Automatic Discovery of Patterns in News Content

MediaPatterns

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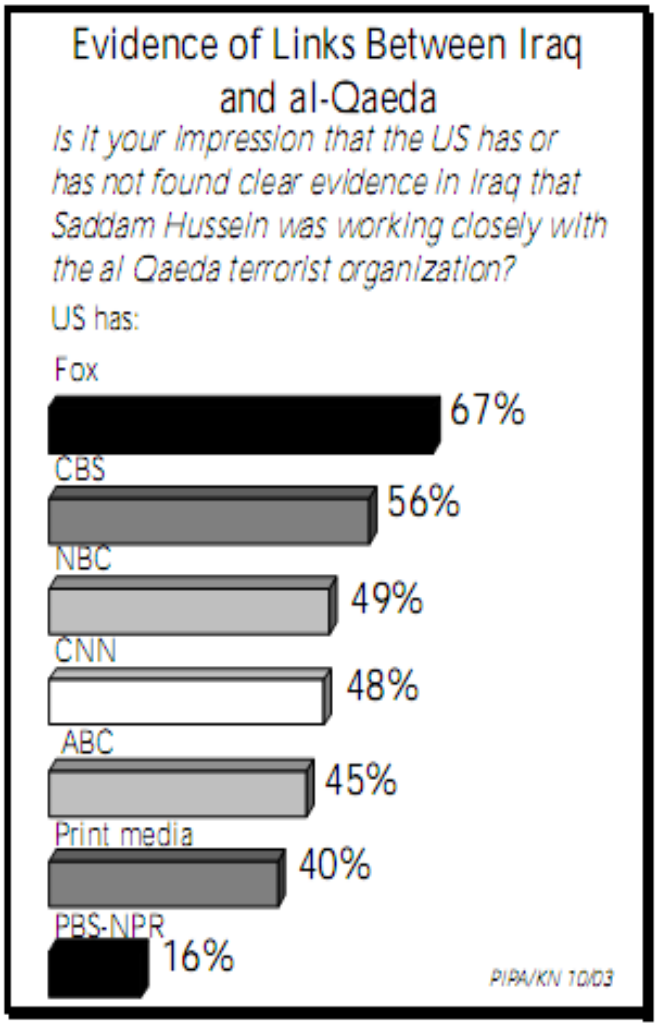
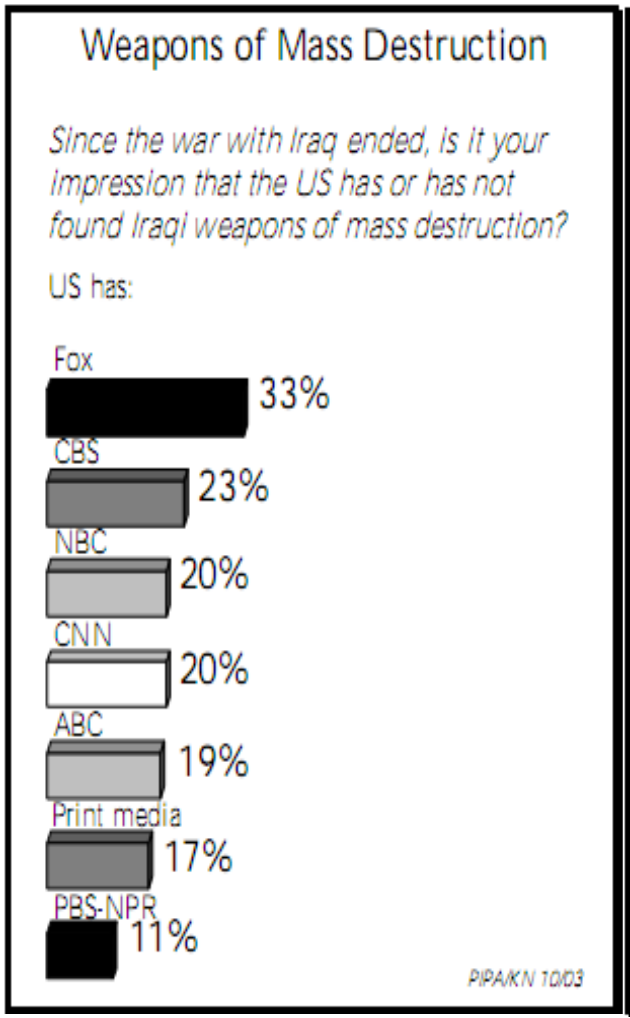
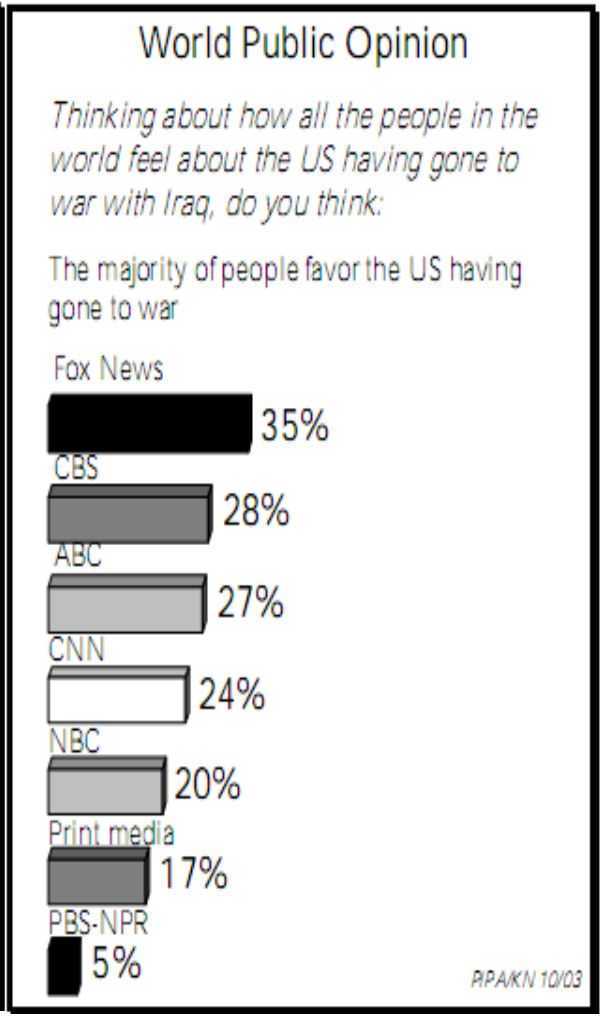
An Interesting Fact







October 2003, PIPA/KN Poll - “Misperceptions, The Media and the Iraq War – Steven Skul

Feedback

- **FACT**: beliefs (not just opinions) of readers depend on the news content they choose to consume.

- **e.g.:** heavy consumers of news have unrealistic expectations about crime rates, usage of drugs, teen sex, (**ove**restimated) and prevalence of ethnic minorities, older people, lower social classes (**under**estimate).

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Cultivation Theory

- **Cultivation theory**: repeated exposure to a message shapes expectations, beliefs.

➔**STUDY BIAS IN NEWS CONTENT**

- Social scientists study how news are chosen, presented, narrated...
as biases in news content can **affect (as well as reflect) biases** in society.

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News Content Analysis

- **Study how news are chosen, presented, narrated... and how this affects (as well as reflects) biases in society / public opinion.**

- This is done "by hand", on small numbers of news outlets, for short periods, for pre-specified questions ("coding approach").

News Coding


Rechters leggen boom onder verkiezingen

Appendix 1 Coding scheme: MDHH television broadcasts (translated fr

1. Date:	
2. Channel:	
3. Title of the item:	
4. Starting time (full four digits):	
5. Ending time (full four digits):	
6. Length (in minutes):	
7. Genre:	1. News 2. Documentary 3. Drama 4. Comedy 5. Ceremony 6. Discussion panel 7. Artistic performance 8. Other
8. Producer:	1. Israeli 2. Non-Israeli 3. Co-production
9. Is the item aired only/mostly on Holocaust Memorial Day?	1. Yes 2. No—airs on other days 3. Other
10. Does the item address the Holocaust?	1. Yes

The MediaPatterns Project

Involved about 10 people
(+ extra social scientists) over 5 years

Goals:

- to automate the analysis of news content,
- to understand the workings of the media system,
- to understand how **science can be automated**,
- to operate with challenging patterns on large datasets..
- to enjoy creating a large-scale infrastructure

MediaPatterns.enm.bris.ac.uk

The Problem with Large Projects...

Cannot cover all aspects

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Getting the Data

The NOAM infrastructure

- We developed a dedicated infrastructure for **N**ews **O**utlet **A**nalysis and **M**onitoring

- To gather and annotate data about:
  - News outlets
  - News items
  - News stories
  - Named entities

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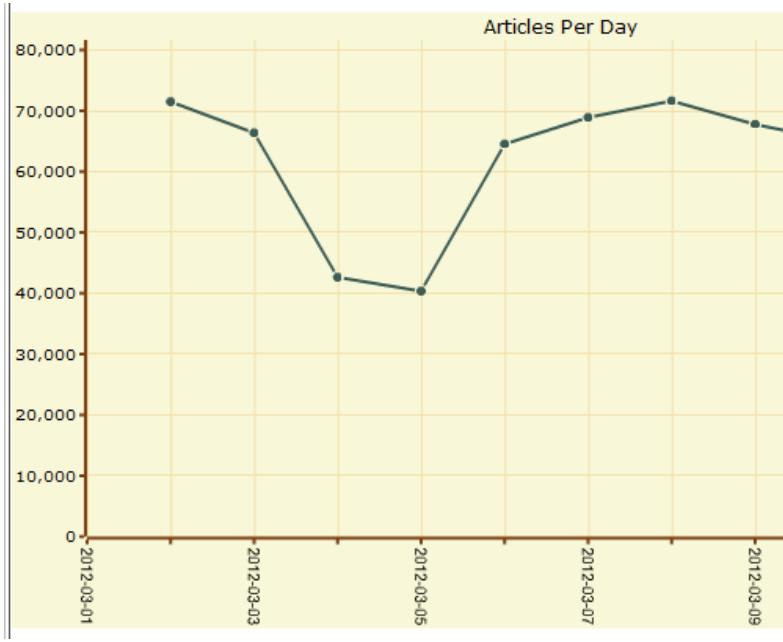
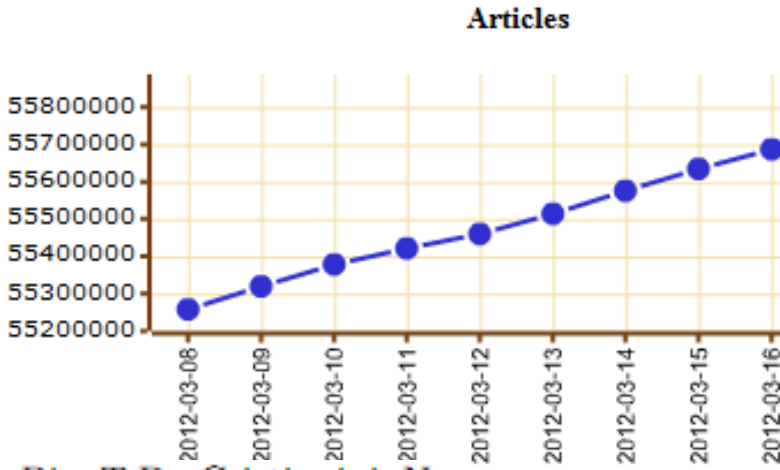
The Data

- We gather about 60K news items per day, from > 1000 outlets , 4400 rss feeds, in 22 languages , from 195 countries (machine translated into English if necessary)
- We have analysed ~55 million news items





Flaounas, I., Ali, O., Turchi, M., Snowsill, T., Nicart, F., Bie, T.D., Cristianini, N.: Noam: News outlets analysis and monitoring system. In: Proceedings of the 2011 ACM SIGMOD international conference on Management of data. ACM (2011)

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Analysis of the Data

- We are interested in macroscopic patterns found in the global news-system contents.

- What kind of stories / people / topics make news?
- What do editors want? What do readers want?
- What patterns in style and narrative can be found?
- Can we measure how people are affected?

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Our Questions

1. What is in the news ?
    1. What people ?
    2. Which stories are covered by whom?
2. What do readers want?
3. Any patterns in style? And narrative?
4. Can we measure public mood?

Question 1: what is in the news?

- There are stories about people.
  But: which stories and which people make it?

- Short answer:
  the same few stories and the same few people occupy the most "real estate"

- A power law...

