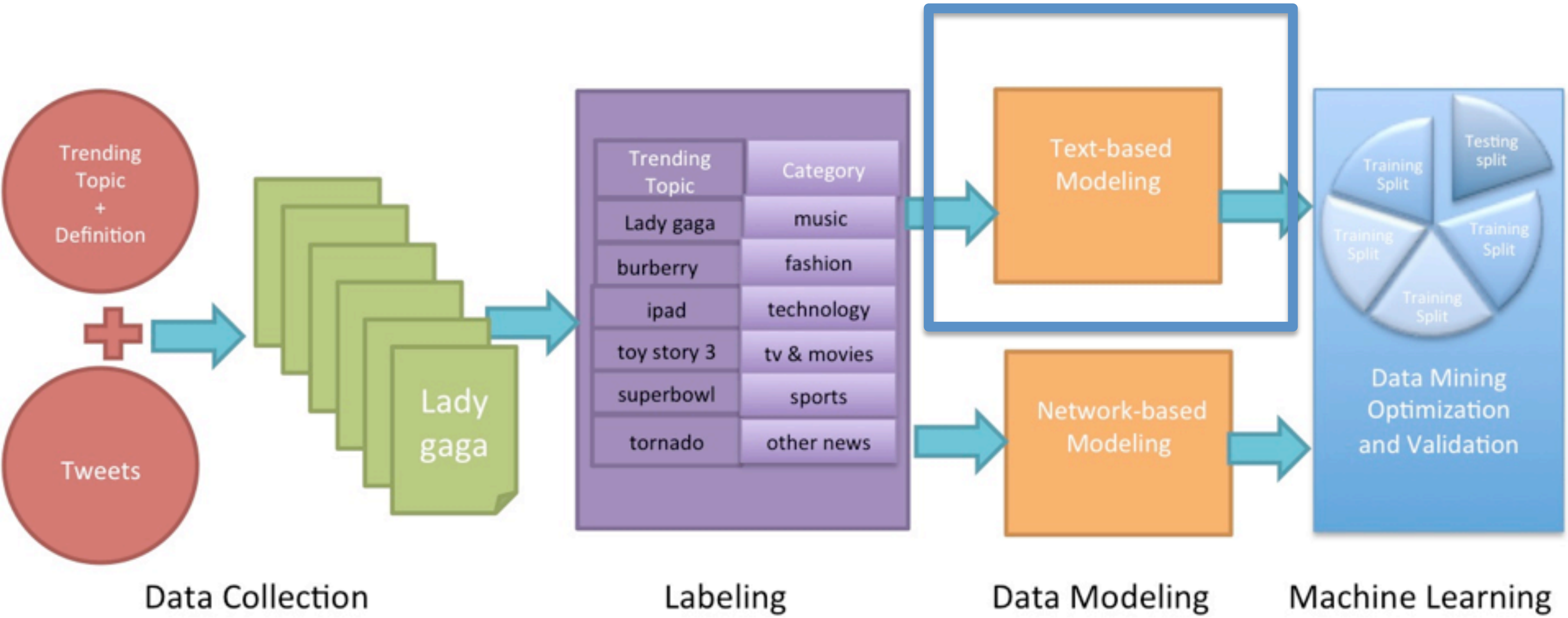
Social Analytics for BI

PART C

Text mining

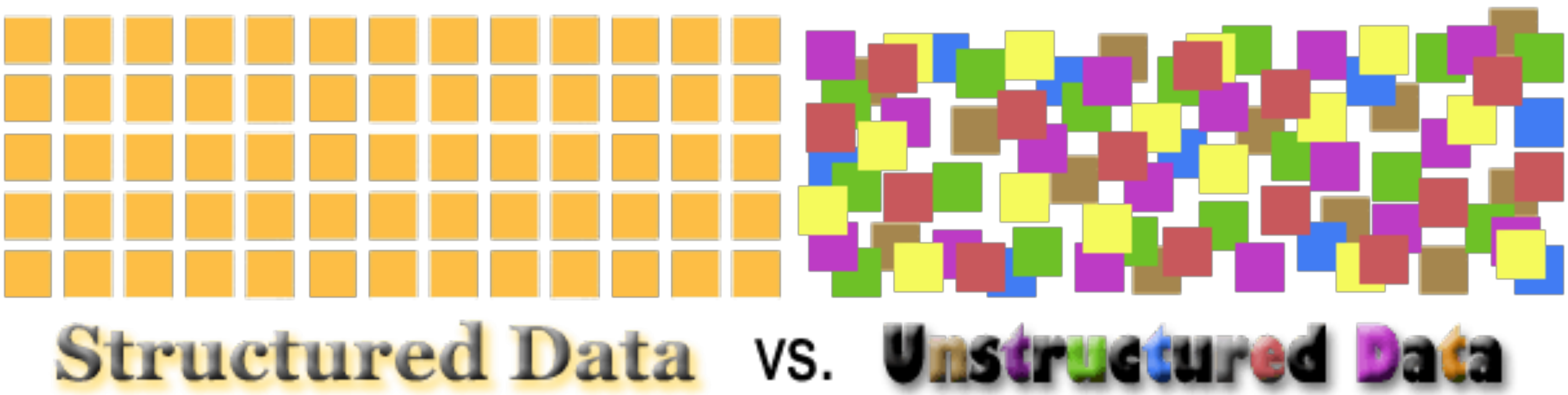
Extracting Social Network data for BI: workflow



Two types of data: network-based and **text-based**

The power of unstructured data

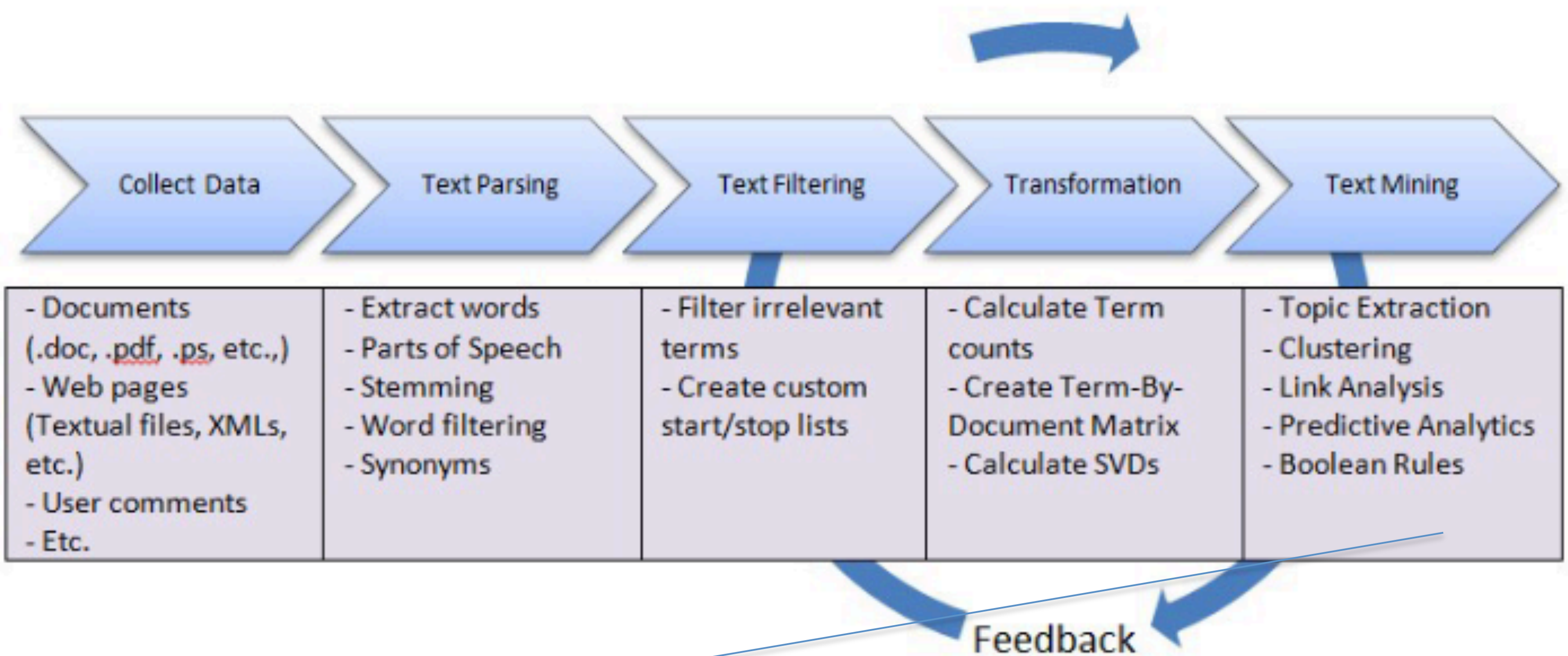
"80% of business-relevant information originates in unstructured form, primarily text."



Text Mining

- Text mining is an emergent technology attempting to extract useful information (and knowledge) from unstructured data
- Text mining is an extension of data mining to textual data
- Social networks contain a lot of information in textual form, such as posts, links, blogs, news articles, emails..

Text processing workflow (more in detail)

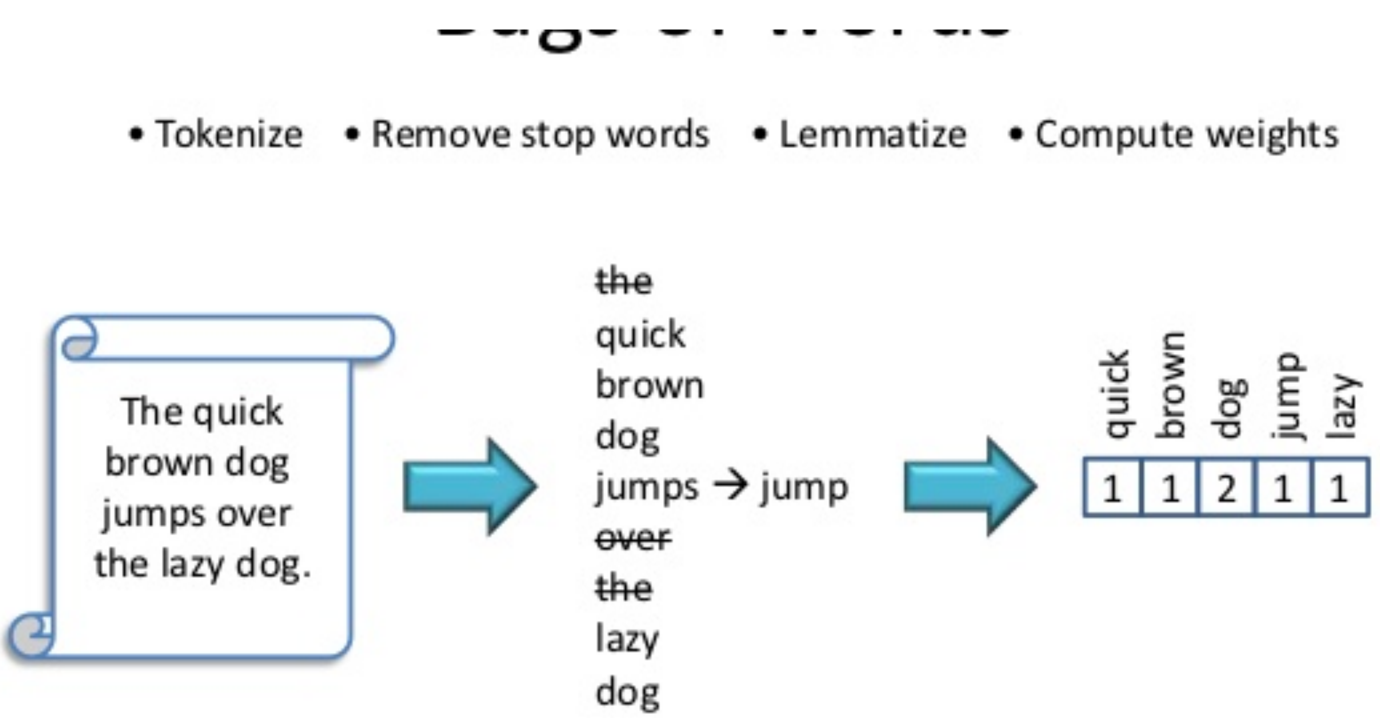


TEXT MINING APPLICATIONS

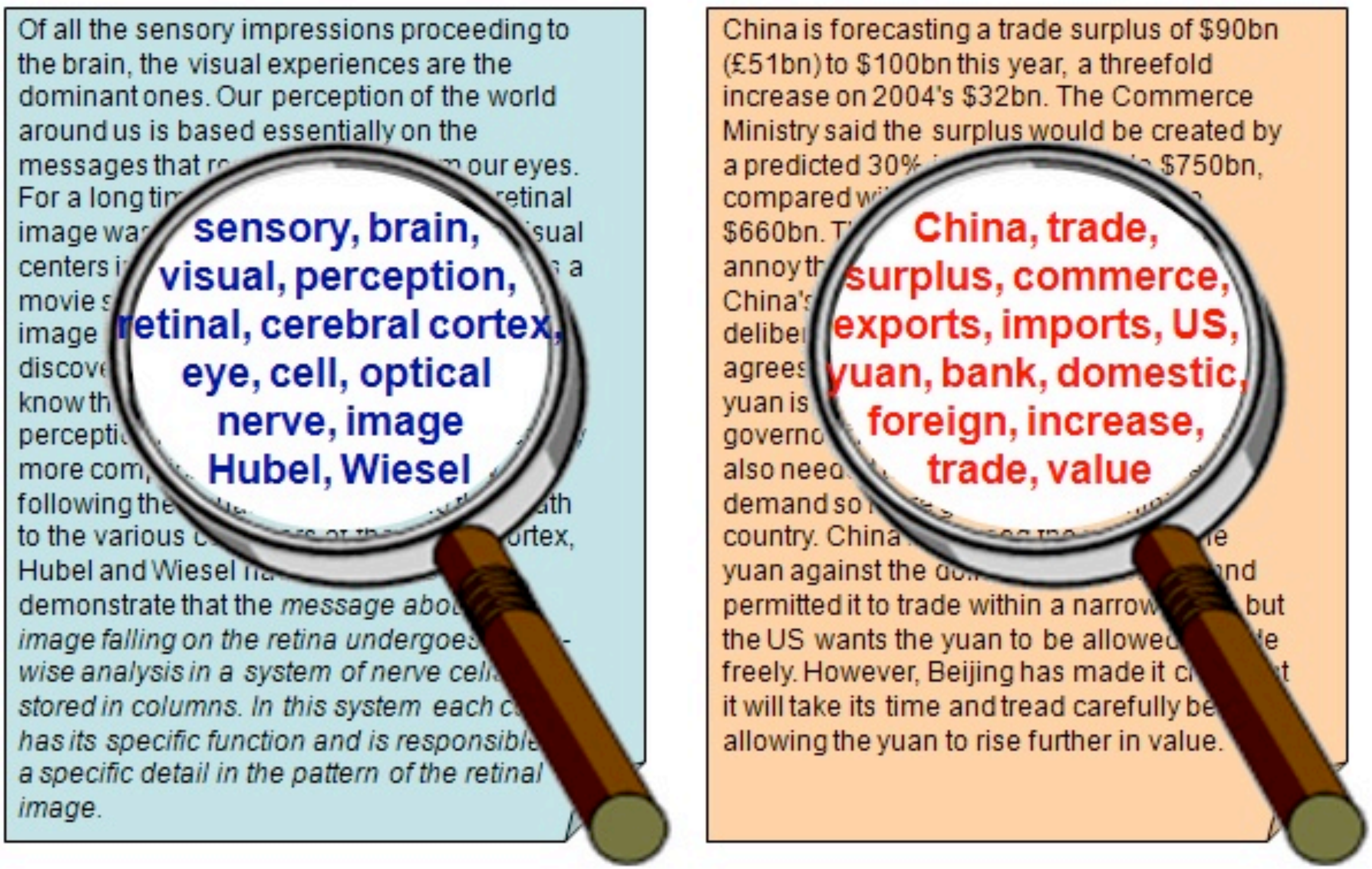
Text Mining: popular applications

- Named Entities	“who/what/where?”
- Themes/Topics	“what’s the buzz?”
- Categories	“what’s it about?”
- Intentions	“what will they do?”
- Sentiment	“how do they feel?”

How do we represent texts? Bag of words



Seems simple.. however-..



Why bag of words?

- Basic idea:
  - Keywords are extracted from texts.
  - These keywords describe the (usually) topical content of Web pages and other text contributions.
  - Each unique word in a corpus of documents (web pages, social messages..) = one attribute
  - Each document is a record with non-zero weight for each word in that document, zero weight for other words

➔ Words become “attributes”, whose values can be binary (the word *is* or **is not** in a text), or real numbers (e.g. the relative frequency of a word in the text)

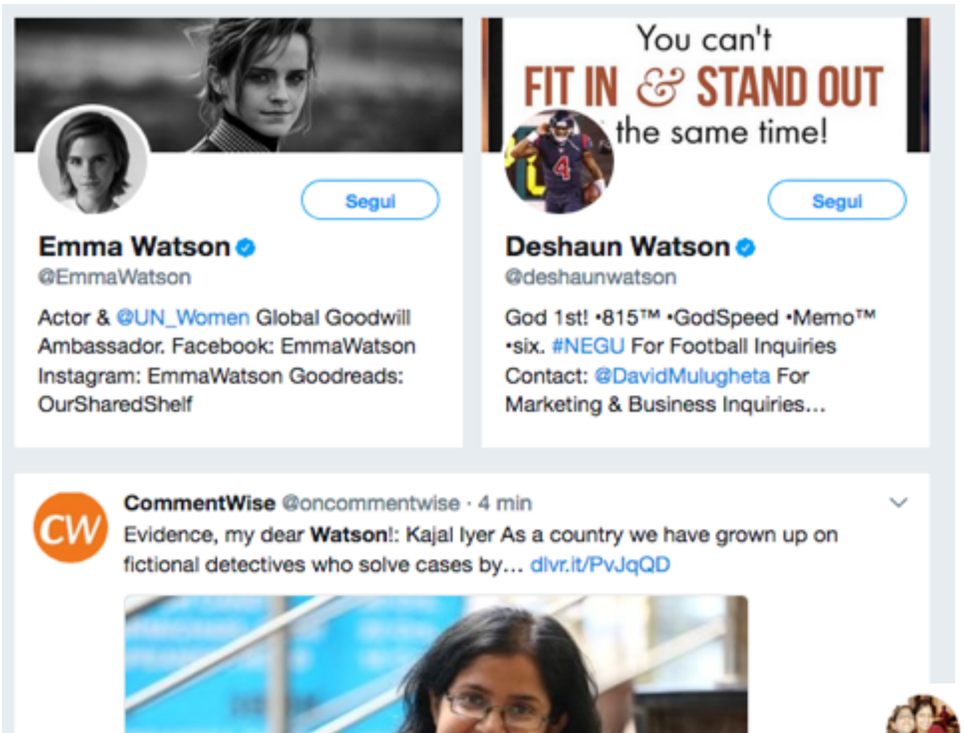
Example

The example considers a vocabulary of 8 words – in the reality the vocabulary has millions of words – document records have millions of attributes

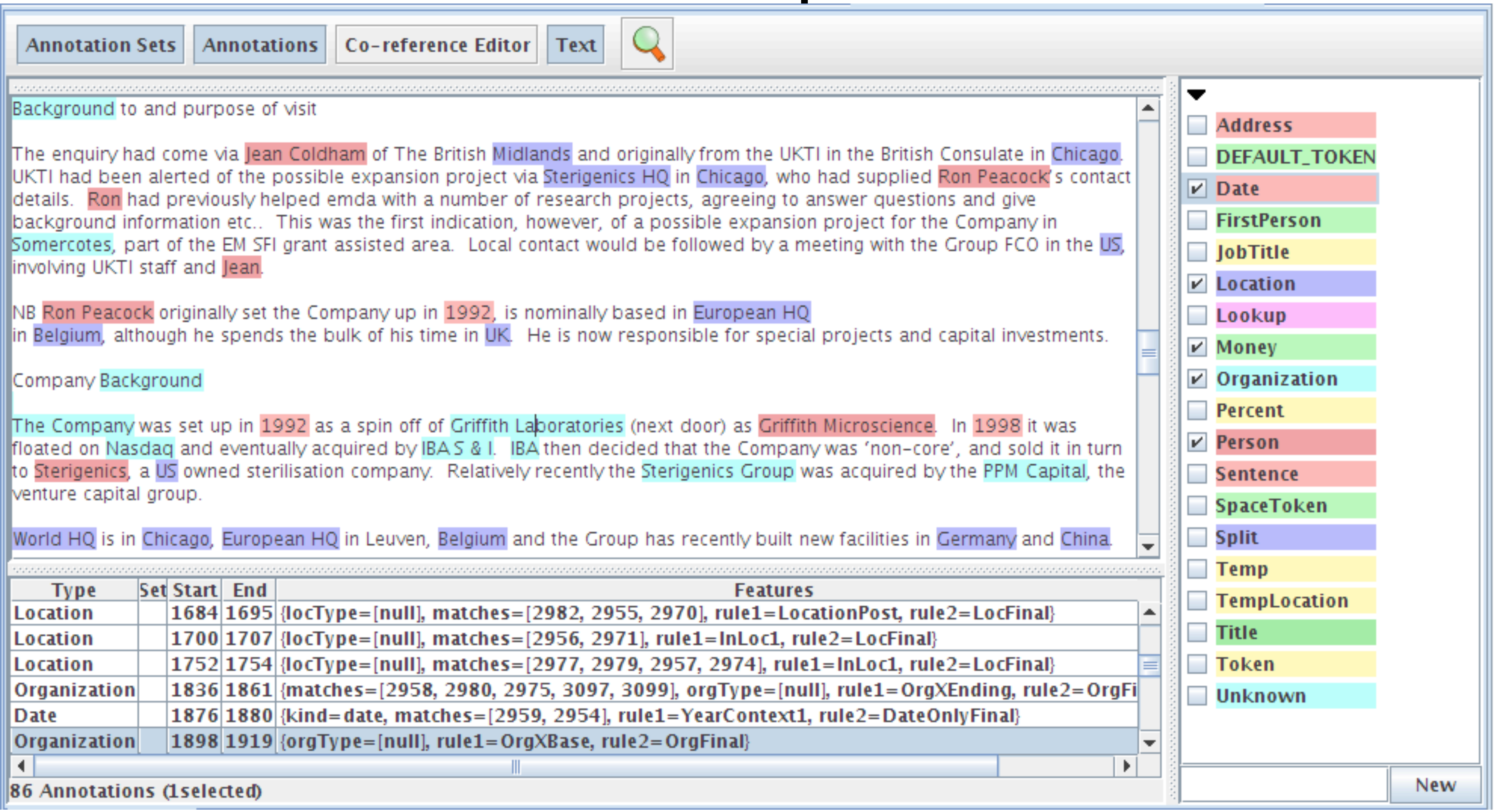
Which words should we care about? A complex problem

- E.g.: Companies assume that people refer to them by name
- Big mistake!!
- There are multiple dimensions for reference: hashtags, names of people (e.g., managers), products, and for each: abbreviations, initials, nicknames
- Additional problems: ambiguity, synonyms..

Example: search “Watson” on Twitter Search



So.. rather than “bag of words”, bag of concepts



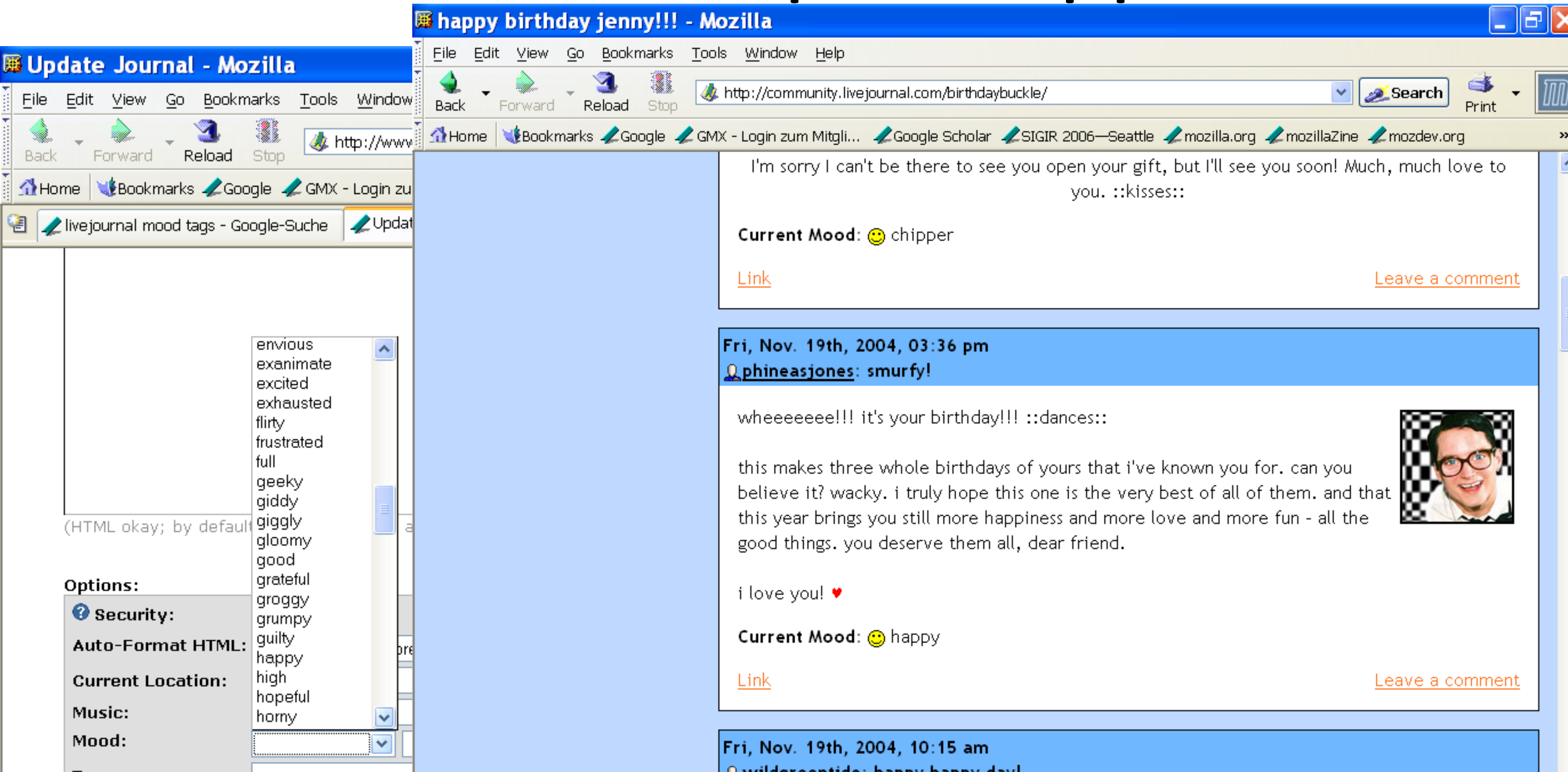
Text Mining tasks

- After pre-processing, text is analyzed to extract useful information, much in the same way as for structured data mining
- Types of processing:
  - Classification: assign a message (or a peace of text) a category
  - Topic extraction: identify (summarize) what the text is about
  - Clustering: grouping similar messages/blogs/posts
  - Sentiment analysis: determine the polarity/ sentiment/opinion expressed in a text

Classification example: mobile apps users

In classification, categories are assigned. Based on messages, classify user in one of these cats