  [skipping method: stories are clusters of articles; entities are extracted, disambiguated, and their properties computed based on large data sets]

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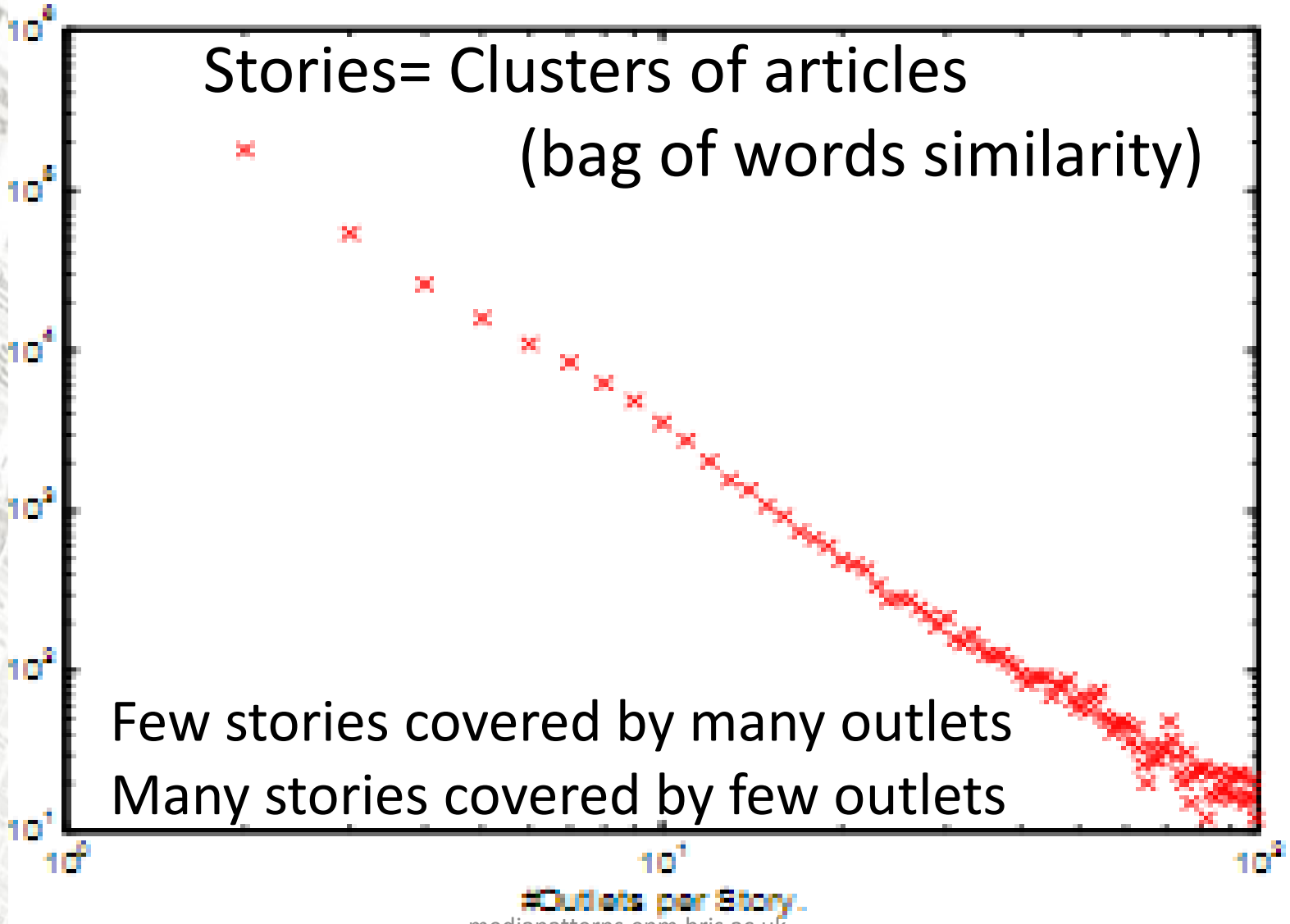
From Articles to Stories



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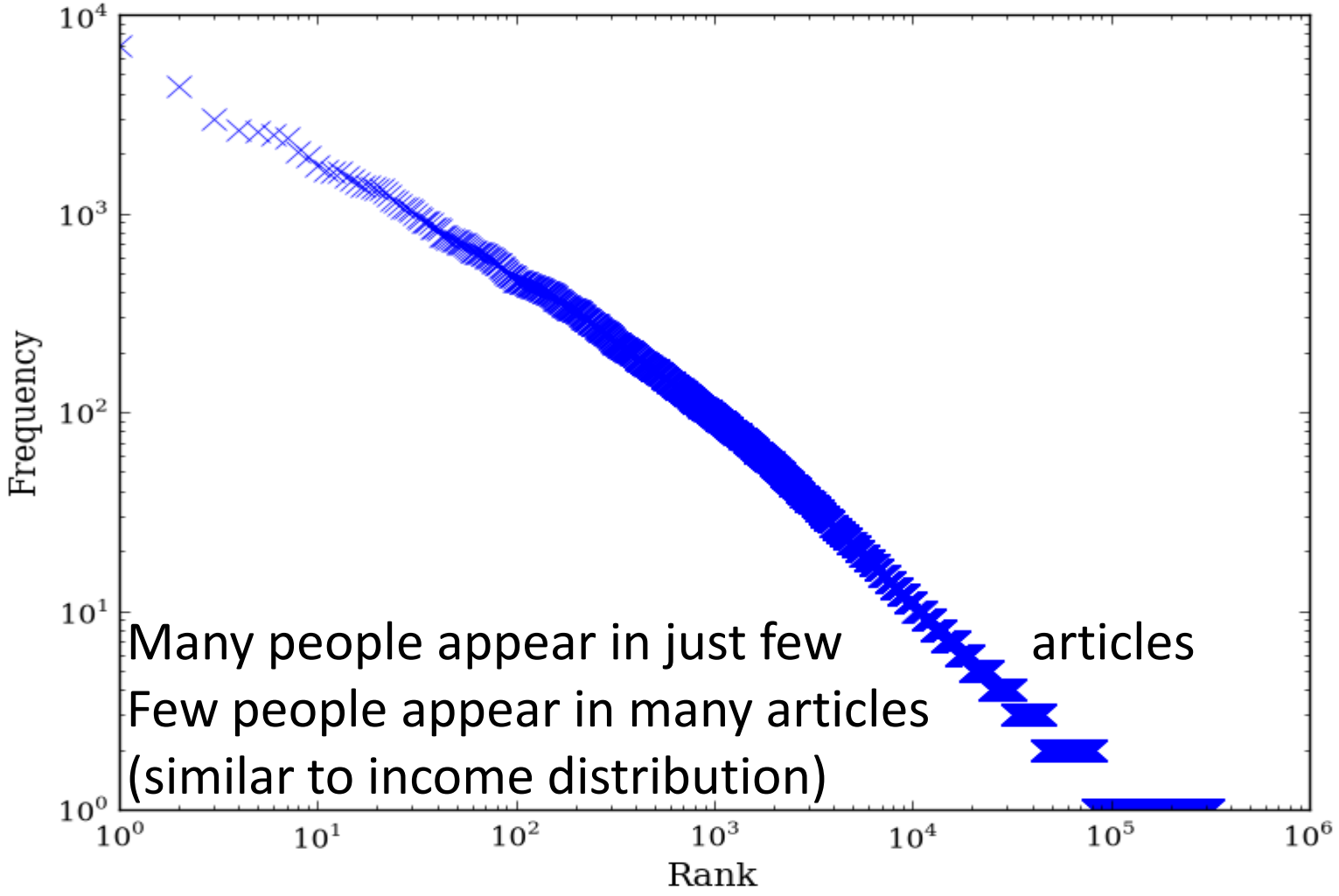
People in the News



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More in detail...

- Which kinds of people are present in which kinds of stories?

- What determines which stories are covered and which ones are neglected in a given outlet ? And in general ?

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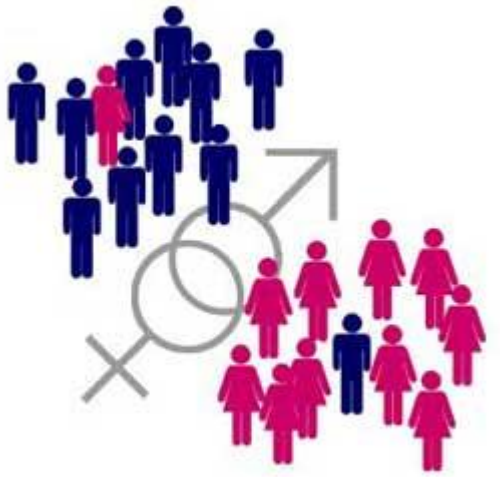
People in the News

M:F Ratio



Consider the Top-100 richest people in the world.
90 are men, 10 are women.

We call this the M/F ratio.

The M/F ratio varies with domain:

-Of the top 50 richest athletes, all 50 are male.

-Of the top 100 celebrities, 35 are female.

-Of the top -10 fashion models all 10 are female.

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Gender Bias in the Media

- What about media attention?
- Of the Top-1000 most mentioned people, how many are male?

- How does this change by topic?

- This involved analysing 476,528 articles in English language, and detecting their topic, as well as people and their gender.

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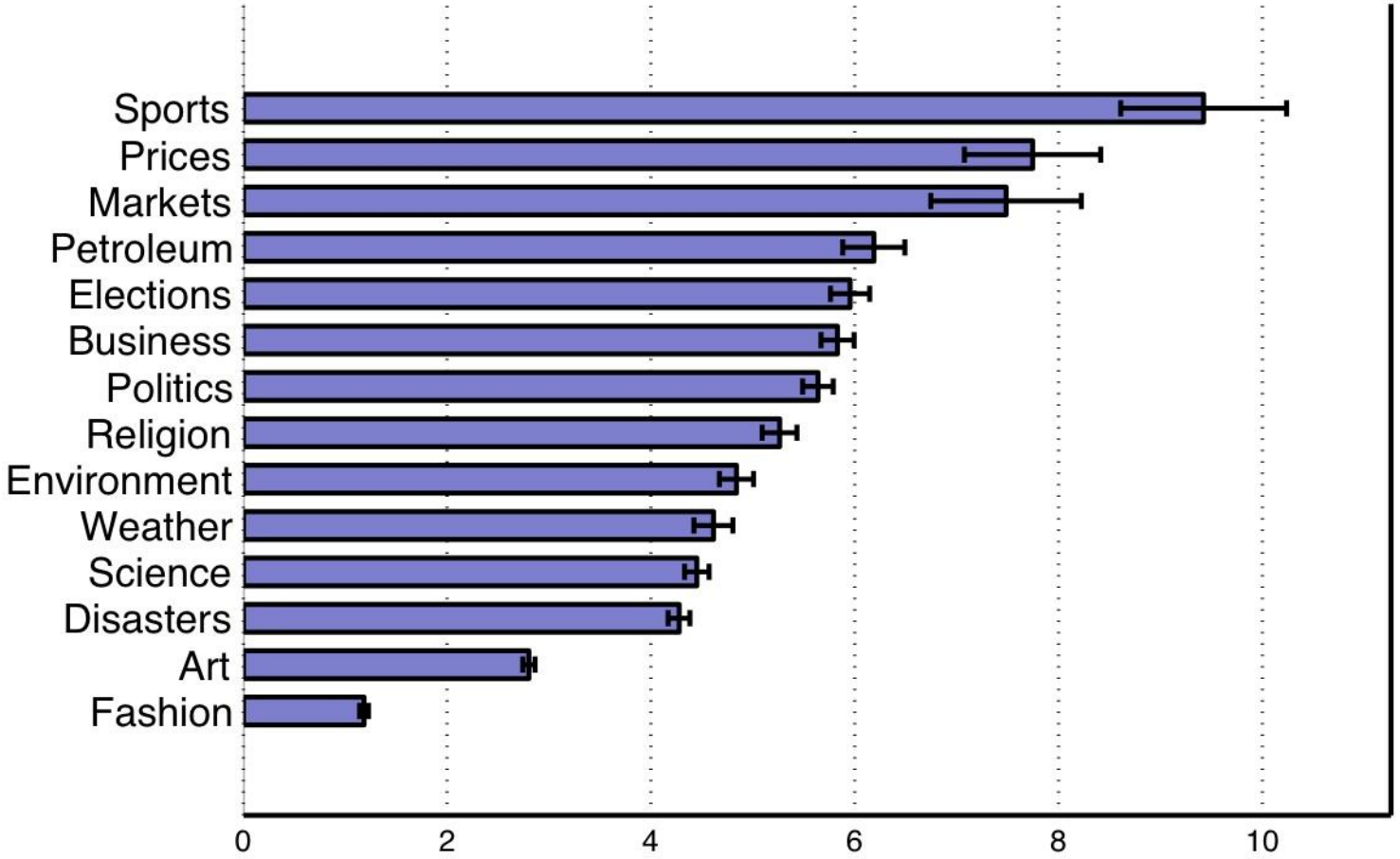
Detecting Topics

- Support Vector Machines trained on Reuters and New York Times tags as ground truth
- High precision requested for tags to be applied
  (so: many articles left untagged)

	Topic
1	SPORTS
2	MARKETS
3	FASHION
4	DISASTERS
5	ART
6	BUSINESS
7	INFLATION-PRICES
8	RELIGION
9	POLITICS
10	SCIENCE
11	WEATHER
12	PETROLEUM
13	ELECTIONS
14	ENVIRONMENT

M:F by Topic



Flaounas, I., Ali, O., Bie, T.D., Mosdell, N., Lewis, J., Cristianini, N.: Massive-scale automated analysis of news-content: Topics, style and gender. Submitted for Publication (2011)

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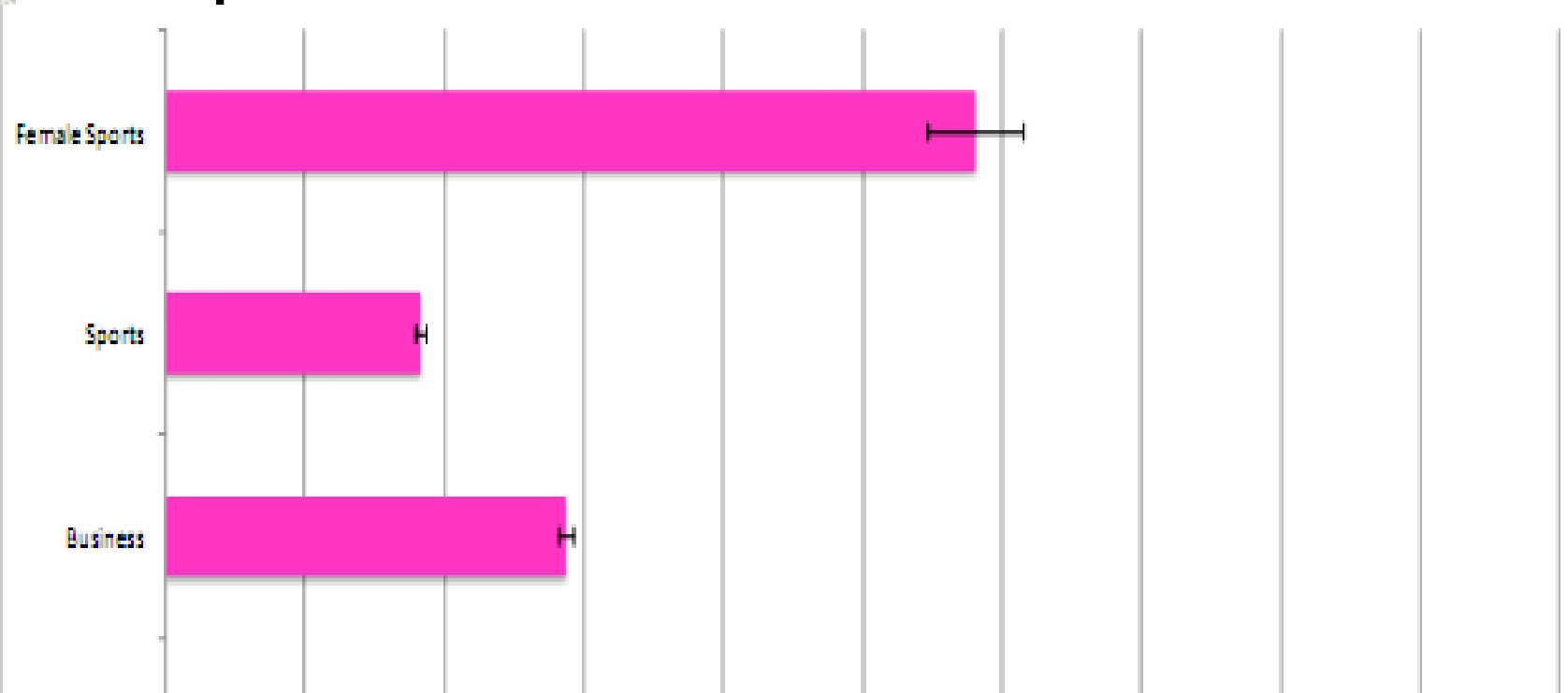
Validation

As validation we added the topic “female sports” where we expected more female names than in general sports.