Another example: Happiness



Since messages are tagged with a mood by the message author, a machine learning classifier can learn to classify new untagged messages

Message Clustering: example

related themes

over the last 50 minutes

#wikipedia
wolframalpha.com/
fructose in onion
with your input
google killer
wolfram
wolfram alpha
@time
days old
meaning of life
i have tried
on the day
was born
engine
#fail

wolfram|alpha
computational
computational knowledge engine
via @time
been alive
bit.ly/sa6be
got the number
wrong answer
queries failed
eg
i was born
search engine
input

tweets by theme

"queries failed"

: not finding #WolframAlpha all I had hoped, data-driven queries failed every time ("ave # job applicants interviewed to fill position") *peterjwolfgang*

So far #WolframAlpha has failed for the two queries that I have tried that weren't a play test #fail *marcad* show 1 similar tweet »

(drilldown ↑)

"google killer"

#WolframAlpha is going to be huge, but it's not a google killer, and most people will never use it *briggsl*

@charlesf11 Yeah, it's bugging me that people are calling it a Google killer. They're not the same animal. #wolframalpha #wikipedia #google *mattbramanti*

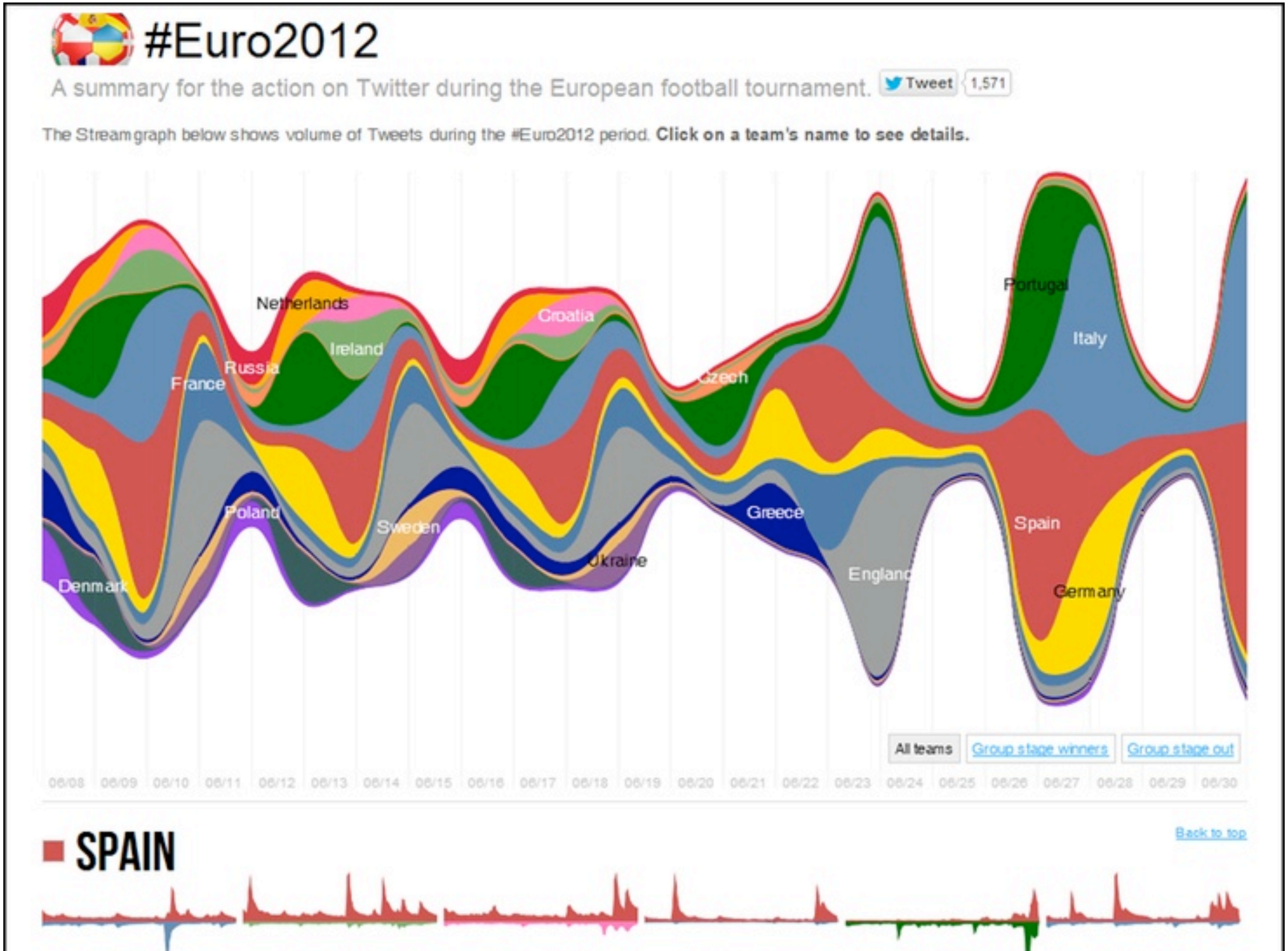
#WolframAlpha is no Google killer, but it's the smartest calculator ever. *PrestonStahley*

Remember: in clustering we have no known categories. Messages are clustered based on similarity of attributes (bag of words)

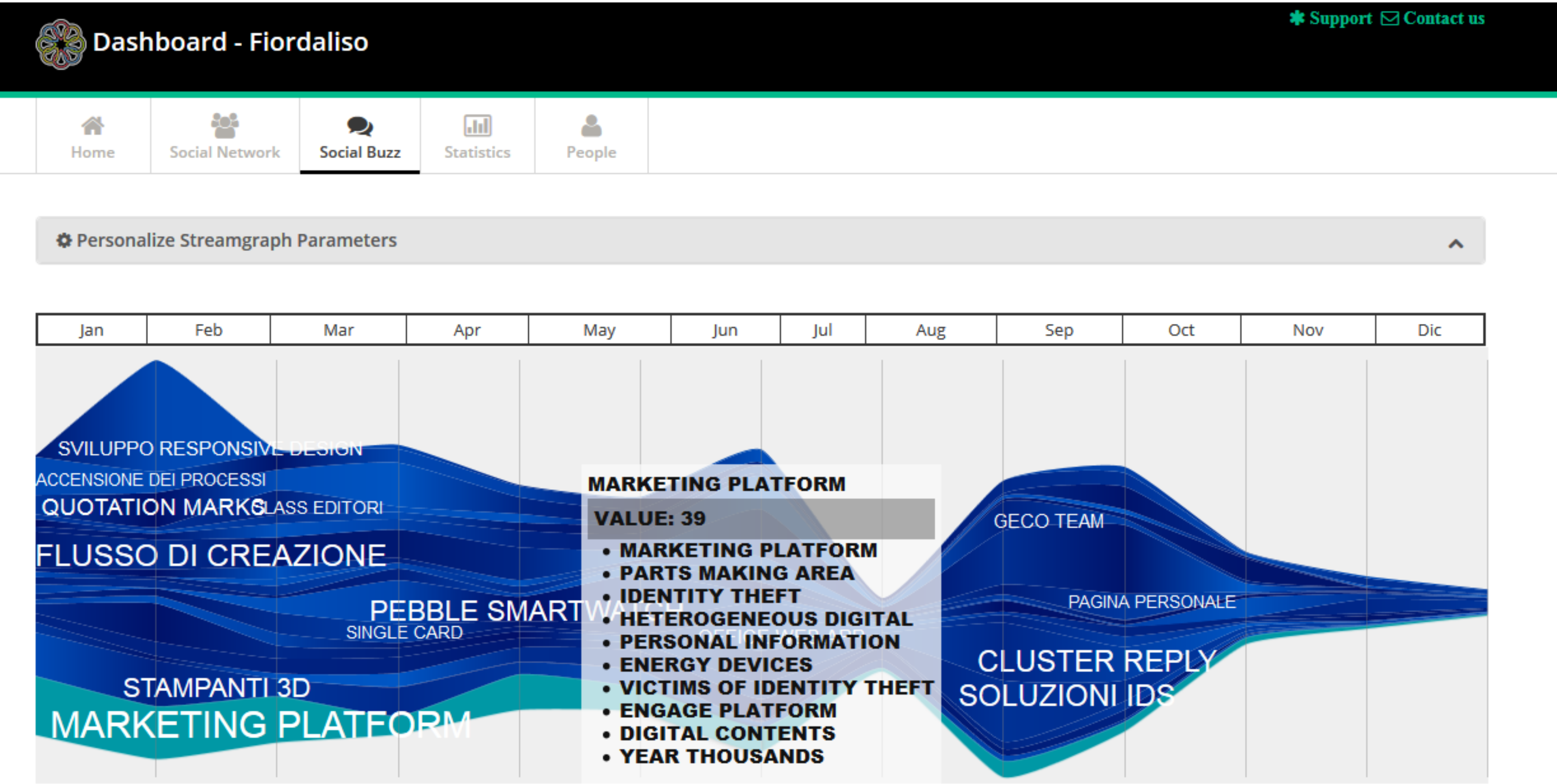
Topic extraction

- In topic extraction, the purpose is to detect group of words that are representative of a "trending" discussion topic
- Based on the analysis of terms that co-occur in many messages
- Example: *Watson, cognitive, IBM, AI*
- Example 2: *#WomenBoycottTwitter , women, sexual, solidarity*

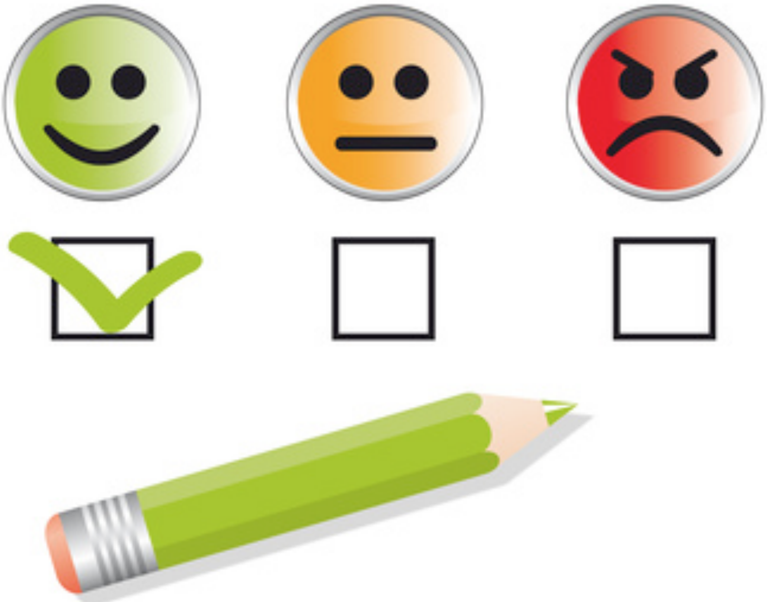
Tracing topics (stream graphs)



Tracing Topics (TamTamy-Reply)



Opinion mining



Introduction – facts and opinions

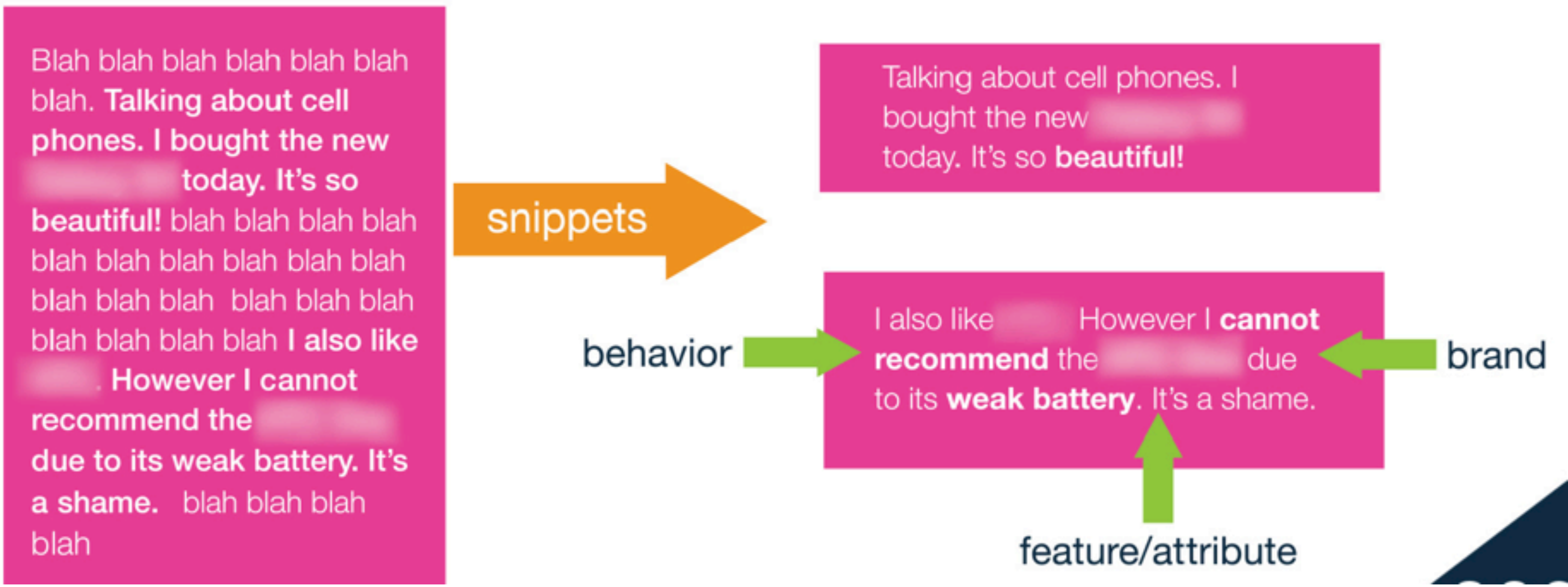
- Two main types of textual information on the Web.
  - Facts and Opinions
- Current search engines search for facts (assume they are true)
  - Facts can be expressed with topic keywords.
- Search engines do not search for opinions
  - Opinions are hard to express with a few keywords
    - What do people think of Motorola Cell phones?
  - Current search ranking strategy is not appropriate for opinion retrieval/search.

Opinions are user-generated content

- Word-of-mouth on the Web
  - One can express personal experiences and opinions on almost anything, at review sites, forums, discussion groups, blogs ... (called the user generated content.)
  - They contain valuable information
  - Web/global scale!!
  - Our interest: to mine opinions expressed in the user-generated content
  - A very challenging problem.
  - Practically very useful.

Applications

- Businesses and organizations: product and service benchmarking. Market intelligence.
  - Business spends a huge amount of money to find consumer sentiments and opinions.
  - Consultants, surveys and focused groups, etc
- Individuals: interested in other's opinions when
  - Purchasing a product or using a service,
  - Finding opinions on political topics,
- Ads placements: Placing ads in the user-generated content
  - Place an ad when one praises a product.
  - Place an ad from a competitor if one criticizes a product.
- Opinion retrieval/search: providing general search for opinions
  - Predicting behaviours and trends in finance, medicine, politics



Blah blah blah blah blah blah blah. **Talking about cell phones. I bought the new** **today. It's so beautiful!** blah blah blah blah blah blah blah blah blah blah blah blah blah blah blah blah blah blah blah blah **I also like** . **However I cannot recommend the** **due to its weak battery. It's a shame.** blah blah blah blah
snippets
Talking about cell phones. I bought the new today. It's so **beautiful!**
behavior
I also like However I **cannot recommend** the due to its **weak battery**. It's a shame.
brand
feature/attribute

Impact

- 81% of Internet users have done online research on a product 20% do so on a typical day
- Among readers of online reviews between 73% and 87% report that reviews had a significant influence on their purchase
- Consumers report being willing to pay from 20% to 99% more for a 5-star-rated item than a 4-star-rated item (the variance stems from what type of item or service is considered);
- 32% have provided a rating on a product, service, or person via an online ratings system, and 30% have posted an online comment or review regarding a product or service.

A formalization of the opinion mining task

- Basic components of an opinion:
  - Opinion holder: The person or organization that holds a specific opinion on a particular object.
  - Object: on which an opinion is expressed (it can be described by features, e.g. for an hotel room: dimension, clean, silent, cost,..)
  - Opinion: a view, attitude, or appraisal on an object (or object feature) from an opinion holder.

Opinion mining “grain”

- At the document (or review) level:
  - Task: sentiment classification of reviews
  - Classes: positive, negative, and neutral
  - Assumption: each document (or review) focuses on a single object (not true in many discussion posts) and contains opinion from a single opinion holder.
  - Example: Movie reviews
- At the sentence level:
  - Task 1: identifying subjective/opinionated sentences
    - Classes: objective and subjective (opinionated)
  - Task 2: sentiment classification of sentences
    - Classes: positive, negative and neutral.
    - Assumption: **a sentence contains only one opinion**; not true in many cases.
    - Then we can also consider clauses or phrases.
- Example: hotel reviews

Opinion Mining Tasks (cont.)

- At the feature level (Example: product reviews, usually you want to know opinions on various features of the product to improve or to compare)
  - *Task 1: Identify and extract object features that have been commented on by an opinion holder*
  - *Task 2: Determine whether the* ***opinions on the features*** *are* positive, negative or neutral.
  - *Task 3: Group feature synonyms.*
- Opinion holders: identify holders is also useful, e.g., in news articles, etc, but they are usually known in the user generated content, i.e., **authors of the posts**.

Feature-Based Opinion Summary

"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. Although the battery life was not long, that is ok for me. 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, and wanted me to return it to the shop. …"

….

Feature-Based Summary:

Feature1: Touch screen
Positive: 212

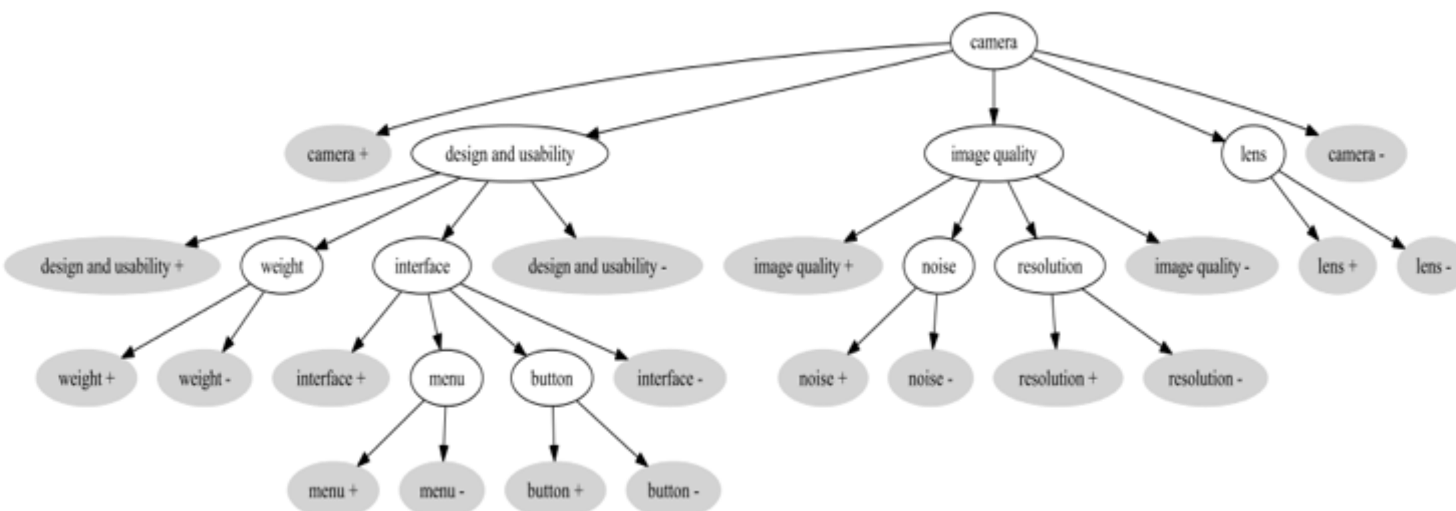
- *The touch screen was really cool.*
- *The touch screen was so easy to use and can do amazing things.*

…
Negative: 6

- The screen is easily scratched.
- I have a lot of difficulty in removing finger marks from the touch screen.

…
Feature2: battery life
…

Needs “knowledge” to represent object features



Opinion Analysis: Methods

- Two approaches to the problem:
  1. Machine-Learning (ML) solutions
  2. Lexicon-based solutions
  3. Hybrid solutions

- Each has advantages and disadvantages…

Data Analytics solutions

- Classification
  - Provide an algorithm with lots of examples
    - Documents that have been *manually/semi-automatically* annotated with a category
      - *Supervised* learning
      - In our case: e.g., positive/negative reviews (e.g. Tripadvisor)
  - Algorithm extracts "characteristic patterns" for each category and builds a *predictive model*
  - Apply *model* to new text -> get prediction

ML for document classification

- Bag-of-words document representation: document ➔ vector (“opinion” words can be considered, or, any word)
  - Example:

    d_1=“good…. average… excellent.. good..”

    d_2=“okay ..good.. average.. fine..”

    d_3=“good… okay.. okay…”
  - Then **Vocabulary**={“good”, “average”, “excellent”, “fine”, “okay”} and d_1 will be represented as:
    - **d_1={2,1,1,0,0}** if features are frequency-based or
    - **d_1={1,1,1,0,0}** if boolean-based

Bag-of-sentiment-words

I love this movie. It's sweet but with satirical humor. The dialogue is great and the adventure scenes are great fun...It manages to be whimsical and romantic while laughing at the conventions of the fairy tale genre. I would recommend it to just about anyone. I've seen it several times as I love it so much, and I'm always happy to see it again whenever I have a friend who hasn't seen it yet.

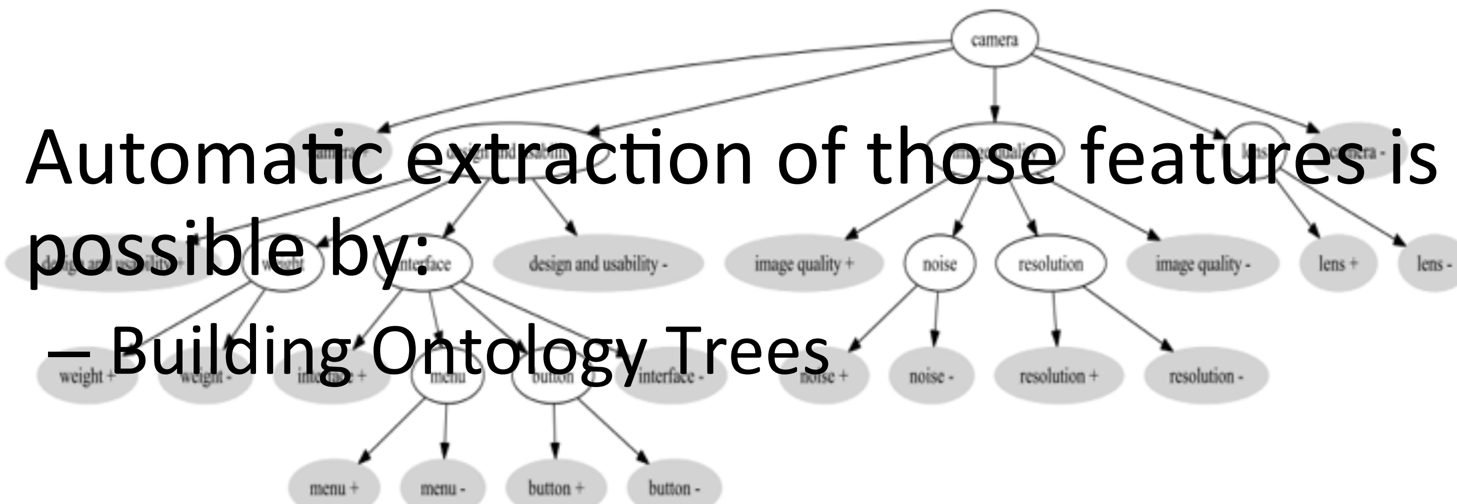
great	2
love	2
recommend	1
laugh	1
happy	1
.....	....

Not only words

- Typical extensions, focus on *extending/ enhancing* the document representation. Instead of/in addition to bag-of-words features, can use:
  - Extra features for *emphasised words , special symbols*
    - *wooooow*
    - *exlamations: !!!! ??*
    - *Emoticons ☺*

Feature-based Opinion Analysis

- As discussed, often the *Opinion Object* has different features
  - e.g., camera: lens, quality, weight.
- Often, such an aspect-based analysis is more valuable than a general +/-
- Automatic extraction of those features is possible by:
  - Building Ontology Trees



Pros/Cons of the approach

- Advantages:
  - Tend to attain good predictive accuracy
    - Assuming you avoid the typical ML mishaps (e.g., over/unde
- Disadvantages:
  - Need for training corpus
    - Solution: automated extraction (e.g., Amazon reviews, Rotten Tomatoes) or crowdsourcing the annotation process (e.g., Mechanical Turk)
  - Domain sensitivity
    - Trained models are well-fitted to particular product category (e.g., electronics) **but underperform if applied to other categories** (e.g., turism)
    - Solution: train a lot of domain-specific models or apply *domain-adaptation* techniques
    - Particularly for Opinion Retrieval, you'll also need to identify the domain of the query!

Example: "small" is positive for a camera, negative for an hotel room

Lexicon-based solutions

- Detect/extract the polarity of opinions, based on affective dictionaries
- Word-lists where each token is annotated with an 'emotional' value
    - e.g., positive/negative words or *words that express anger, fear, happiness, etc.*

Examples of affective dictionaries follow…

- Add syntactic and prose rules to estimate the overall polarity of text:
    – Negation detection: "the movie wasn't good"
    – Exclamation detection: "great show!!"
    – Emoticon detection: "went to the movies ☺"
    – Emphasis detection: "You are goooooood"
    – Intensifier, diminisher word detection: "Very good movie" vs. "good movie"

(Basic) lexicon-based approach

1. Detect emotion in two independent dimensions (numbers are weights of positive/negative opinionated words):
   1. Positive: D_{pos}: {1, 2,… 5}
   2. Negative: D_{neg}: {-5, -4,… -1}
2. (optional) Predict overall polarity by comparing them :
   - If $D_{pos} > |D_{neg}|$ then positive

   Example: "He is brilliant but boring"
   - Emotion('brilliant')=+3
   - Emotion('boring')=-2

   D_{pos} =+3, D_{neg}=-2 => *positive*
3. Negation detection: "He isn't brilliant and he is boring"
   - *Emotion(NOT 'brilliant') = -2*
   - *Decreased by 1 and sign reversed*
4. *Exclamation detection: "He is brilliant but boring!!"*
   - *Increase weight of emphasized words*
   - *'boring'=-3*

Pros/Cons of the approach

- Advantages:
  - Can be fairly accurate independent of environment
  - No need for training corpus
  - Can be easily extended to new domains with additional affective words
    - e.g., “amazeballs”
  - More often used in Opinion Retrieval
- Disadvantages:
  - Compared to a well-trained, in-domain ML model they typically underperform
  - Sensitive to affective dictionary coverage

Affective Lexicons

- They have been extensively used in the field either for lexicon-based approaches or in machine-learning solutions
  - Additional features
  - Bootstrapping: unsupervised solutions (see previous)
- Can be created manually, automatically or semi-automatically
- Can be domain-dependent or independent
- A lot of them are already available:
  - Manual
    - LIWC: Linguistic Inquiry and Word Count
    - ANEW: Affective norms for English words
  - Automatic:
    - WordNet-Affect
    - SentiWordNet …