While this was observed, the bias was still in favour of males.

The general pattern observed for income was also observed for media attention:

MF Sport > MF General > MF Fashion



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Observations

- Q: How does this shape beliefs, attitudes and opinions about gender?

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Which stories are covered by which outlets?

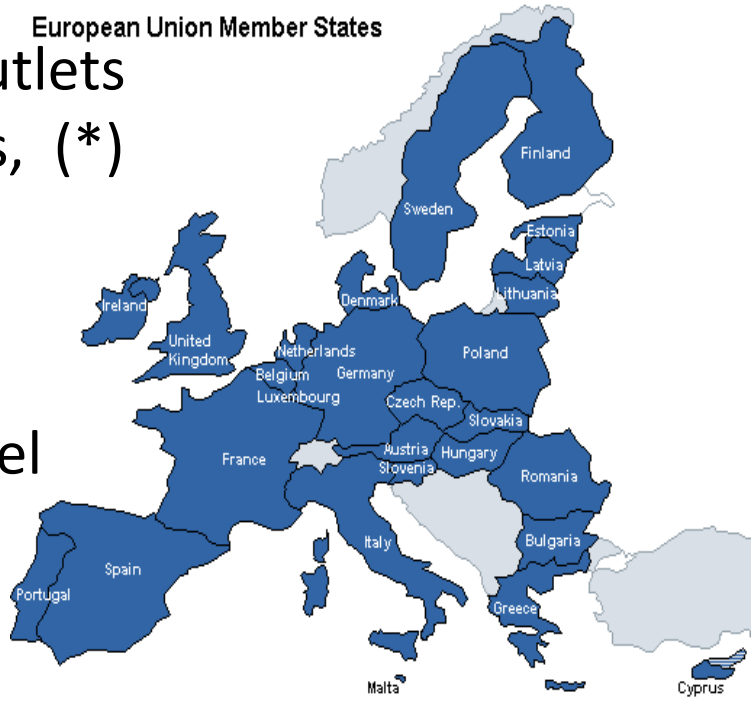
Mapping the EU Mediasphere

We machine translated the top EU outlets into English (Moses + our innovations, (*) trained on europarl + other corpora)

Details skipped but fun:
eg we re-create a new language model every day automatically

Clustered all articles into stories (bag of words)

Question: **which outlets tended to carry the same stories?**



(*) phrase-based SMT

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The Data

- Top-10 media outlets per country
- over the 27 EU countries
- in 22 different languages
- for a 6 months period
- A total of 1.3M news items.

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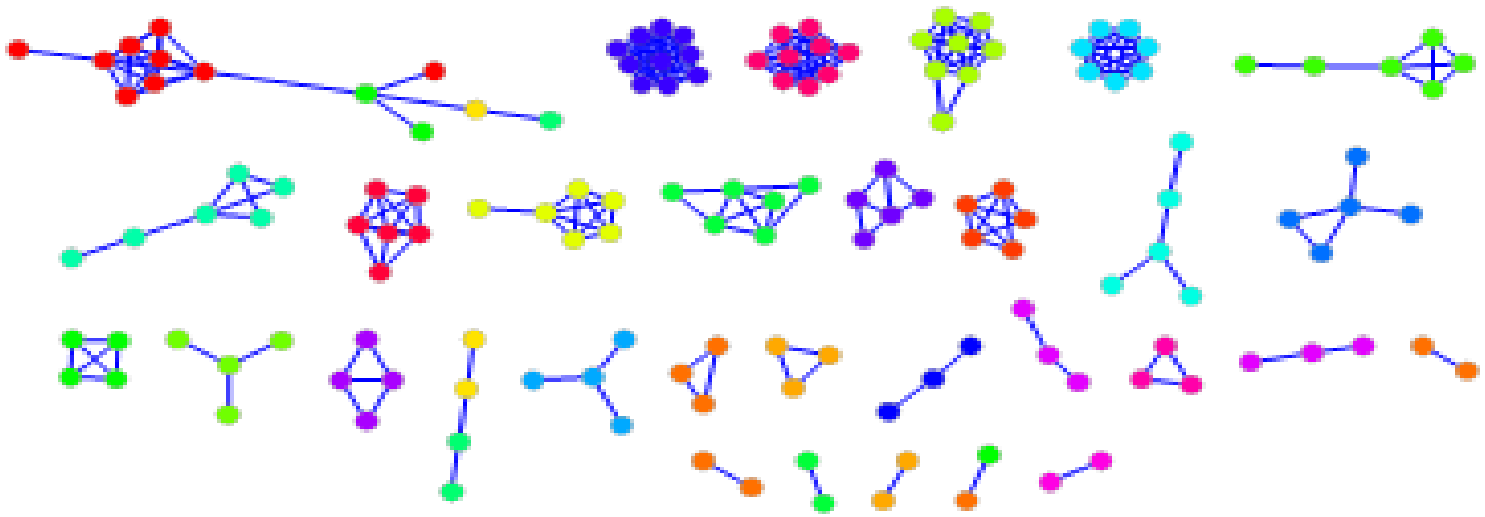
Outlets Covering Same Stories

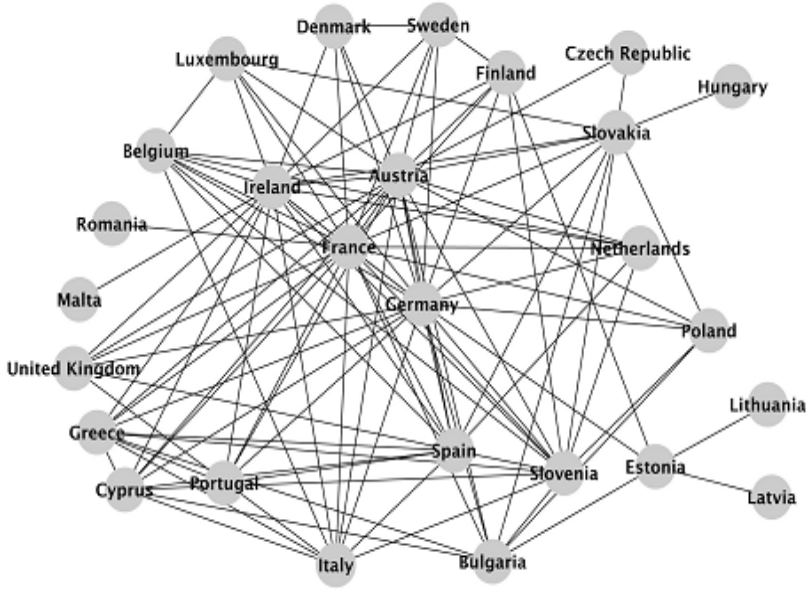
Link outlets if they share more stories than expected by chance (chi-square scores).



The probability of two non-singleton nodes from the same country to end up in the same connected component is **82.9%** ($p < 0.001$).

Linking Countries

- Since countries essentially match the communities, we generate a network of countries



We go as sparse as possible while keeping the network connected.

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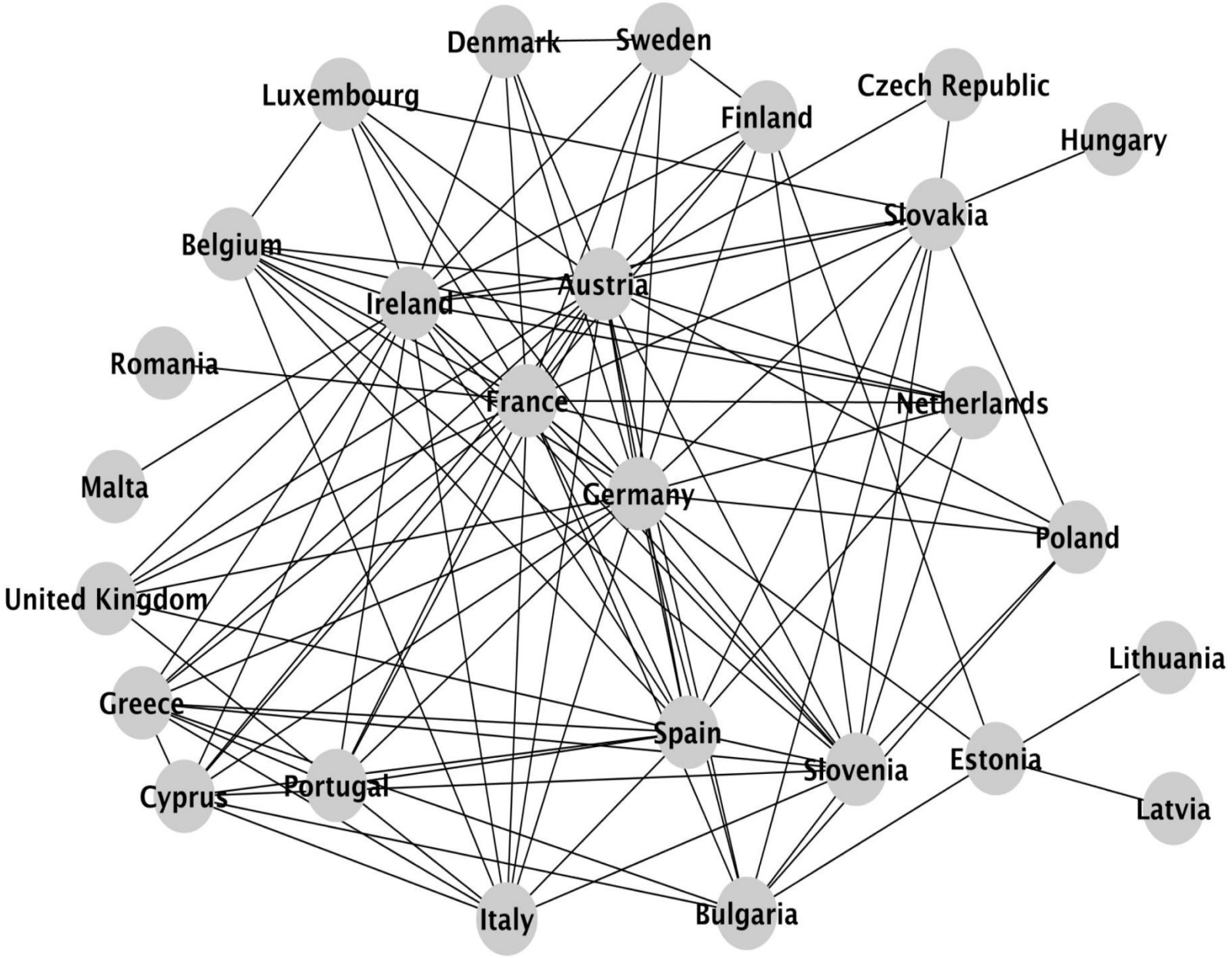

Flaounas, I., Turchi, M., Ali, O., Fyson, N., Bie, T.D., Mosdell, N., Lewis, J., Cristianini, N.: The structure of eu mediasphere. PLoS ONE p. e14243 (2010)

Explaining the Relations

- Thousands of different editors make their choices independently every morning based on their own different goals.... yet ...