LIWC: Linguistic Inquiry and Word Count

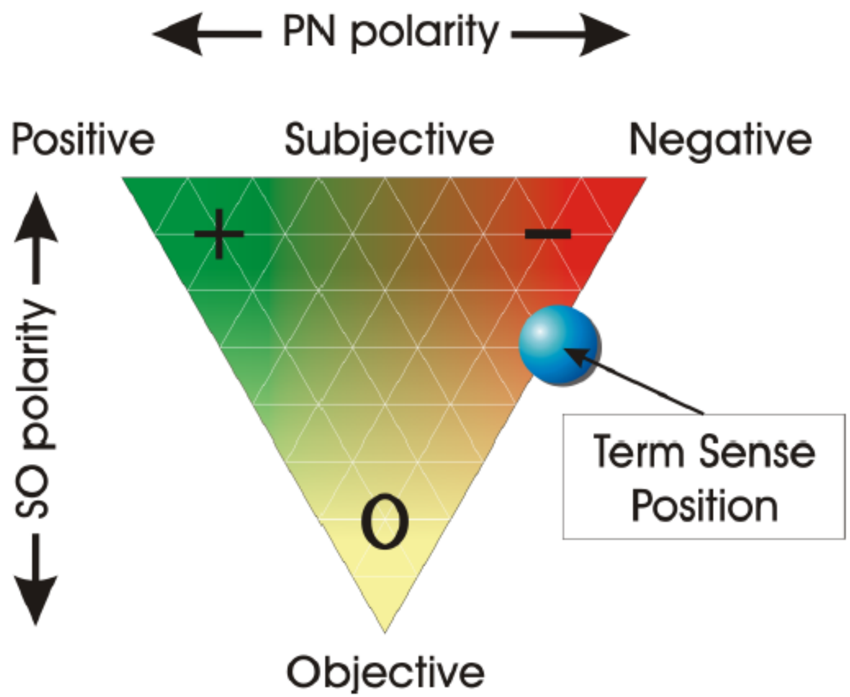
125 Affect						126 Posemo			127 Negemo			
abandon*	damn*	fume*	kindn*	privileg*	supporting	accept	freed*	partie*	abandon*	enrag*	maddening	snob*
abuse*	danger*	fuming	kiss*	prize*	supportive*	accepta*	freeing	party*	abuse*	envie*	madder	sob
abusi*	daring	fun	laidback	problem*	supports	accepted	freely	passion*	abusi*	envious	maddest	sobbed
accept	darlin*	funn*	lame*	profit*	suprem*	accepting	freeness	peace*	ache*	envy*	maniac*	sobbing
accepta*	daze*	furious*	laugh*	promis*	sure*	accepts	freer	perfect*	aching	evil*	masochis*	sobs
accepted	dear*	fury	lazie*	protest	surpris*	active*	frees*	play	advers*	excruciat*	melanchol*	solemn*
accepting	decay*	geek*	lazy	protested	suspicio*	admir*	friend*	played	afraid	exhaust*	mess	sorrow*
accepts	defeat*	genero*	liabilit*	protesting	sweet	ador*	fun	playful*	aggravat*	fail*	messy	sorry
ache*	defect*	gentle	liar*	proud*	sweetheart*	advantag*	funn*	playing	aggress*	fake	miser*	spite*
aching	defenc*	gentler	libert*	puk*	sweetie*	adventur*	genero*	plays	agitat*	fatal*	miss	stammer*
active*	defens*	gentlest	lied	punish*	sweetly	affection*	gentle	pleasant*	agoniz*	fatigu*	missed	stank
admir*	definite	gently	lies	radian*	sweetness*	agree	gentler	please*	agony	fault*	misses	startl*
ador*	definitely	giggl*	like	rage*	sweets	agreeab*	gentlest	pleasing	alarm*	fear	missing	steal*
advantag*	degrad*	giver*	likeab*	raging	talent*	agreed	gently	pleasur*	alone	feared	mistak*	stench*
adventur*	delectabl*	giving	liked	rancid*	tantrum*	agreeing	giggl*	popular*	anger*	fearful*	mock	stink*
advers*	delicate*	glad	likes	rape*	tears	agreement*	giver*	positiv*	angr*	fearing	mocked	strain*
affection*	delicious*	gladly	liking	raping	teas*	agrees	giving	prais*	anguish*	fears	mocker*	strange
afraid	deligh*	glamor*	livel*	rapist*	tehe	alright*	glad	precious*	annoy*	feroc*	mocking	stress*
aggravat*	depress*	glamour*	LMAO	readiness	temper	amaz*	gladly	prettie*	antagoni*	feud*	mocks	struggl*
aggress*	depriv*	gloom*	LOL	ready	tempers	amor*	glamor*	pretty	anxi*	fiery	molest*	stubborn*
agitat*	despair*	glori*	lone*	reassur*	tender*	amus*	glamour*	pride	apath*	fight*	mooch*	stunk
agoniz*	desperat*	glory	longing*	rebel*	tense*	aok	glori*	privileg*	appall*	fired	moodi*	stunned
agony	despis*	goddam*	lose	reek*	tensing	appreciat*	glory	prize*	apprehens*	flunk*	moody	stuns
agree	destroy*	good	loser*	regret*	tension*	assur*	good	profit*	argh*	foe*	moron*	stupid*
agreeab*	destruct*	goodness	loses	reject*	terribl*	attachment*	goodness	promis*	argu*	fool*	mourn*	stutter*
agreed	determina*	gorgeous*	losing	relax*	terrific*	attract*	gorgeous*	proud*	arrogan*	forbid*	murder*	submissive*
agreeing	determined	gossip*	loss*	relief	terrified	award*	grace	radian*	asham*	fought	nag*	suck
agreement*	devastat*	grace	lost	reliev*	terrifies	awesome	graced	readiness	assault*	frantic*	nast*	sucked
agrees	devil*	graced	lous*	reluctan*	terrify	beaut*	graceful*	ready	asshole*	freak*	needy	sucker*
alarm*	devot*	graceful*	love	remorse*	terrifying	beloved	graces	reassur*	attack*	fright*	neglect*	sucks
alone	difficult*	graces	loved	repress*	terror*	benefic*	graci*	relax*	aversi*	frustrat*	nerd*	sucky
alright*	digni*	graci*	lovely	resent*	thank	benefit	grand	relief	avoid*	fuck	nervous*	suffer

ANEW: Affective norms for English words

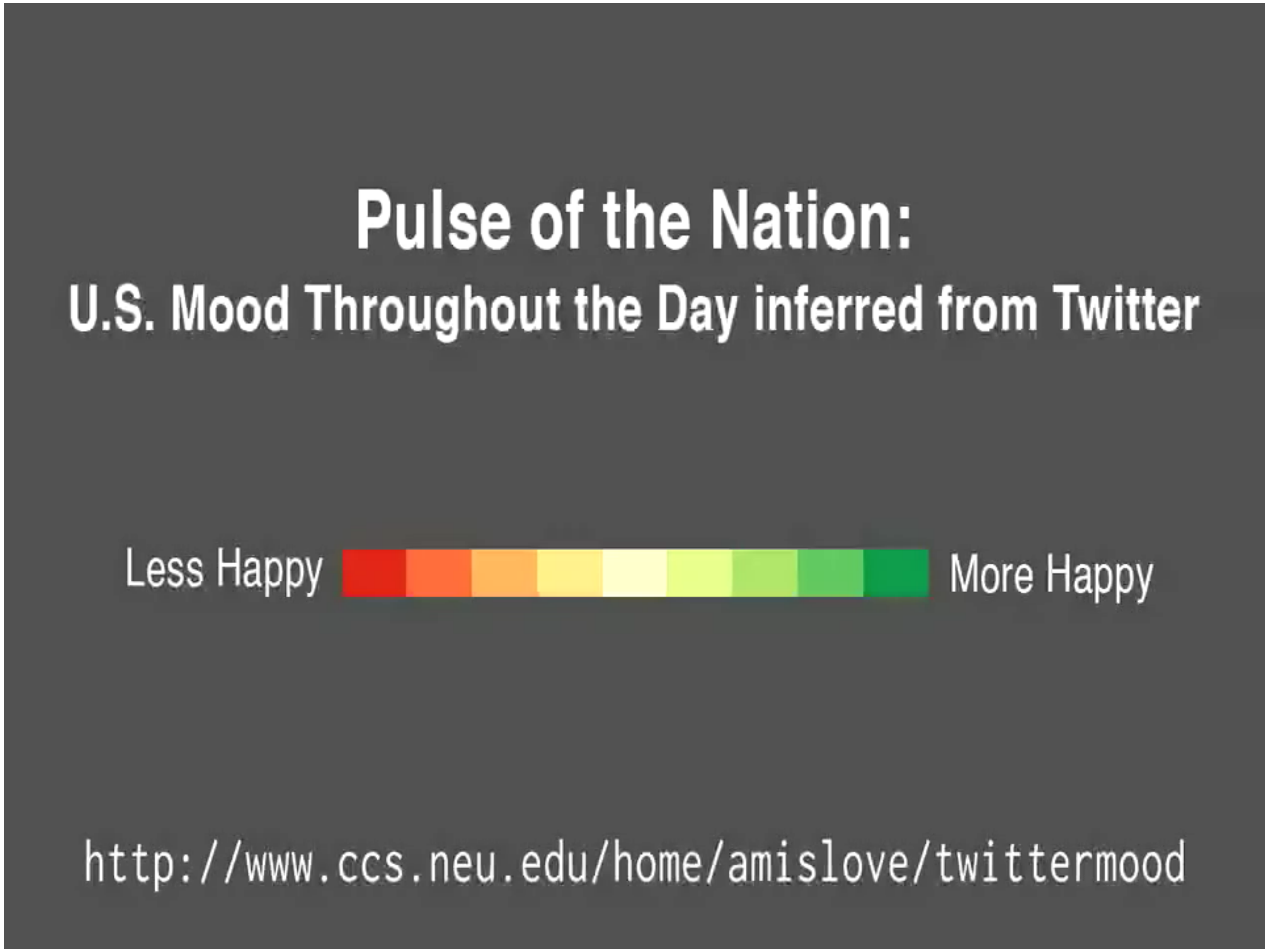
Description	Word No.	Valence Mean(SD)	Arousal Mean(SD)	Dominance Mean (SD)	Word Frequency
abduction	621	2.76 (2.06)	5.53 (2.43)	3.49 (2.38)	1
abortion	622	3.50 (2.30)	5.39 (2.80)	4.59 (2.54)	6
absurd	623	4.26 (1.82)	4.36 (2.20)	4.73 (1.72)	17
abundance	624	6.59 (2.01)	5.51 (2.63)	5.80 (2.16)	13
abuse	1	1.80 (1.23)	6.83 (2.70)	3.69 (2.94)	18
acceptance	625	7.98 (1.42)	5.40 (2.70)	6.64 (1.91)	49
accident	2	2.05 (1.19)	6.26 (2.87)	3.76 (2.22)	33
ace	626	6.88 (1.93)	5.50 (2.66)	6.39 (2.31)	15
ache	627	2.46 (1.52)	5.00 (2.45)	3.54 (1.73)	4
achievement	3	7.89 (1.38)	5.53 (2.81)	6.56 (2.35)	65
activate	4	5.46 (0.98)	4.86 (2.56)	5.43 (1.84)	2
addict	581	2.48 (2.08)	5.66 (2.26)	3.72 (2.54)	1
addicted	628	2.51 (1.42)	4.81 (2.46)	3.46 (2.23)	3
admired	5	7.74 (1.84)	6.11 (2.36)	7.53 (1.94)	17
adorable	6	7.81 (1.24)	5.12 (2.71)	5.74 (2.48)	3
adult	546	6.49 (1.50)	4.76 (1.95)	5.75 (2.21)	25
advantage	629	6.95 (1.85)	4.76 (2.18)	6.36 (2.23)	73
adventure	630	7.60 (1.50)	6.98 (2.15)	6.46 (1.67)	14
affection	7	8.39 (0.86)	6.21 (2.75)	6.08 (2.22)	18
afraid	8	2.00 (1.28)	6.67 (2.54)	3.98 (2.63)	57