We found significant ($p < 0.001$) correlation of countries' *media-content similarity* to their:

Geographical proximity — based on sharing of borders	33.86%
Economical proximity — based on trade volume	31.03%
Cultural proximity — based on song contest votting patterns	32.05%

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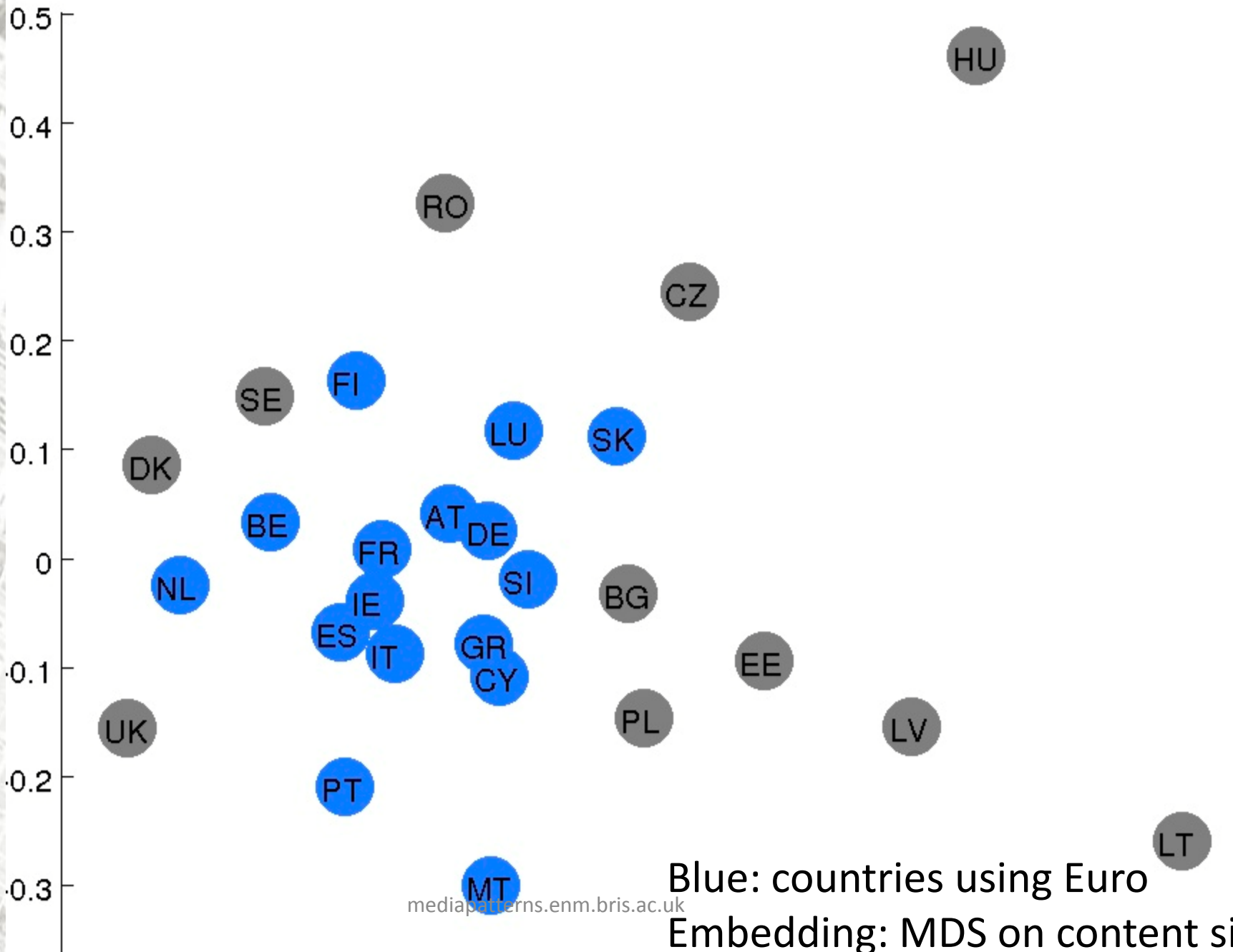


Blue: countries using Euro

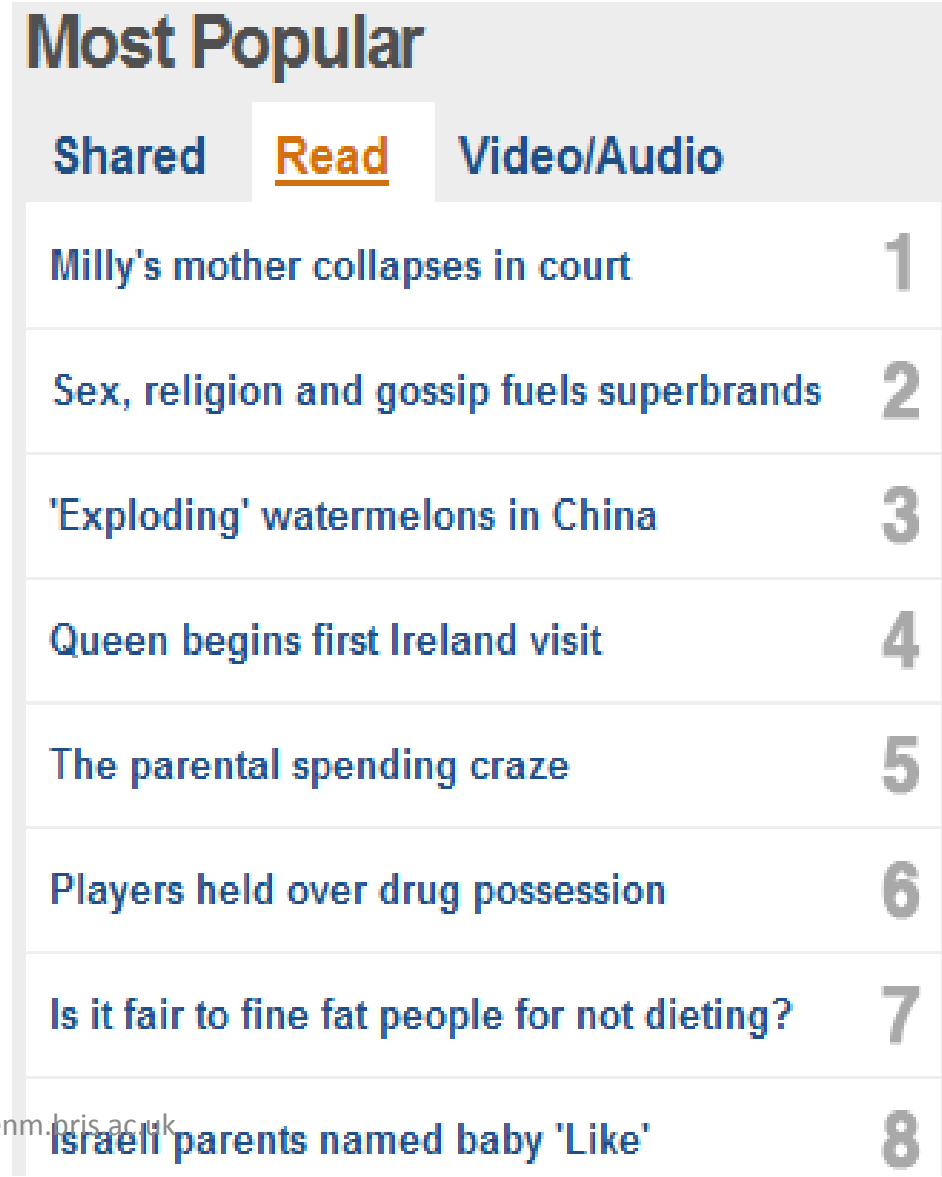
Embedding: MDS on content si

Question 2

What Readers Want

What Readers Want

- Can we predict the preferences of readers?
- Data is available through RSS feeds...
- How to exploit it?



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What Readers Want

- Even just using very basic data (textual content of title and snippet) it is possible to predict the preferences of readers...
- Not a simple classification task, needs to be framed as a “learning to rank” task (competitive nature of the process)
- Linear scoring function inferred from data, with SVMs, and used to choose which of 2 articles is likely to be preferred, by average reader...

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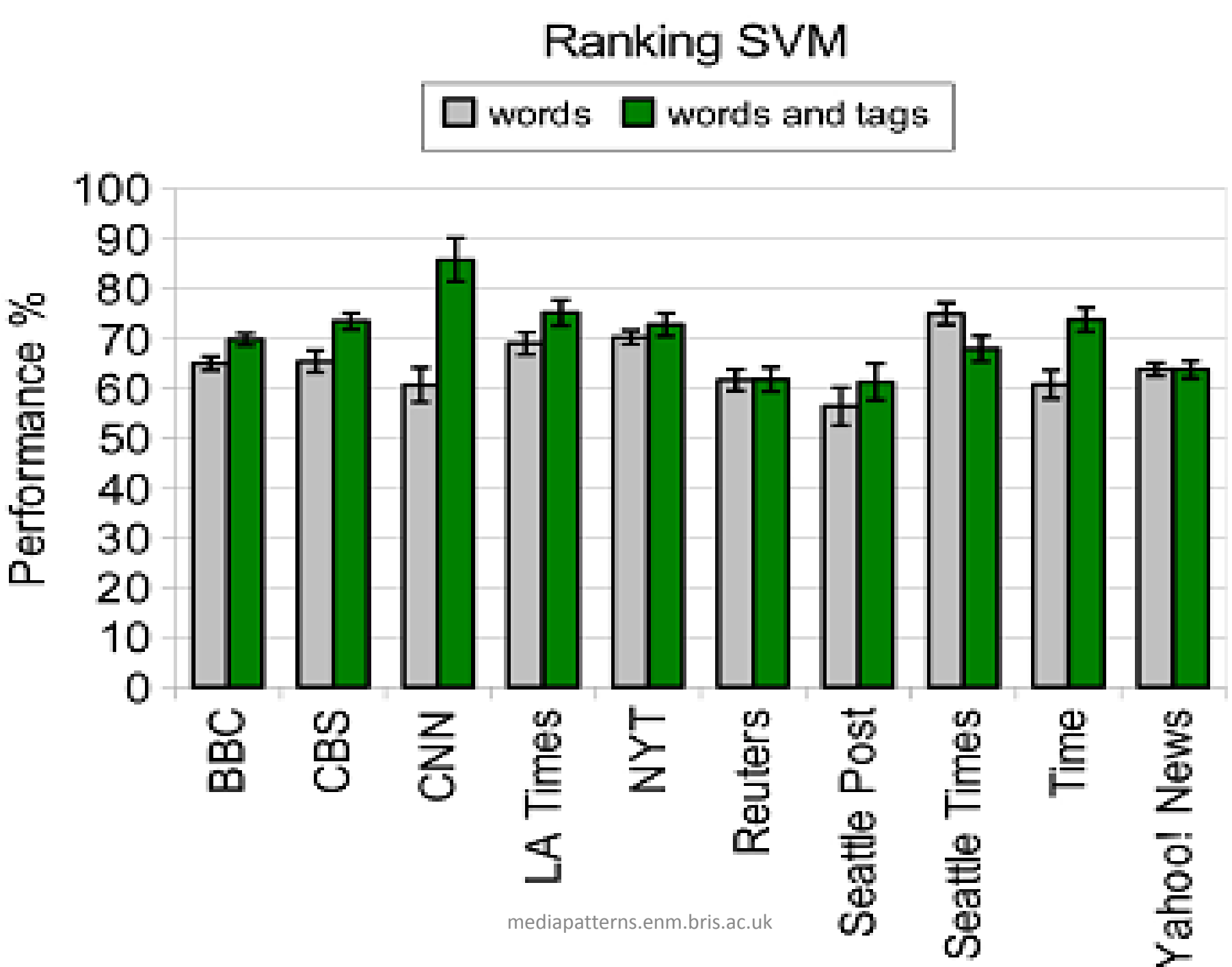
Ranking SVM
words
words and tags
Performance %
100
90
80
70
60
50
40
30
20
10
0
BBC
CBS
CNN
LA Times
NYT
Reuters
Seattle Post
Seattle Times
Time
Yahoo! News


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actor
babi
behead
boi
castrat
british
caught
cheat
circumcis
channel
dad
dead
di
duchess
facebook
gaga
girl
honour
iphon
dismemb
dog
expos
islam
kid
lotteri
mother
mum
nake
nordegren
paralys
peni
porn
pregnant
princ
rape
reportedli
reveal
rumour
sex
woman
storei
strip
taronga
tiger
zoo
star
strangl
sue
thrown
wife
abbott
afghan
afghanistan
alleg
australian
asylum
boat
bomb
centr
carbon
coal
coast
crash
defenc
detent
dollar
flood
gillard
govern
haiti
higher
injur
lower
man
nsw
melbourn
miner
minist
profit
protest
obama
oil
overnight
pakistan
peopl
premier
quak
queensland
polic
qanta
seeker
soldier
stab
sydnei
tax
todai
toll
victoria
warn
victorian