sentiwordnet.*isti.cnr.it/*

SentiWordNet

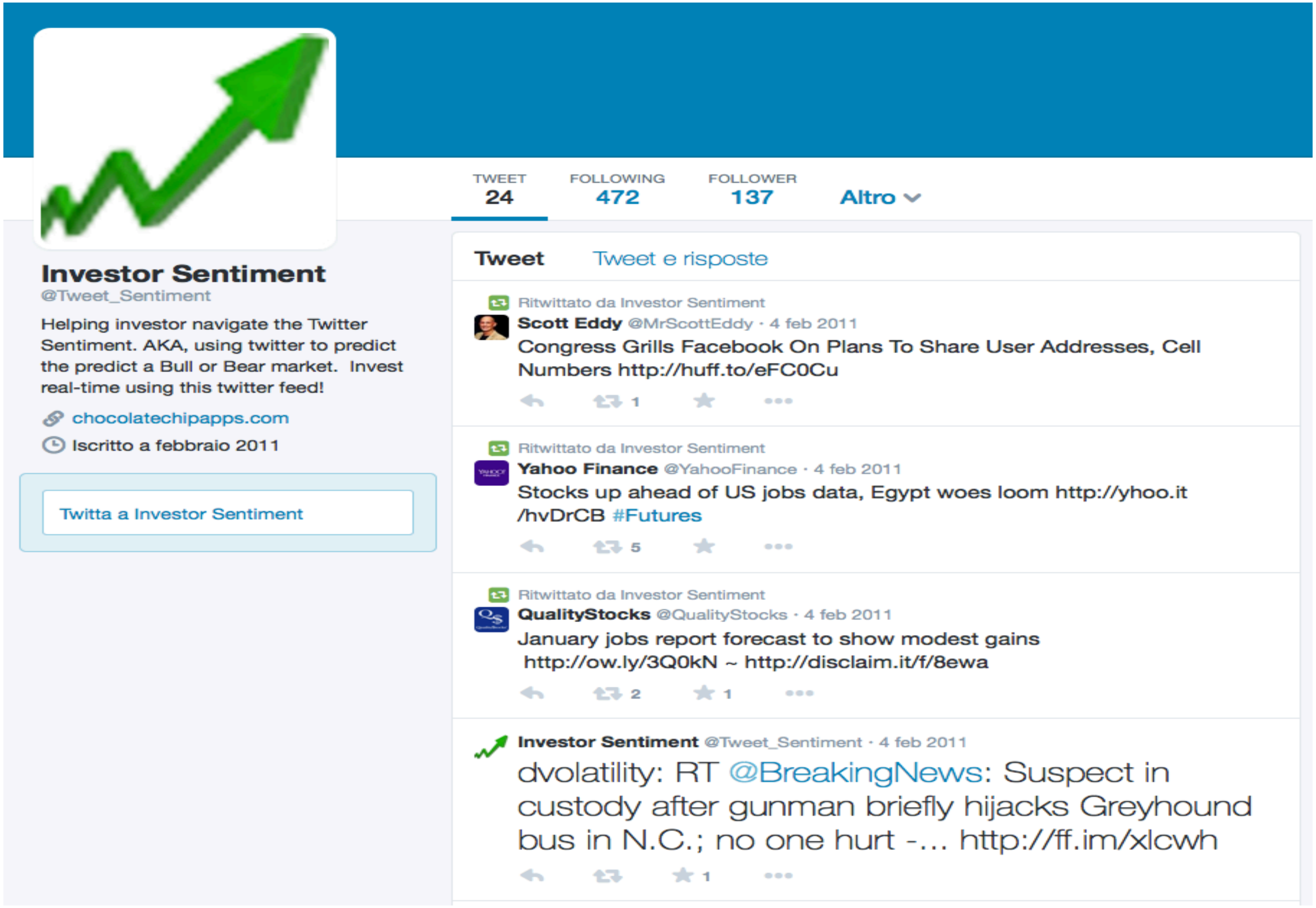


Opinion-Mining Tools



http://www.ccs.neu.edu/home/amislove/twittermood/

Twitter investor sentiment



TRACKING OPINIONS ON TWITTER

twitrratr

SEARCH

Discover what people are really saying on Twitter. With Twitrratr you can distinguish negative from positive tweets surrounding a brand, product, person or topic.

TERM	POSITIVE TWEETS	NEUTRAL TWEETS	NEGATIVE TWEETS	TOTAL TWEETS
st ives	70	384	11	465

15.05% POSITIVE

i really want to love st. ives apricot scrub, but it irritates my skin soo much :((view)

rt @kesiahosking: sunshine was smiling at you annie =)) rt @anniegreenwood st ives harbour basking in november sunshine http://flic.kr/p/8tk2sq (view)

sunshine was smiling at you annie =)) rt @anniegreenwood st ives harbour basking in november sunshine http://flic.kr/p/8tk2sq (view)

looking at st ives (uk:siv). great stats, but printing? (view)

82.58% NEUTRAL

@oldergirlbeauty GURL, I was all about the Aqua Net & the St. Ives liquid hairspray in the purple bottle. Where's my banana clip? (view)

RT @inscriptions: Loved the final episode of Junior Masterchef! Alexwill be at St Ives Village Sat 11th to show us a thing or two! (view)

Loved the final episode of Junior Masterchef! Alex from top12 is coming to St Ives Village Sat 11th to show us a thing or two about cooking! (view)

A Town On Canvas Called St Ives http://ping.fm/onNWi (view)

2.37% NEGATIVE

st. ives apricot scrub is bad for your face. you may not notice it but it scratches up your face and its bad... http://bit.ly/dttmci (view)

st ives face scrub receive negative comments. lots of it o.o (view)

@fandomonymous not sure how bad your acne is, but st. ives green tea cleanser works well on my skin. really cleans out my pores. (view)

sco prem: goal st ives city 2 towerhill blues 0 lucas k (43) (view)

sco prem: goal st ives city 1

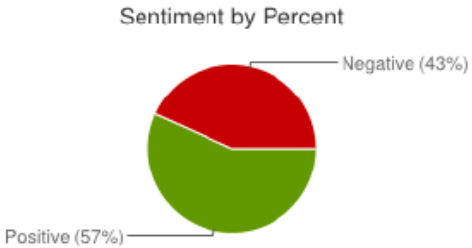

tweetfeel
Bonanza
Search
Try some Twitter trends: Romo Bonanza
4
3
= 57%
RT @BuildYourLoveUp: RT @BuildYourLoveUp: I wish @itsimreeeee went to the same school as me. I miss my best friend, and almost everyone at Bonanza sucks. ;/
shout out to the helicopter circling our school this morning with a spot light.. I love Bonanza http://t.co/j2EDX0cS
RT @ADReamGONe: RT @ADReamGONe: Man, I love Bonanza lmfao.
RT @ADReamGONe: RT @ADReamGONe: Man, I love Bonanza lmfao.

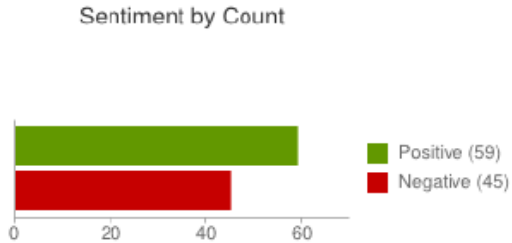
Sentiment140

Tweet 353 | Like 140 | +1 74

microsoft | English | Search | Save this search

Sentiment analysis for microsoft





Tweets about: microsoft

Isaydumb: @Youporn, in my humble opinion you have nothing to do on the @Xbox Live. What the fuck is **@Microsoft** doing?!
Posted 46 seconds ago

Megan_Maracle: I hate this class. **#Microsoft** #die
Posted 2 minutes ago

dilwortha: @carasmith10 oh okay, you'll have to explain when i see you as i dont understand this disk haha. is it for **microsoft** project do you

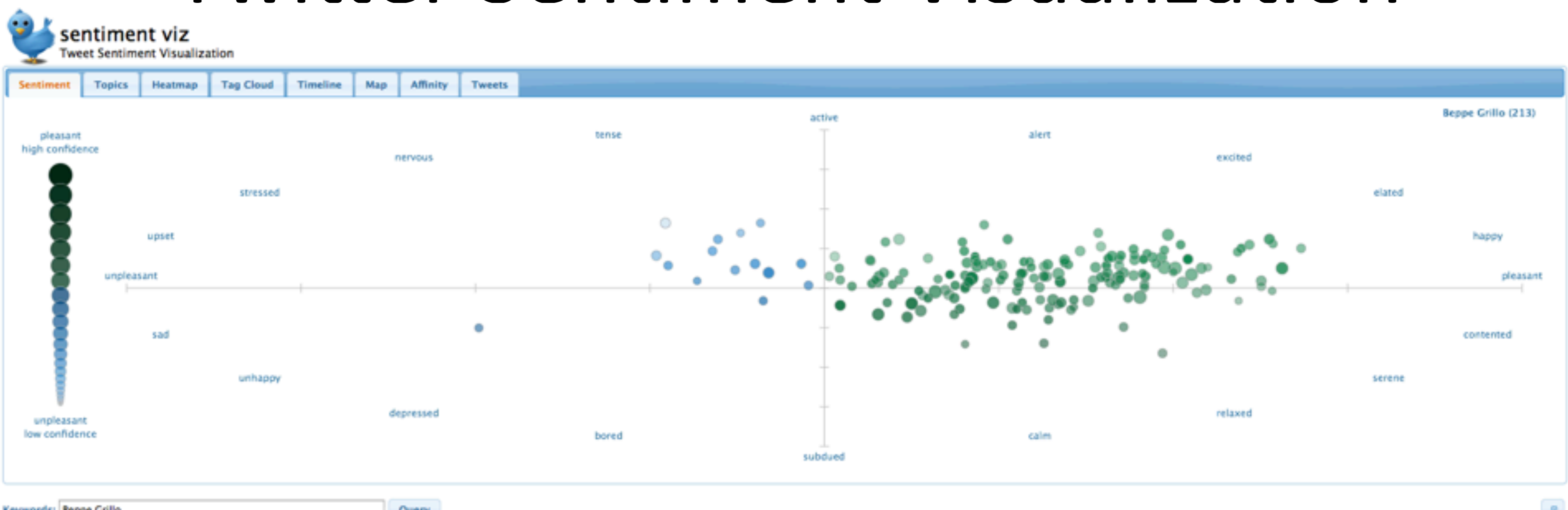
Posted 5 minutes ago

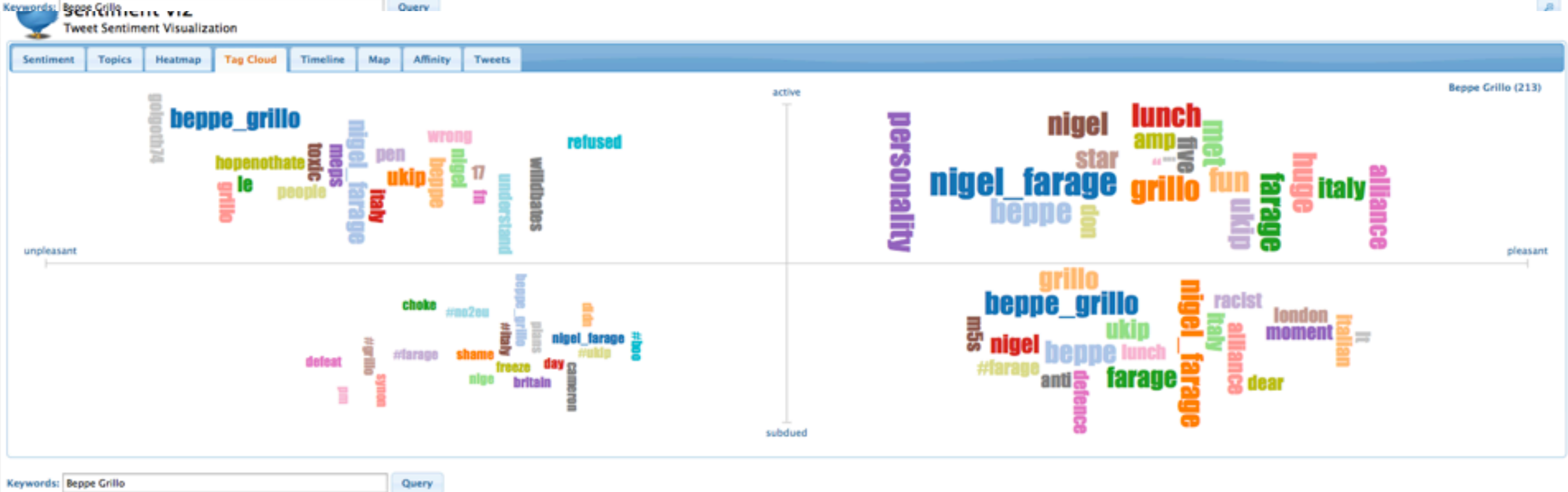
jlebrech: @rsslldnphy it happens to be **microsoft** this time, but a superset is the next best thing from a compiled bytecode, as valid JS is also

http://www.sentiment140.com/

The results for this query are: Accurate

Twitter Sentiment Visualization





Opinion Finder

Multi-
Perspective
Question
Answering

Main	Corpora	Lexicons	Annotation	OpinionFinder
MPQA Home	News, debates, etc.	Subj. clues, etc.	GATE, MPQA scheme	Subjectivity detector

OpinionFinder

Version 1.x

- Version 1.5
- Version 1.4
- Sample Annotations

Version 2.x

OpinionFinder 1.x Release Page

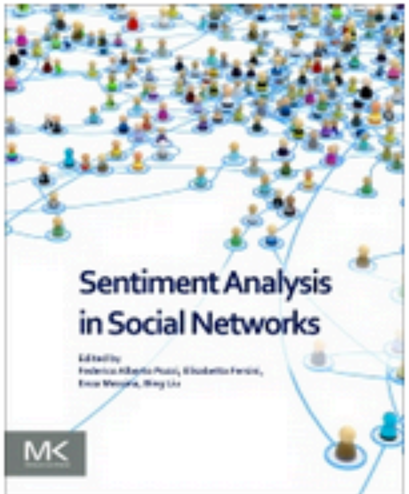
OpinionFinder 1.x Available versions

OpinionFinder 1.x relies on many external software packages (e.g. SUNDANCE, SCOL, BoosTexter) which are neither built nor supported by our group. Since OpinionFinder was originally released in 2005, there are some compatibility issues with versions of various software and packages. We have reports that these problems sometimes result in an exhausting and even unsuccessful installation process of OpinionFinder. Since many of the people involved in the original development have graduated and left the group, we do not currently have the resources to address these compatibility issues concerning the required external software packages. Although we do not have the resources to bring OpinionFinder 1.x fully up-to-date, we are currently working on a new version of OpinionFinder. OpinionFinder 2 is being written in Java and will be platform-independent.