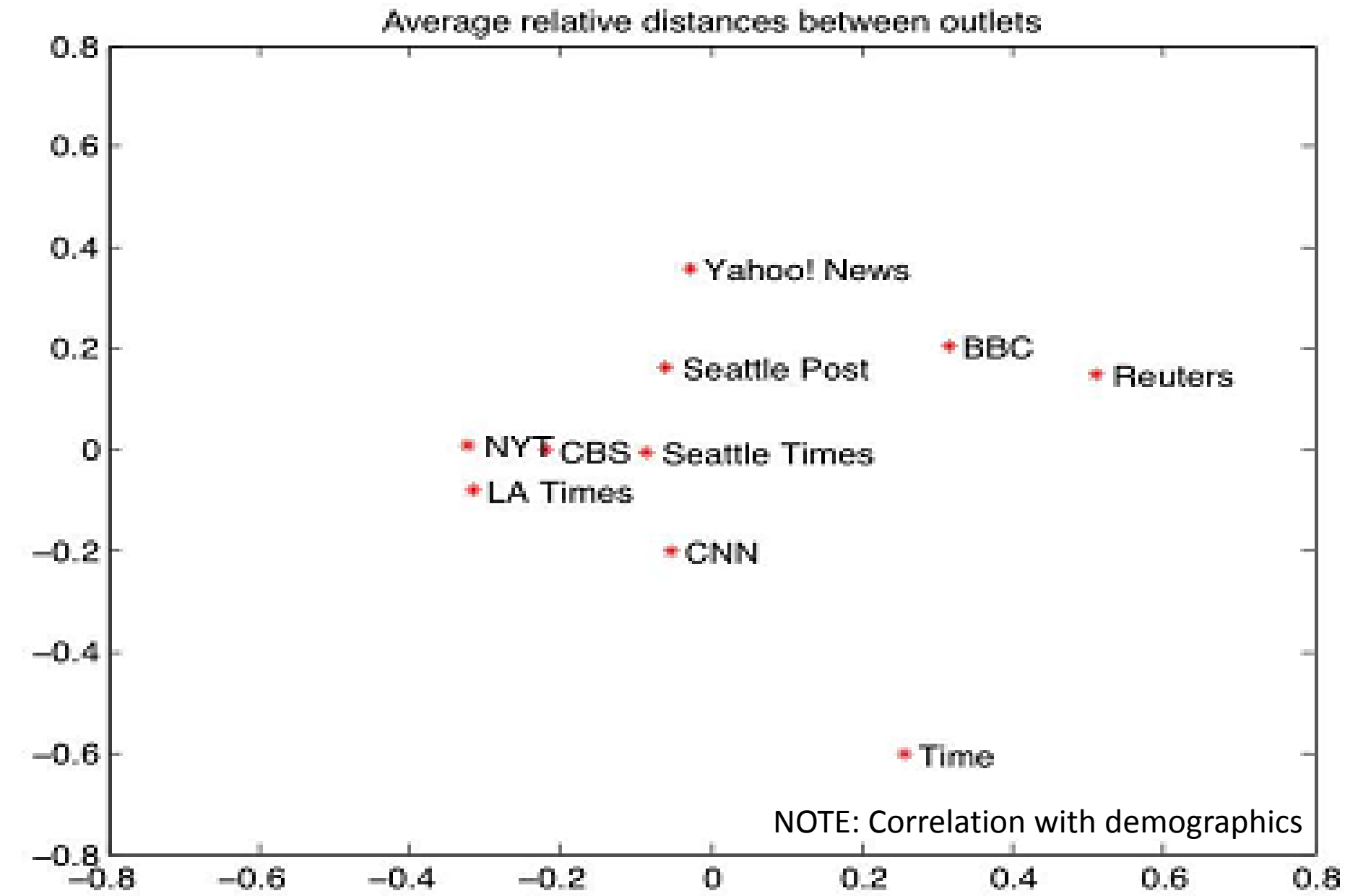
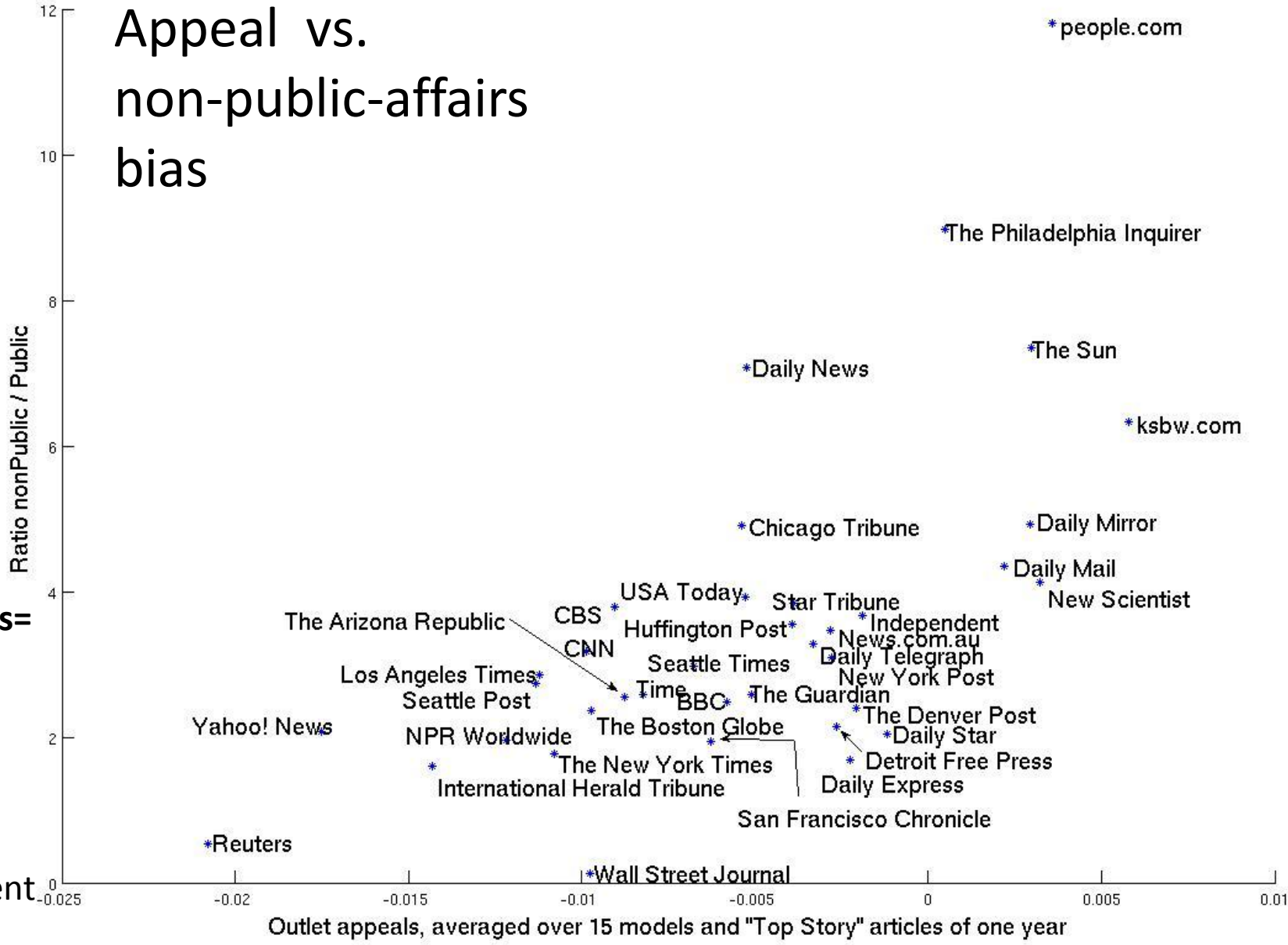


Fig. 3 Relative distances of outlets, plottet in the first two dimensions of multidimensional scaling.

Appeal vs. non-public-affairs bias



Public affairs=
politics
economics
finance...

Non-PA=
entertainment
sport
...

Question 3

Writing Style and Narrative Patterns

Writing Style

Interested in large scale patterns involving writing style:
-Readability
-Language subjectivity

-The first is captured with a standard measure (FRET) that has been shown to correlate well with ease of comprehension.

-The second quantity was captured by detecting the adjectives in the text and measuring their “polarity”.

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Readability

Flesch Reading Ease Test
The higher the FRET the easier the text to read.

Scores range from 0-100.

10K random news items per topic
FRET (article) = 206.835 - (1.015 · ASL) - 84.6 · ASW

ASL=average sentence length
ASW = average syllables per word

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Linguistic Subjectivity

- We measure the percentage of sentimental adjectives over the total number of adjectives.
- Adjectives detection by Stanford POS tagger.
- We check for each adjective the presence of a SentiWordnet sentimental score >0.25 (percentage of adjectives that have either positive or negative sentiment score >25%)

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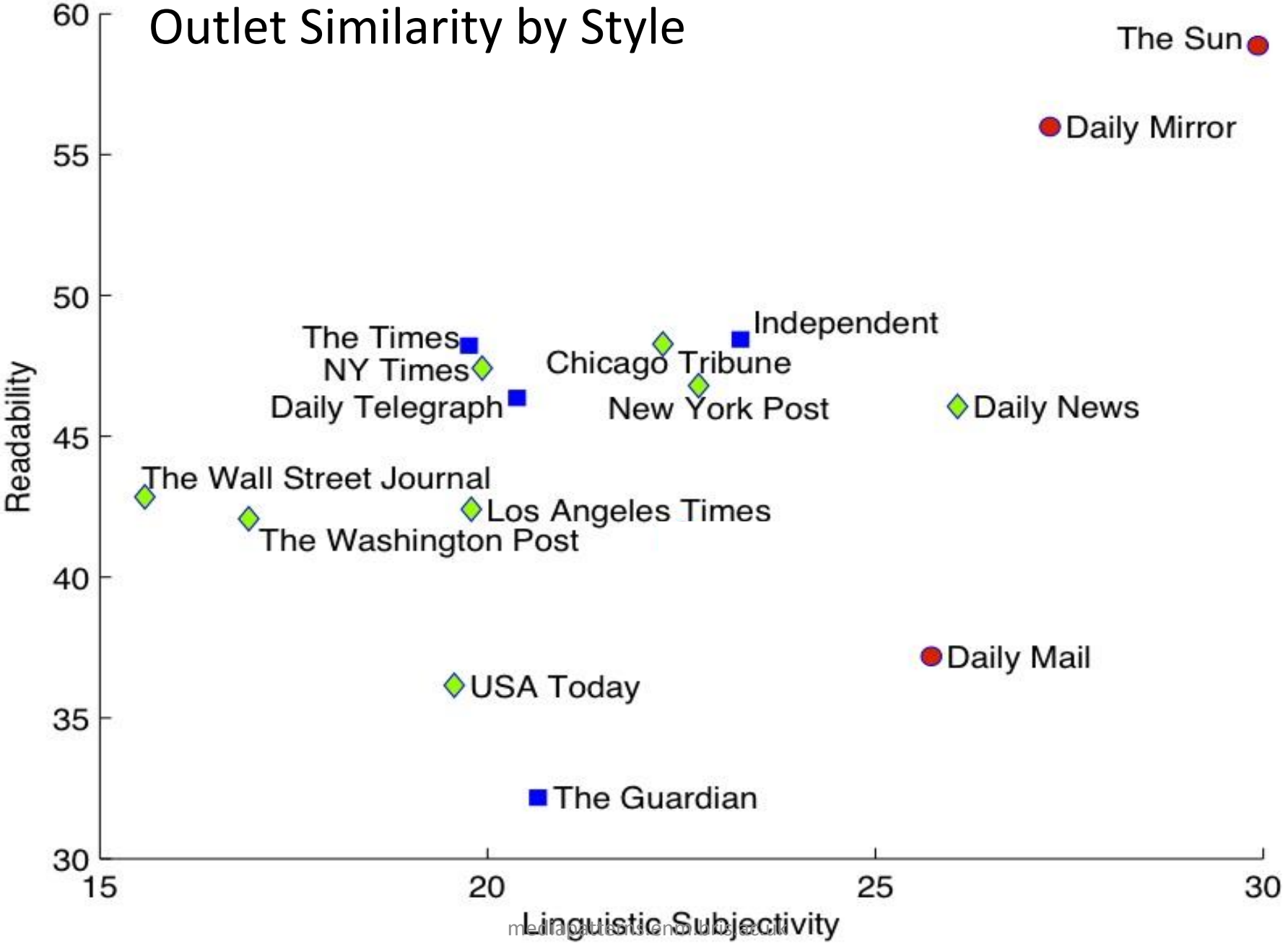
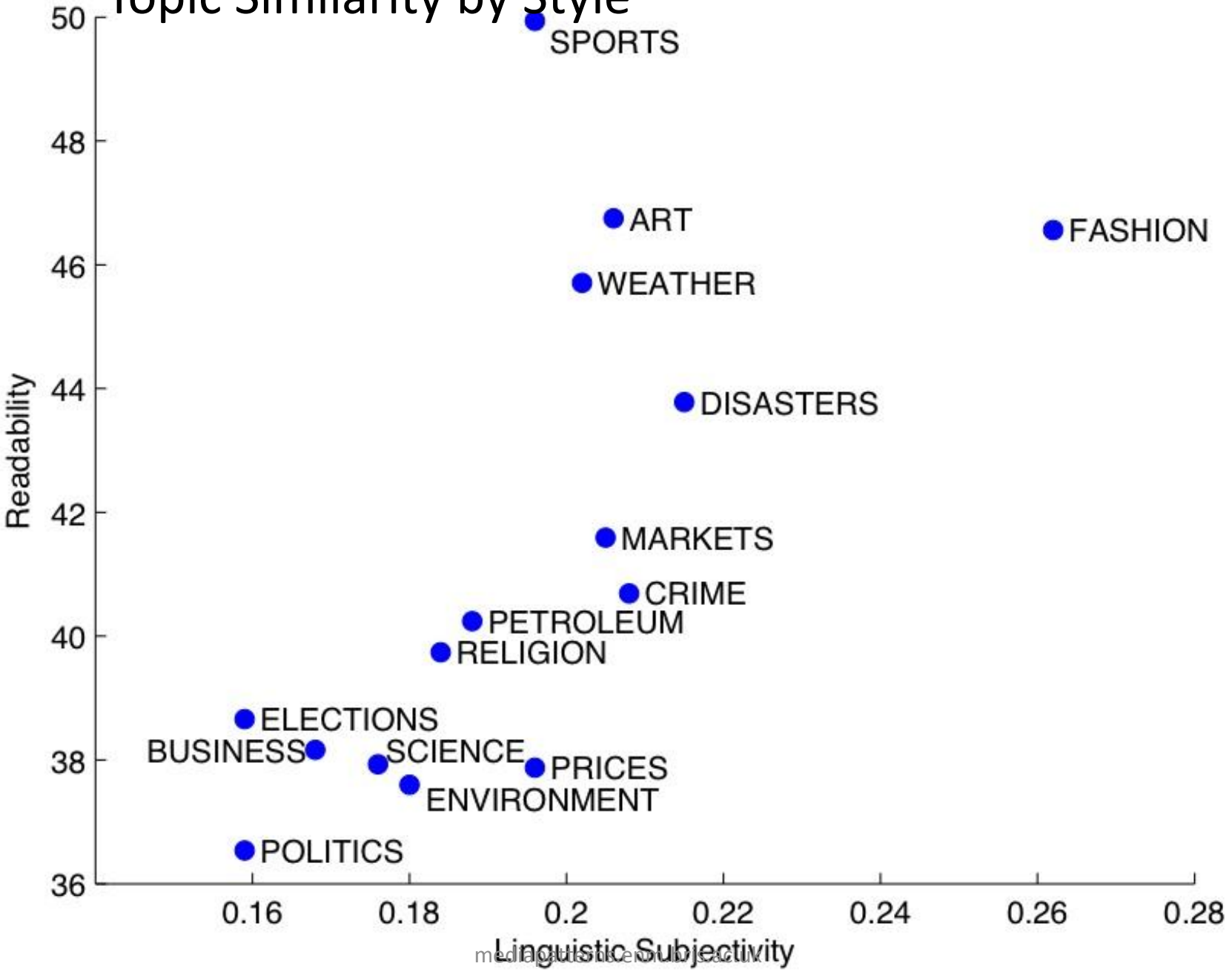
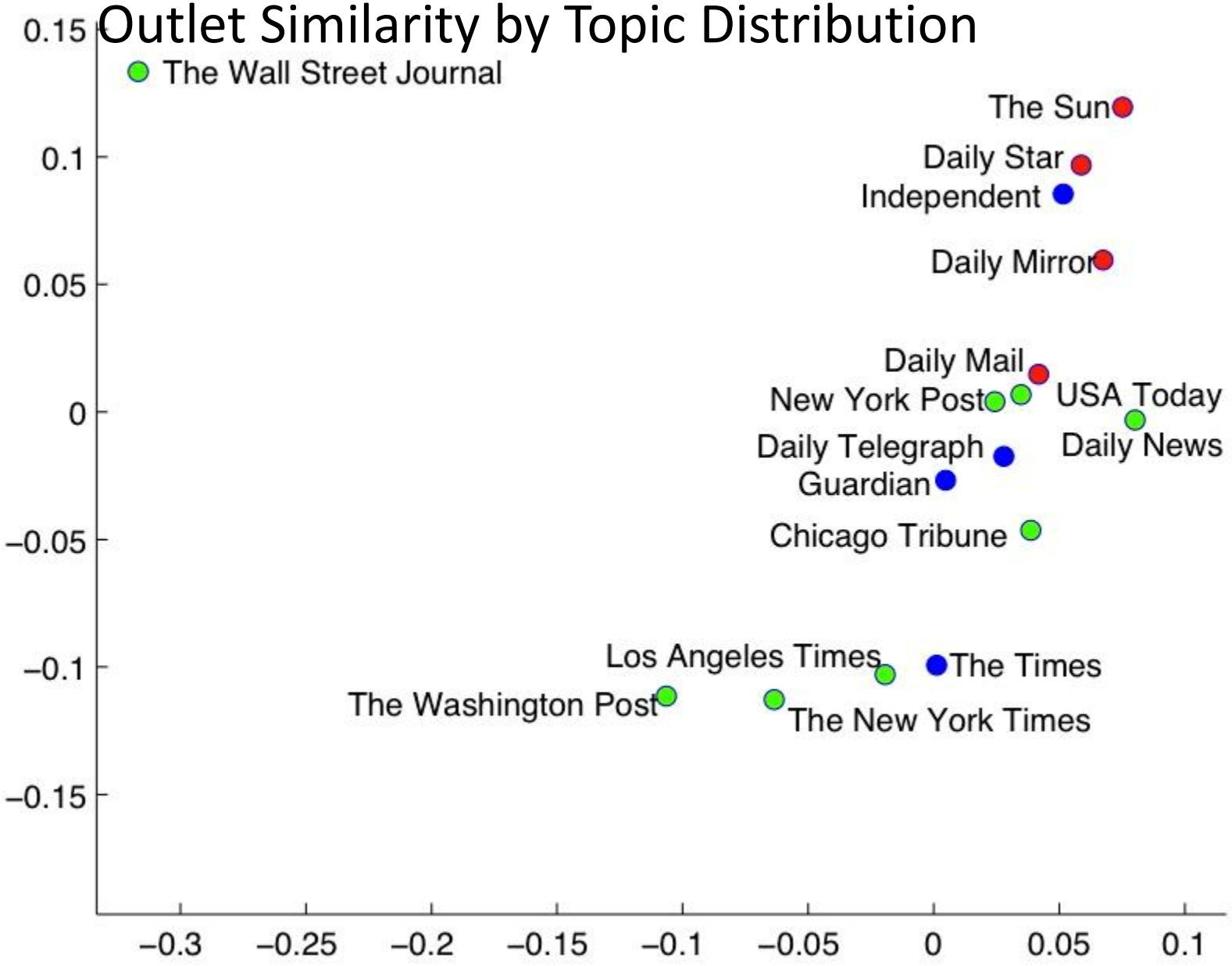
Outlet Similarity by Style