LICENSE AGREEMENT

Version 1.5

- README - OpinionFinder 1.5
- Download OpinionFinder 1.5



Sentiment Analysis in Social Networks

1st Edition

View on ScienceDirect ↗

Authors: Federico Alberto Pozzi, Elisabetta Fersini, Enza Messina, Bing Liu

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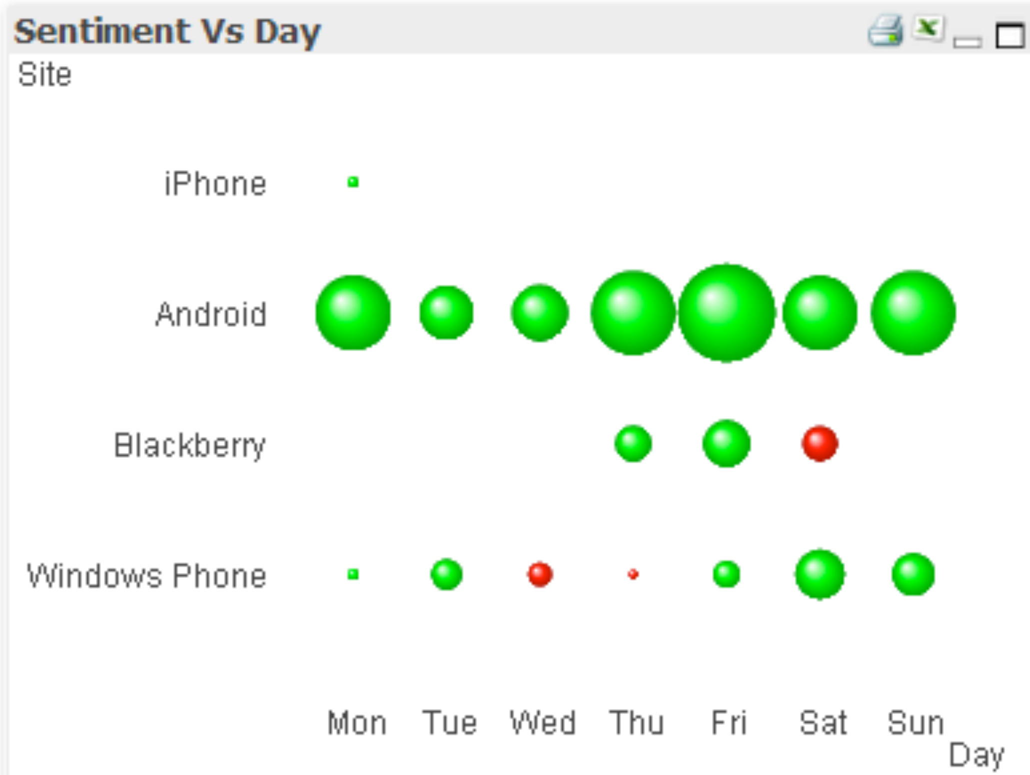
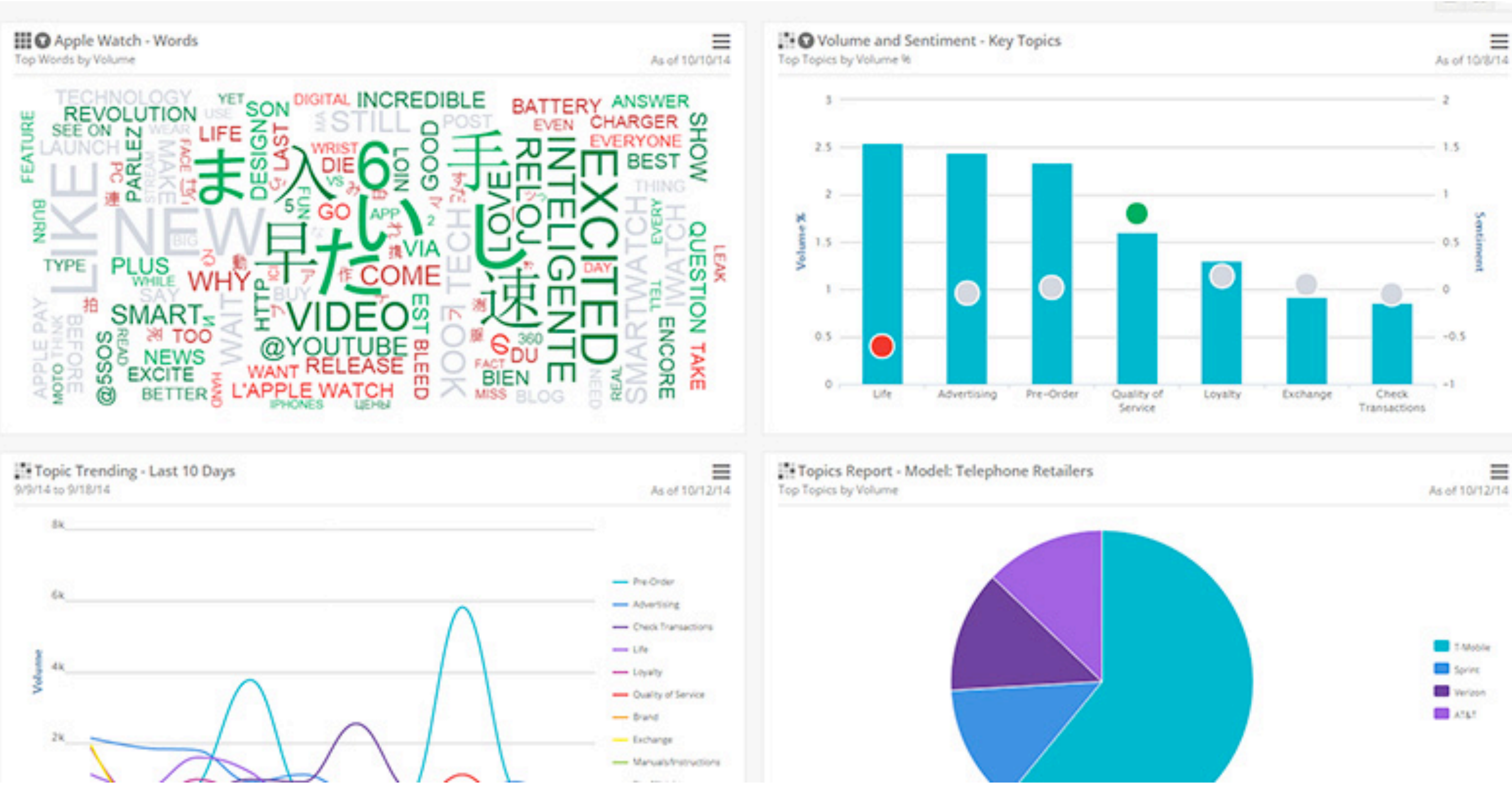
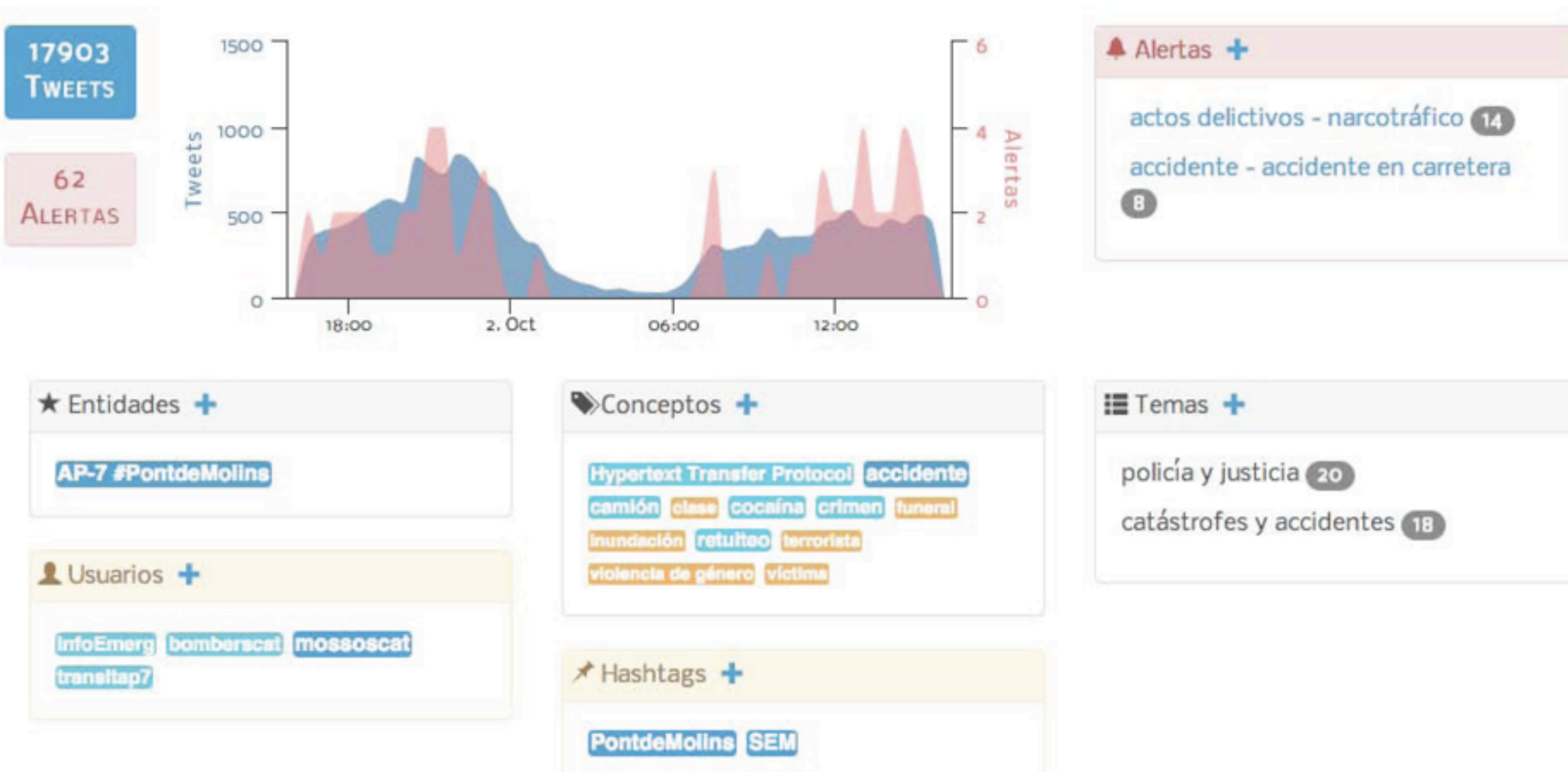


Sentiment Vs Day
Site
iPhone
Android
Blackberry
Windows Phone
Mon
Tue
Wed
Thu
Fri
Sat
Sun
Day

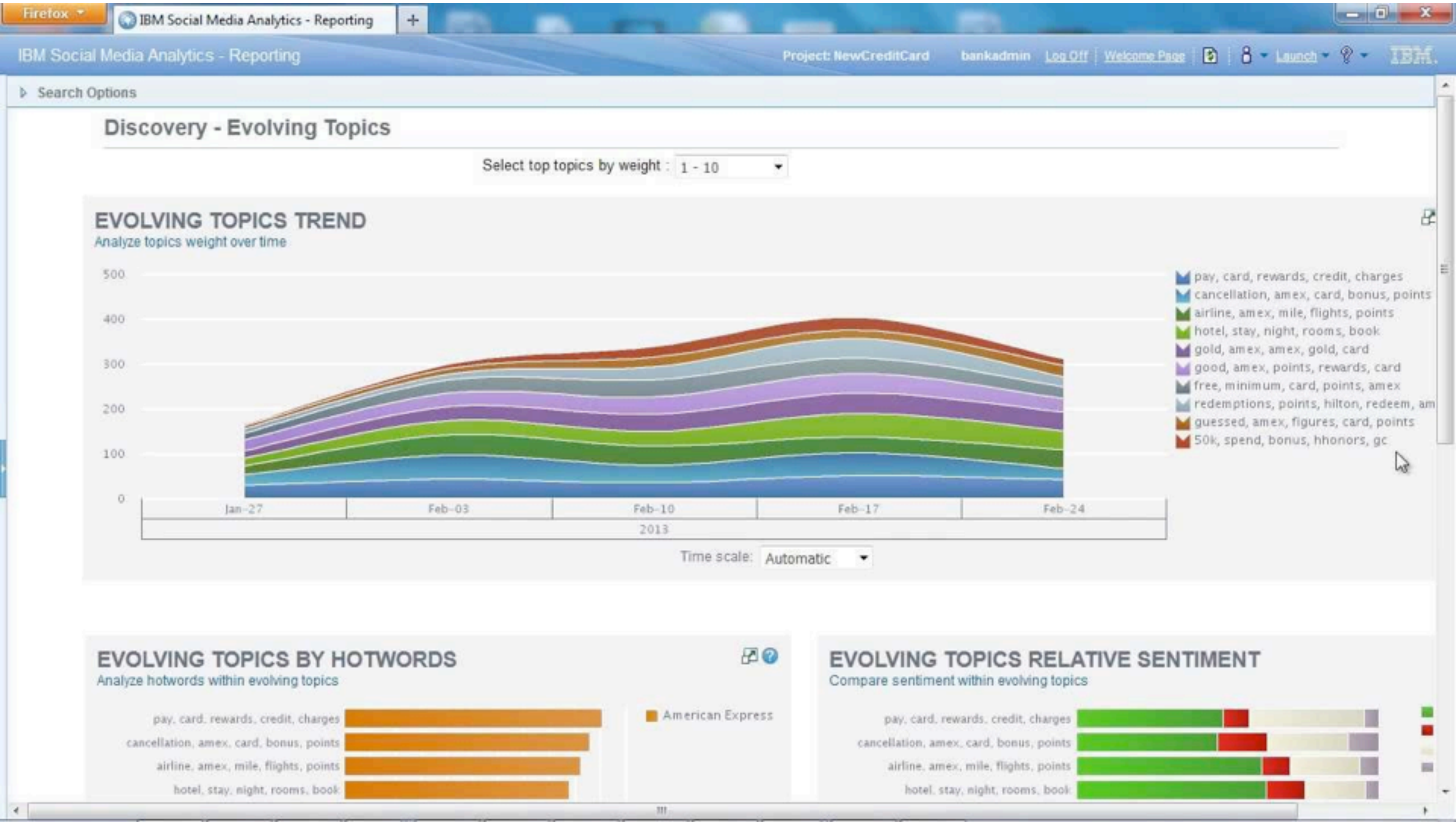


Apple Watch - Words
Top Words by Volume
As of 10/10/14
TECHNOLOGY
REVOLUTION
INCREDIBLE
BATTERY
ANSWER
CHARGER
EVERYONE
BEST
SHOW
DIGITAL
STILL
POST
LIFE
LAUNCH
FEATURE
LIKE
NEW
EXCITED
INTELIGENTE
RELOJ
LOVE
VIDEO
@YOUTUBE
RELEASE
L'APPLE WATCH
SMART
PLUS
COME
WHY
SMARTWATCH
IWATCH
QUESTION
TAKE
ENCORE
BIEN
NEWS
EXCITE
BETTER
@5SOS
APPLE PAY
Volume and Sentiment - Key Topics
Top Topics by Volume %
As of 10/8/14
Volume %
Sentiment
3
2.5
2
1.5
1
0.5
0
2
1.5
1
0.5
0
-0.5
-1
Life
Advertising
Pre-Order
Quality of Service
Loyalty
Exchange
Check Transactions
Topic Trending - Last 10 Days
9/9/14 to 9/18/14
As of 10/12/14
Volume
8k
6k
4k
2k
Pre-Order
Advertising
Check Transactions
Life
Loyalty
Quality of Service
Brand
Exchange
Manuals/Instructions
Topics Report - Model: Telephone Retailers
Top Topics by Volume
As of 10/12/14
T-Mobile
Sprint
Verizon
AT&T

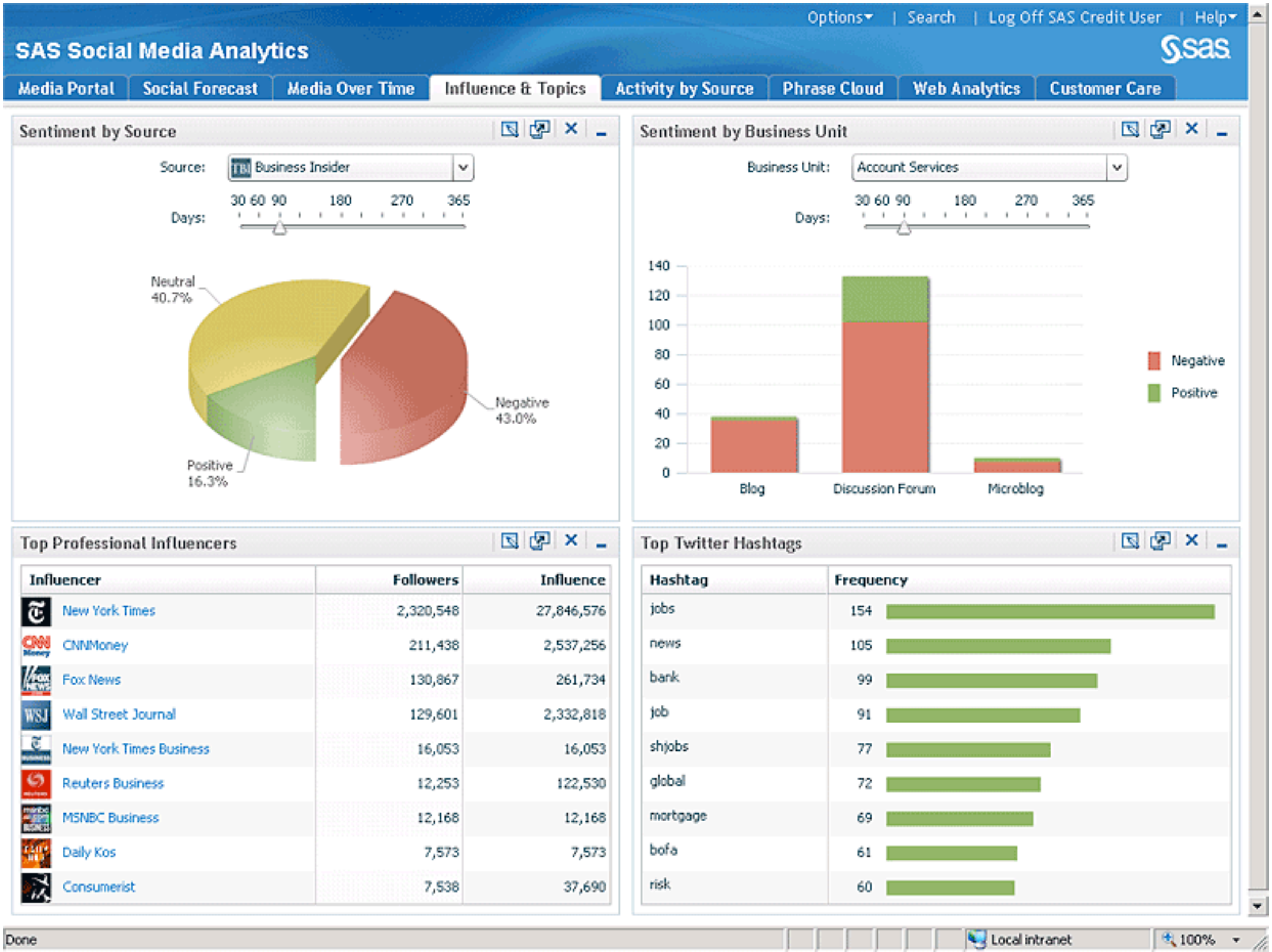

17903 TWEETS
62 ALERTAS
1500
1000
500
0
Tweets
6
4
2
0
Alertas
18:00
2. Oct
06:00
12:00
Alertas
actos delictivos - narcotráfico 14
accidente - accidente en carretera 8
Entidades
AP-7 #PontdeMolins
Usuarios
infoEmerg
bomberscat
mossoscat
transitap7
Conceptos
Hypertext Transfer Protocol
accidente
camión
clase
cocaína
crimen
funeral
inundación
retuiteo
terrorista
violencia de género
víctima
Hashtags
PontdeMolins
SEM
Temas
policía y justicia 20
catástrofes y accidentes 18

PLATFORMS FOR SENTIMENT ANALYSIS

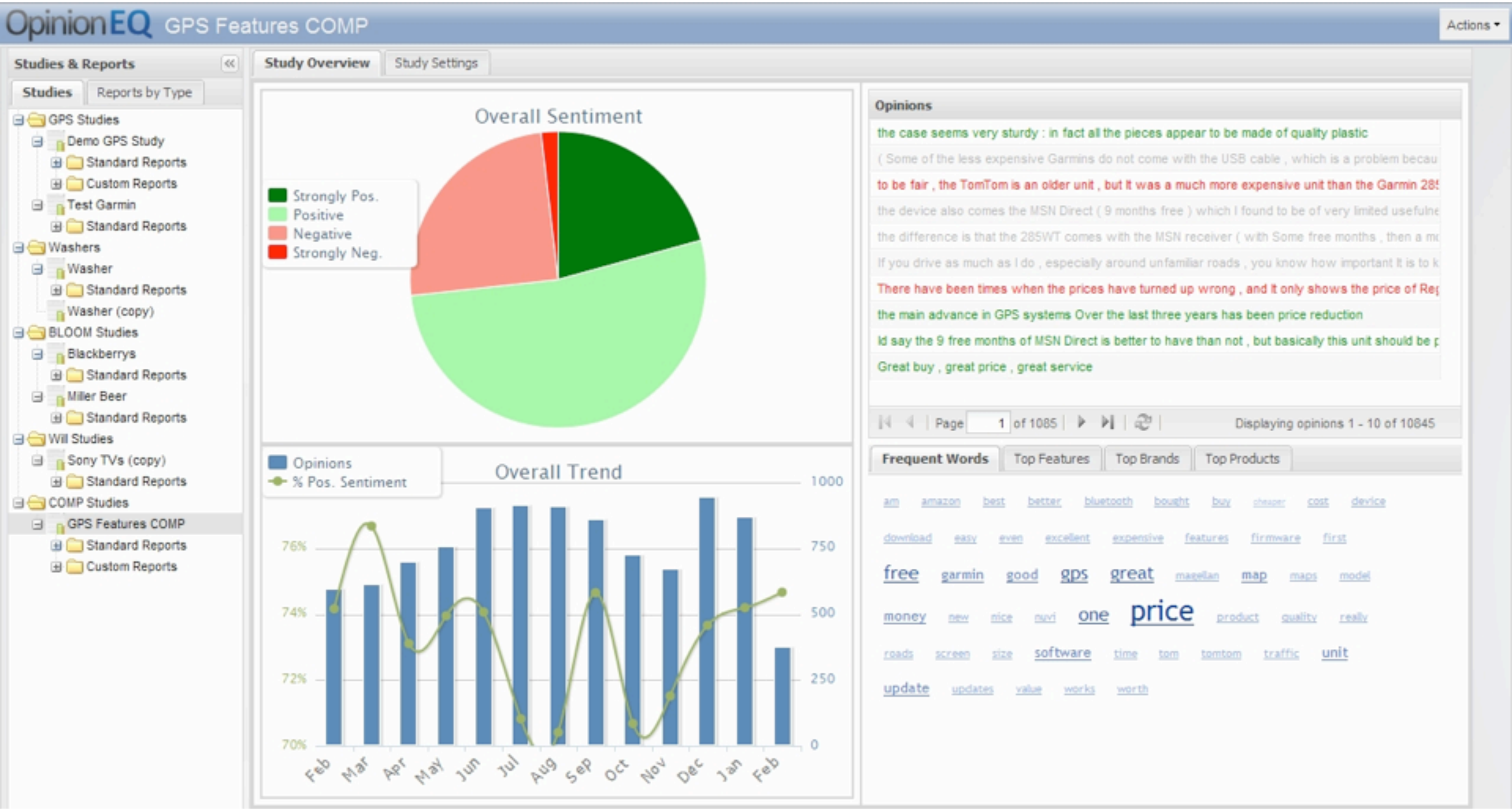
https://www.ibm.com/support/knowledgecenter/SSJHE9



http://www.sas.com/en_us/industry/media.html

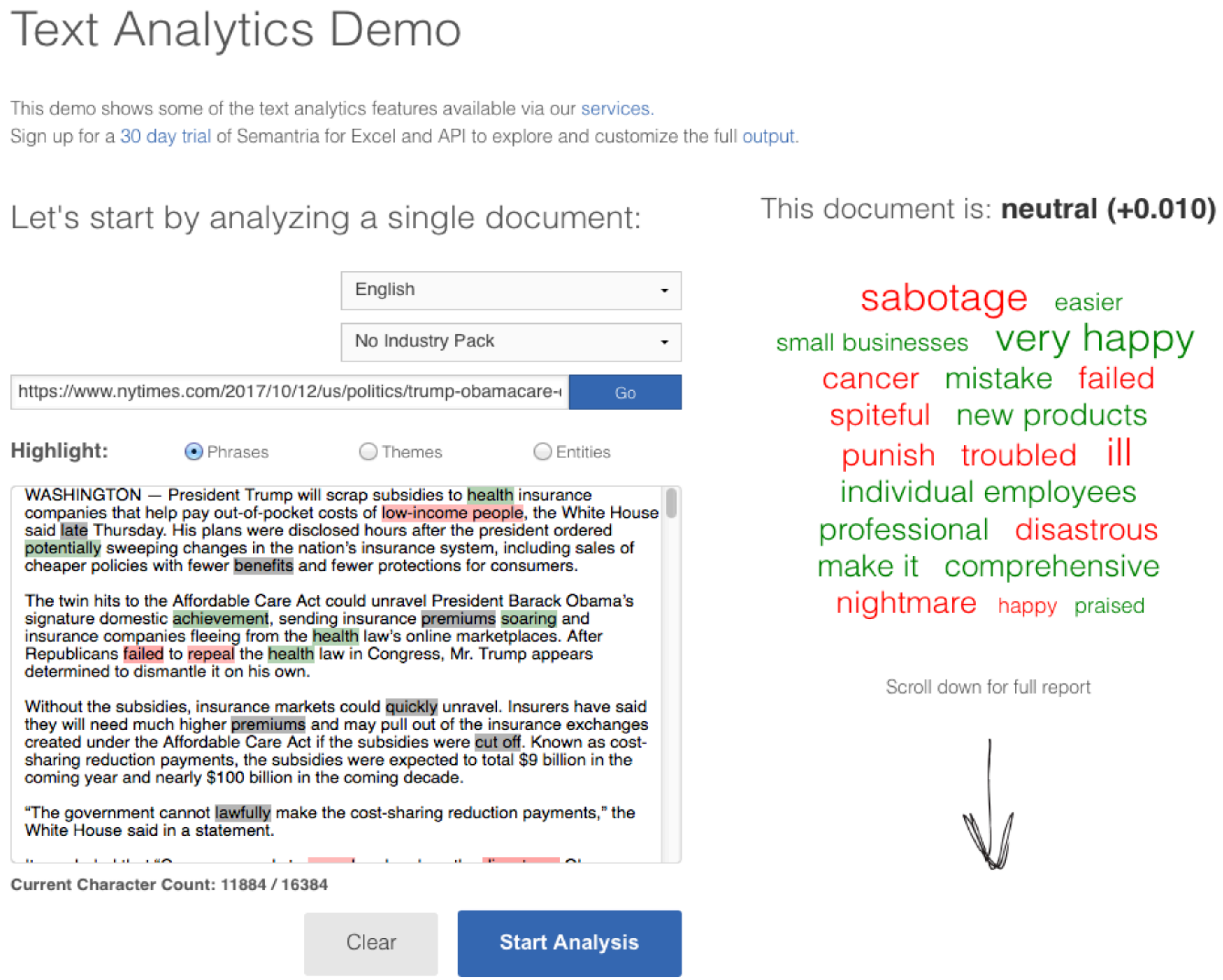


http://www.opinioneq.com/



http://www.netvibes.com

Semantria (free demo available)



Other platforms

- More on https://blog.hootsuite.com/social-media-sentiment-analysis-tools/

- http://barnraisersllc.com/2017/01/best-tools-sentiment-analysis-free-fee/