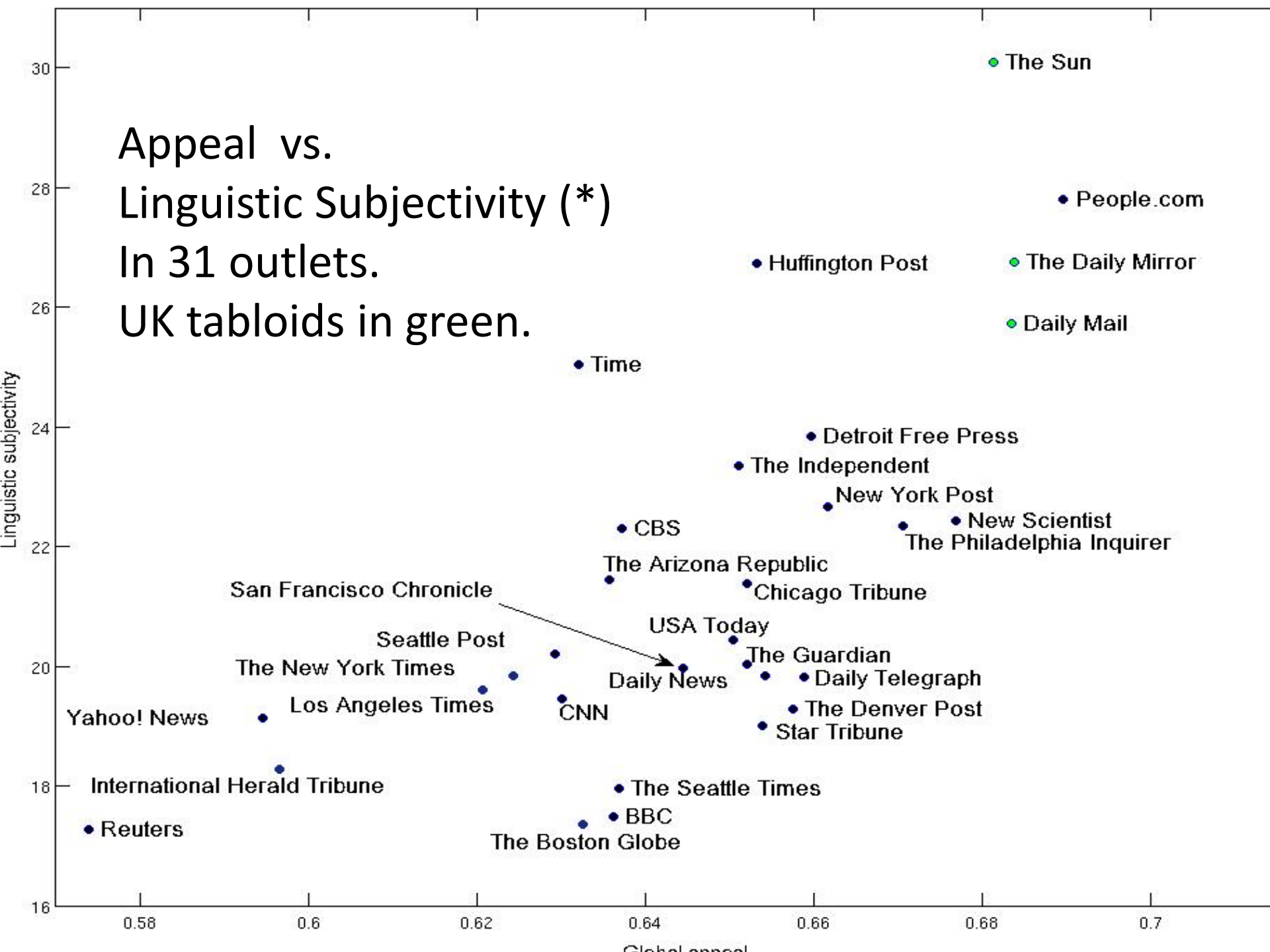


Topic Similarity by Style



Outlet Similarity by Topic Distribution




Appeal vs.
Linguistic Subjectivity (*)
In 31 outlets.
UK tabloids in green.
The Sun
People.com
Huffington Post
The Daily Mirror
Daily Mail
Time
Detroit Free Press
The Independent
New York Post
New Scientist
CBS
The Philadelphia Inquirer
The Arizona Republic
San Francisco Chronicle
Chicago Tribune
USA Today
Seattle Post
The Guardian
The New York Times
Daily News
Daily Telegraph
Los Angeles Times
CNN
The Denver Post
Yahoo! News
Star Tribune
International Herald Tribune
The Seattle Times
BBC
Reuters
The Boston Globe
Linguistic subjectivity
Global appeal
30
28
26
24
22
20
18
16
0.58
0.6
0.62
0.64
0.66
0.68
0.7

Validations

- **CBC Newsround is the most easily readable outlet**.
  than For validation reasons we added a set of articles from the BBC show CBBC-Newsround, which is a current affairs programme written specifically for children. As expected the CBBC news were found to be the most readable collection of articles with a mean readability score of 62.50 (S.E.M. = 0.27).

- **Op/Ed Articles are more subjective than average.**
  We collected 5766 **Op/Ed articles** of that kind in our period of study from 57 different media and we found that their linguistic subjectivity has a mean of 26.15% (S.D.=0.29%) while the mean subjectivity of main articles is 19.45% (S.D. = 0.22%).

- Note: we also found a 72.5% correlation between readability and subjectivity (Spearman correlation, p=0.003).

Relation: style vs. demographics

- For UK newspapers we obtained reader-demographics:
  [gender, age group, income group]
  and we computed similarity between outlets.
- (from: Newspaper Marketing Agency at: www.nmauk.co.uk)

- **Writing Style Correlates with Reader Demographics - 31.43%**
  (Kendall correlation of the pairwise euclidean distances between outlets, **p=0.048**)

NARRATIVE ANALYSIS

- Social scientists like to think in terms of social actors, their actions, and the narrative linking them.
- Roberto Franzosi of Emory University developed Quantitative Narrative Analysis (QNA) to identify key actor / action patterns in a set of articles.
- Actors and actions (and sphere of action) are hand annotated...
- We identified ACTORS with NOUN PHRASES, and ACTIONS with VERBS, and SVO triplets with narrative units

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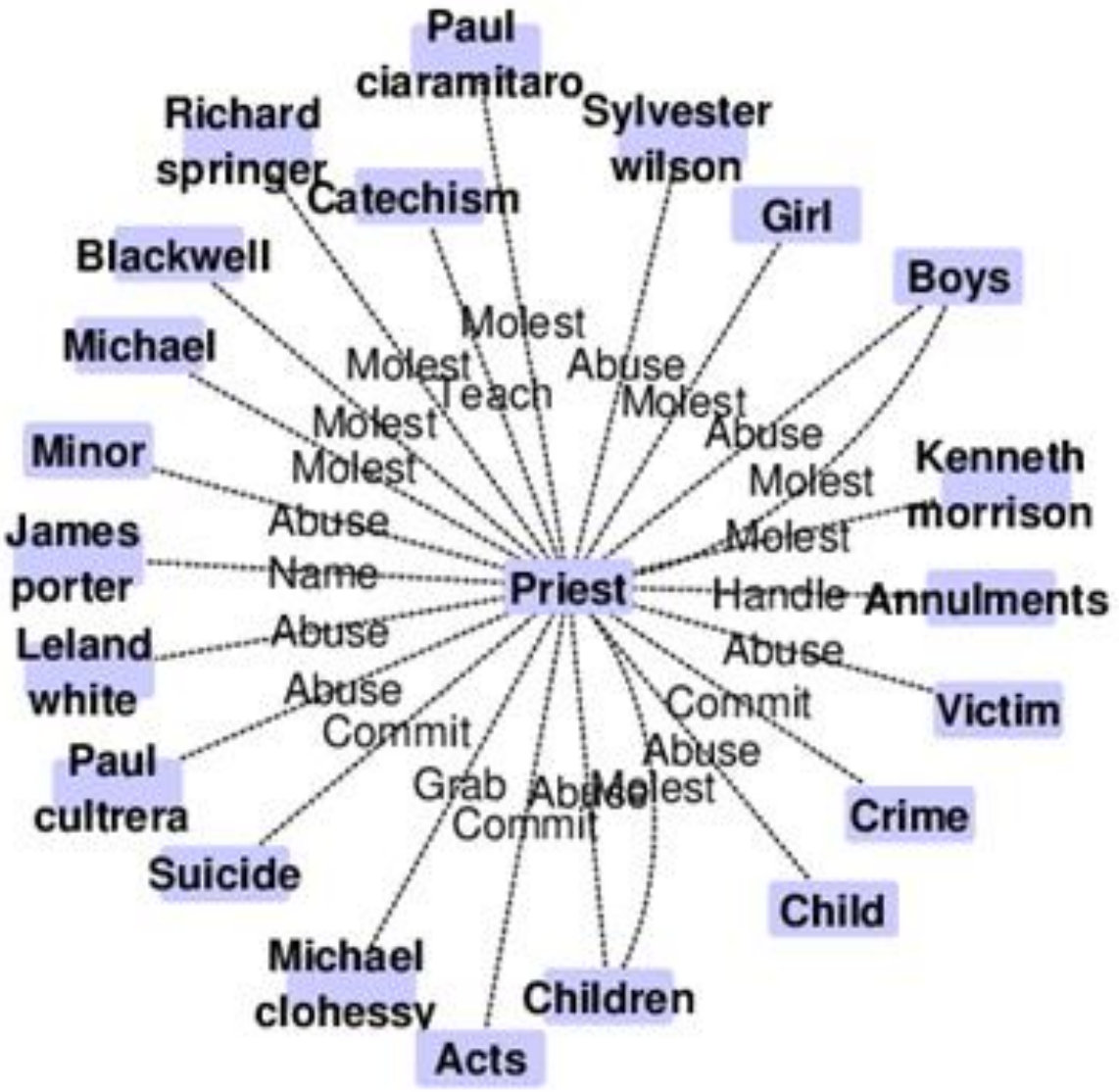

NY Times Corpus, Year 2002 – crime stories

Crime against Person		Crime against Property	
Subjects	**Objects**	**Subjects**	**Objects**
Priest	People	Man	Money
Man	Boy	Police	Bank
Troops	**Child**	Soldiers	Records
Reyes	**Girl**	Winona Ryder	Millions
Geoghan	Man	Priest	Weapons
Shanley	**Woman**	People	Wallet
Forces	Jogger	Jason Bogle	Trade Secret
Police	Victim	Investigators	Steven Seagal
United States	Minors	Employee	Most
Others	Me	Agents	Man

Networks of political support

Example: US Presidential Elections

Types of information about actors:

- Party loyalties
- Subject / object bias
- Positive / negative action bias

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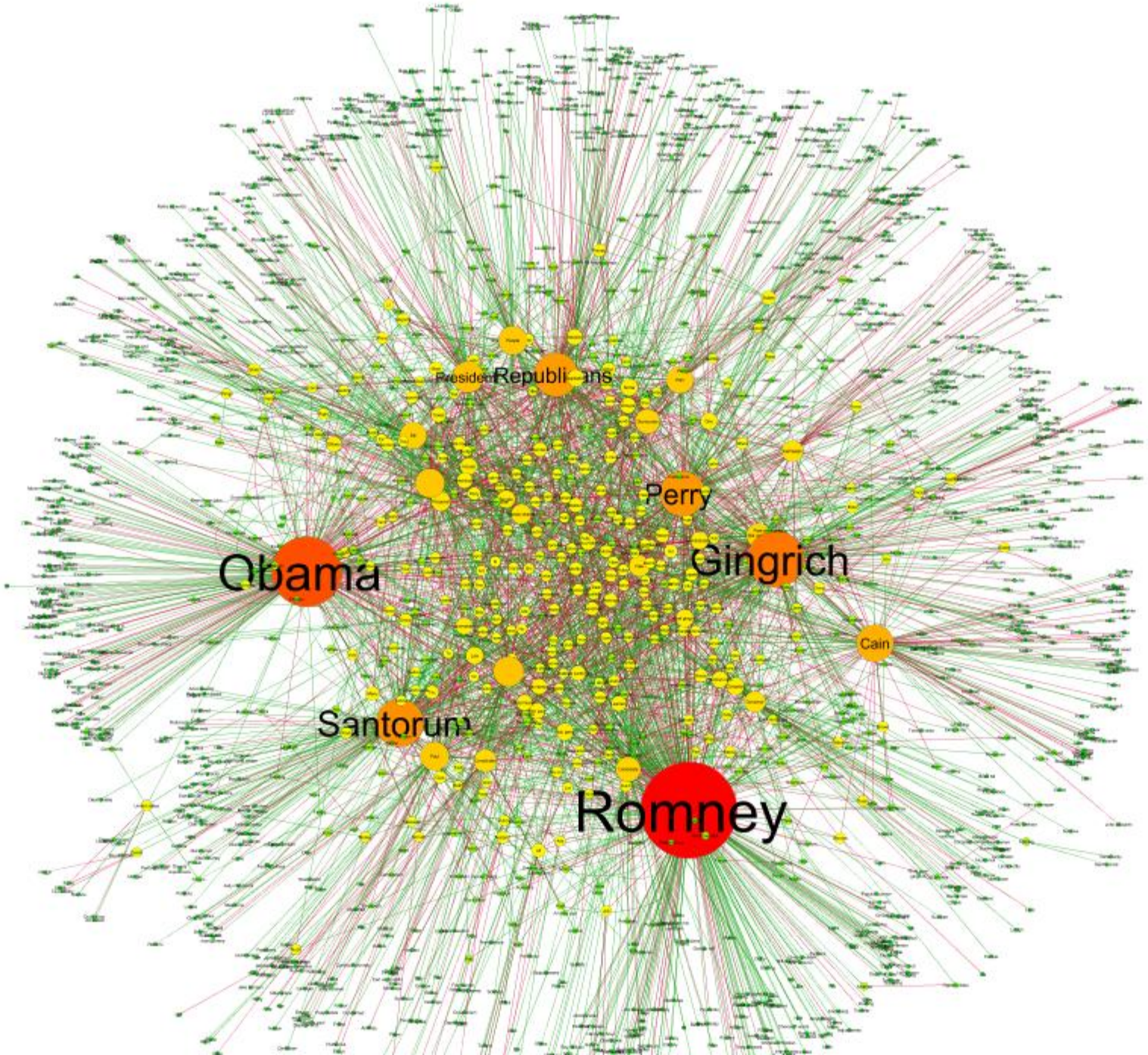
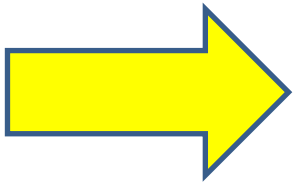
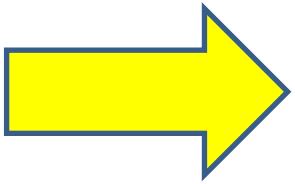

Republi ans
Perry
Obama
Gingrich
Cain
Romney

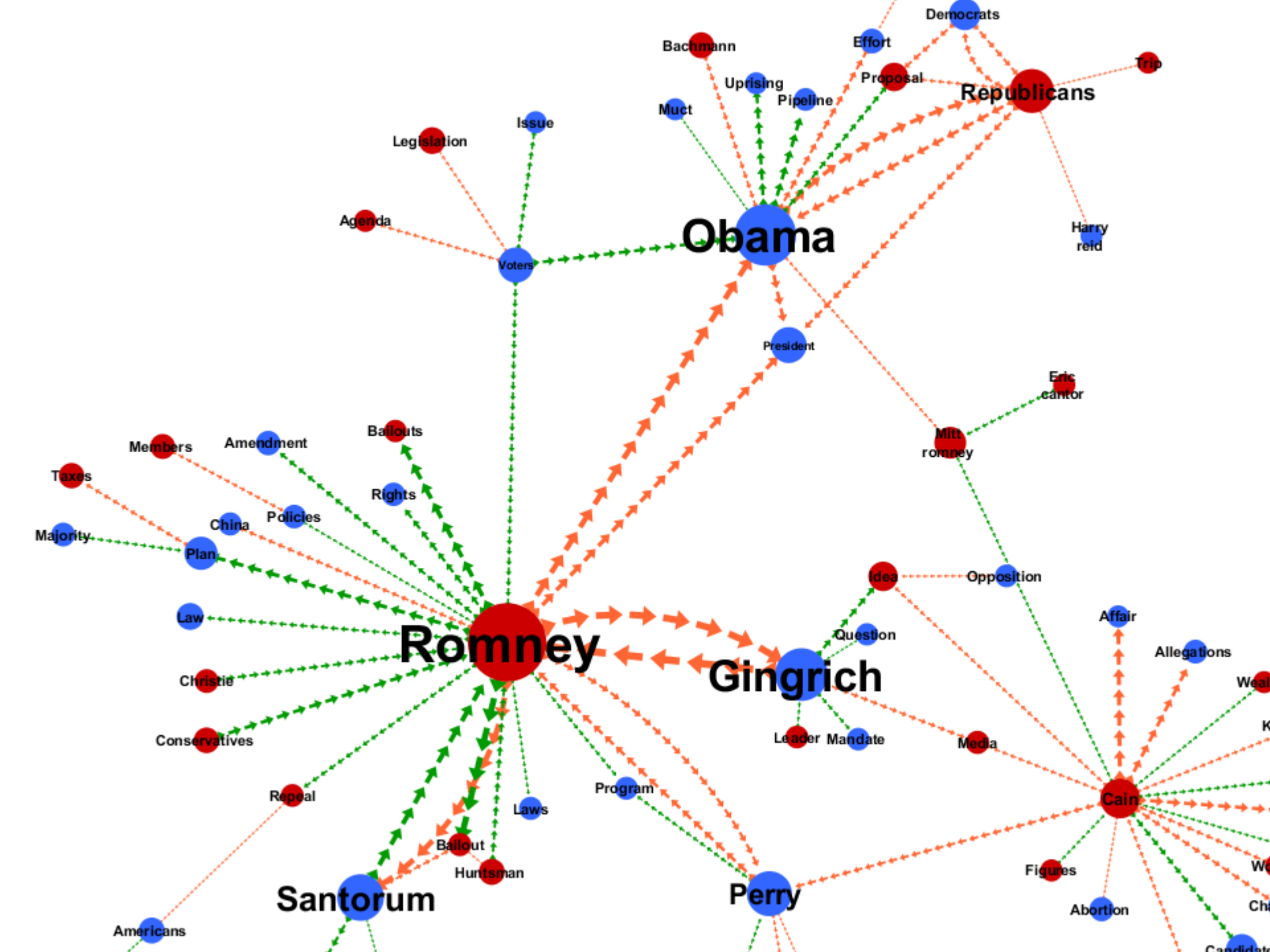
- Gingrich Oppose Romney
- Romney Oppose Gingrich
- Romney Endorse Bailout
- Romney Oppose Obama
- Romney Oppose Santorum
- Santorum Endorse Romney
- Romney Endorse Bailouts
- Romney Oppose President
- Obama Oppose Republicans
- Mitt Romney Oppose President
- Republicans Oppose Obama
- Obama Oppose President
- Conservatives Endorse Romney
- Cain Oppose Allegations
- Cain Oppose Accusations
- Perry Oppose Romney
- Obama Endorse Uprising
- Santorum Endorse Earmarks
- Romney Endorse Rights
- Romney Oppose Perry

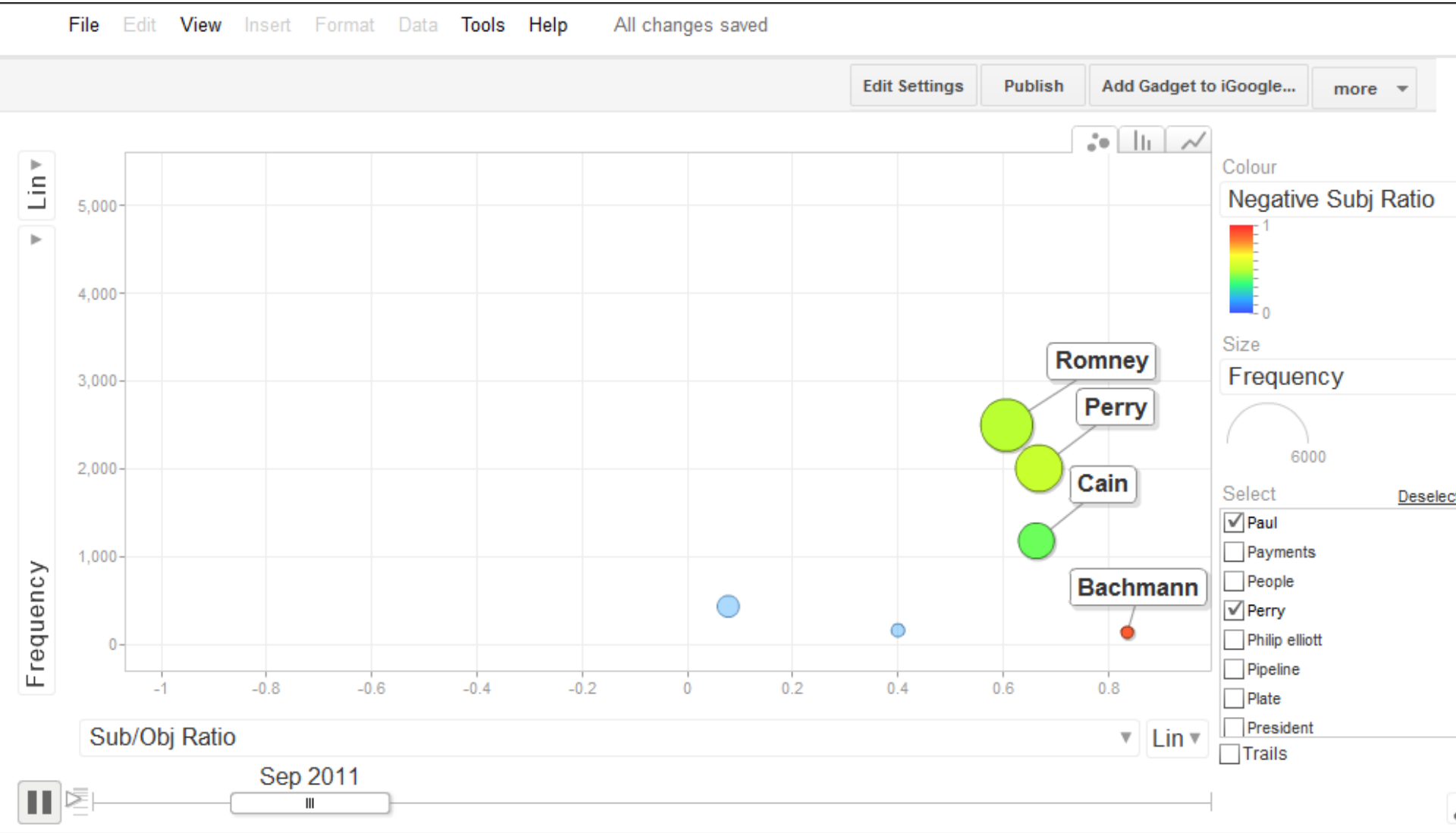




- Obama
- Perry
- Gingrich
- President
- Democrats
- China
- Santorum
- Muct
- Uprising
- Harry Reid
- Bailouts
- Bailout
- Christie
- Future
- Repeal
- Mitt Romney
- Cain
- People
- Republicans
- Romney

Note: in primary phase many people oppose Romney Creating errors


Democrats
Bachmann
Effort
Trip
Uprising
Proposal
Republicans
Pipeline
Muct
Issue
Legislation
Agenda
Obama
Voters
Harry reid
President
Eric cantor
Mitt romney
Ballouts
Members
Amendment
Taxes
Rights
Policies
China
Majority
Plan
Idea
Opposition
Law
Romney
Question
Gingrich
Affair
Allegations
Christie
Conservatives
Leader
Mandate
Media
Repeal
Program
Laws
Cain
Ballout
Huntsman
Figures
Santorum
Perry
Abortion
Americans


File Edit View Insert Format Data Tools Help All changes saved
Edit Settings
Publish
Add Gadget to iGoogle...
more
Lin
Frequency
5,000
4,000
3,000
2,000
1,000
0
-1
-0.8
-0.6
-0.4
-0.2
0
0.2
0.4
0.6
0.8
Romney
Perry
Cain
Bachmann
Colour
Negative Subj Ratio
1
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Size
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6000
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Deselec
Paul
Payments
People
Perry
Philip elliott
Pipeline
Plate
President
Trails
Sub/Obj Ratio
Lin
Sep 2011
Sheet 1
Gadget3
Gadget2
Gadget1


Nello Cristianini
Share
Motion Chart_Updated
File Edit View Insert Format Data Tools Help
Last edit was made 22 hours ago by nello.cristianini
Edit Settings
Publish
Add Gadget to iGoogle...
more
Lin
Frequency
5,000
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Perry
Bachmann
Colour
Negative Subj Ratio
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Select
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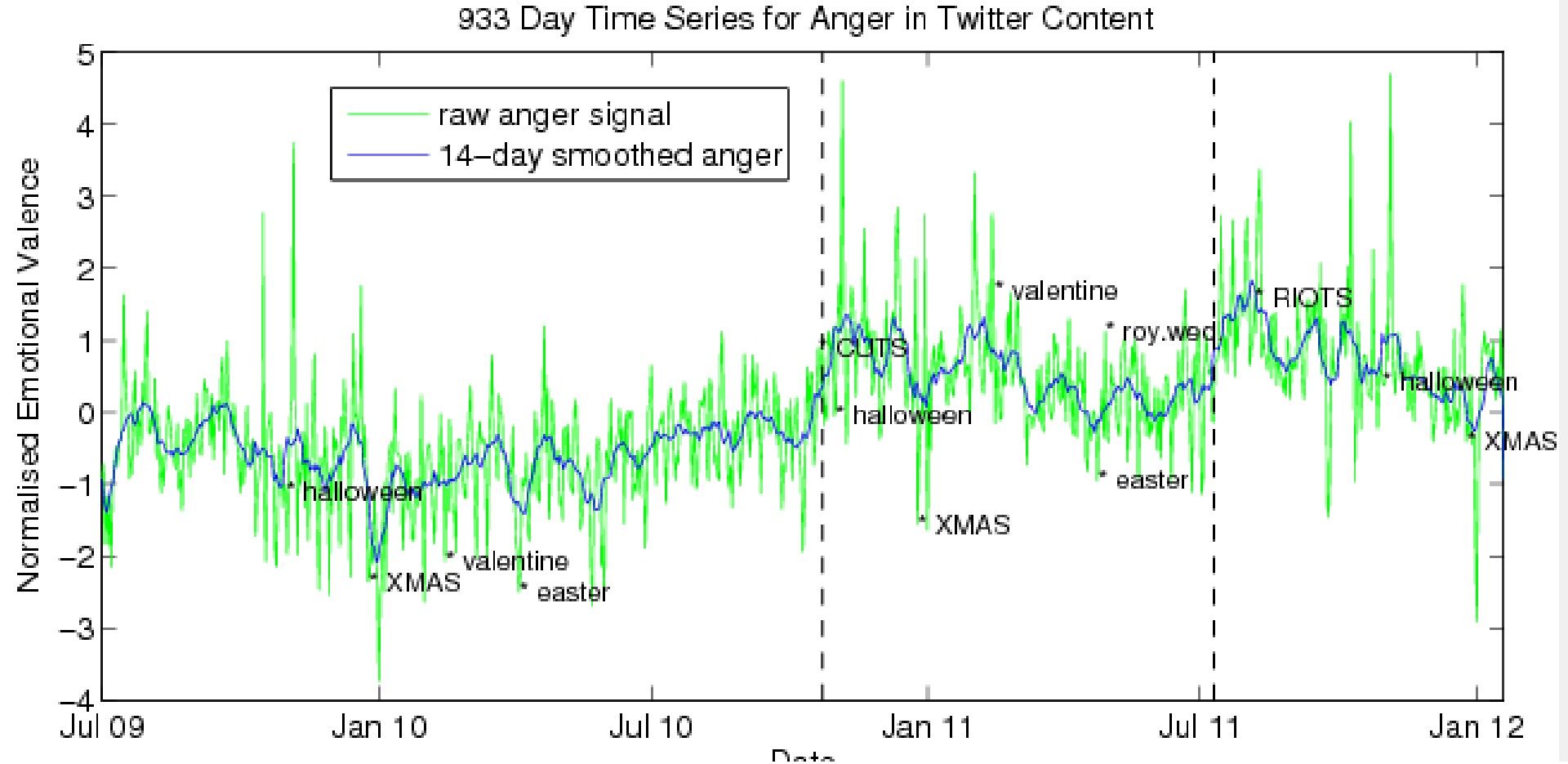
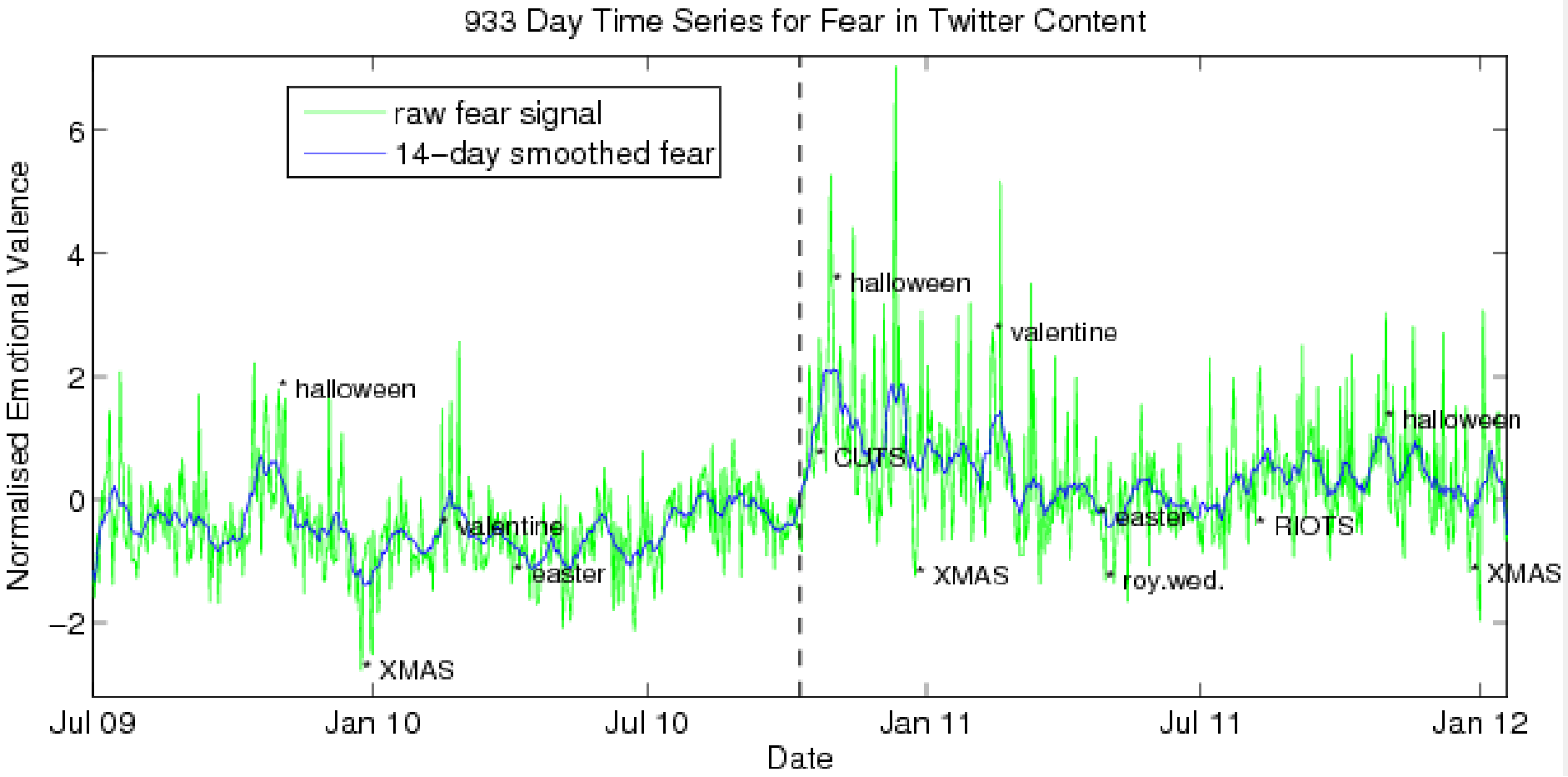
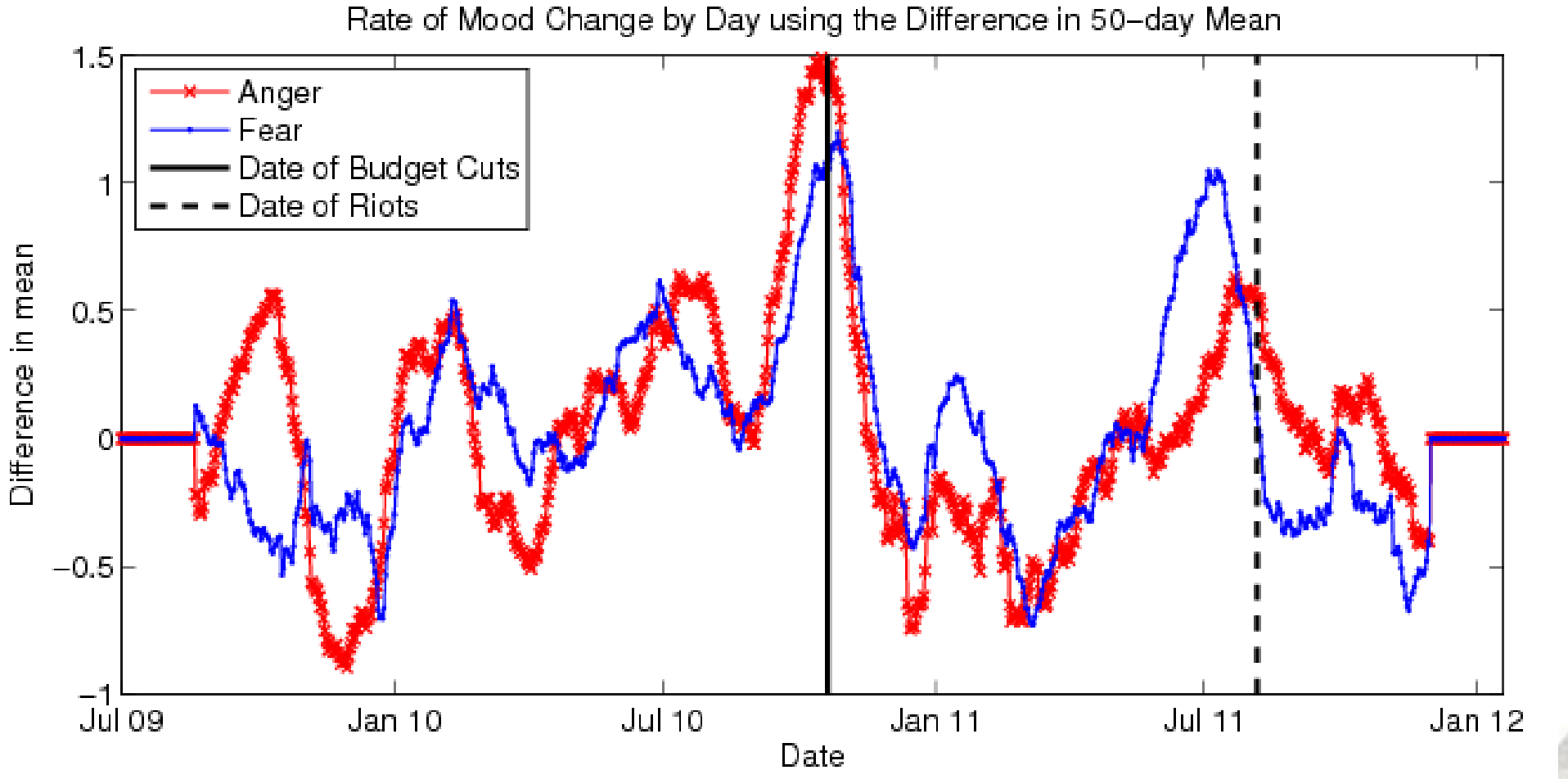
Anderson
Appointment
Bachmann
Bailout
Bailouts
Trails
Sub/Obj Ratio
Lin
Sep 2011
Play
Sheet 1
Gadget3
Gadget2
Gadget1

Question 4

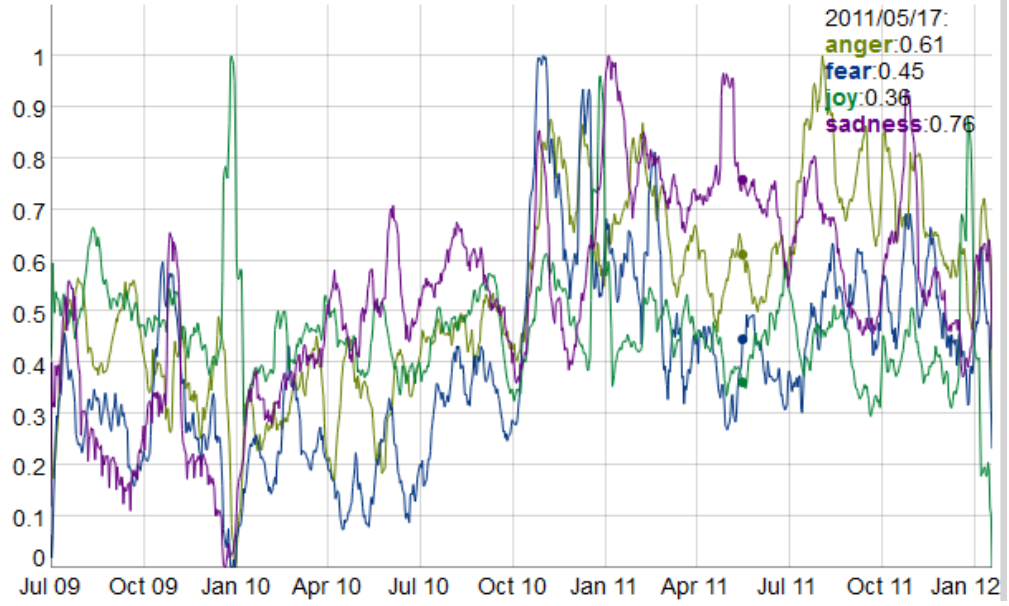
Measuring Public Mood


933 Day Time Series for Anger in Twitter Content
raw anger signal
14–day smoothed anger
Normalised Emotional Valence
5
4
3
2
1
0
−1
−2
−3
−4
Jul 09
Jan 10
Jul 10
Jan 11
Jul 11
Jan 12
halloween
XMAS
valentine
easter
CUTS
halloween
valentine
XMAS
roy.wed
easter
RIOTS
halloween
XMAS


933 Day Time Series for Fear in Twitter Content
raw fear signal
14−day smoothed fear
Normalised Emotional Valence
6
4
2
0
−2
halloween
valentine
easter
XMAS
halloween
CUTS
valentine
XMAS
easter
roy.wed.
RIOTS
halloween
XMAS
Jul 09
Jan 10
Jul 10
Jan 11
Jul 11
Jan 12
Date


Rate of Mood Change by Day using the Difference in 50−day Mean
Anger
Fear
Date of Budget Cuts
Date of Riots
Difference in mean
1.5
1
0.5
0
−0.5
−1
Jul 09
Jan 10
Jul 10
Jan 11
Jul 11
Jan 12
Date

The Face of Britain...

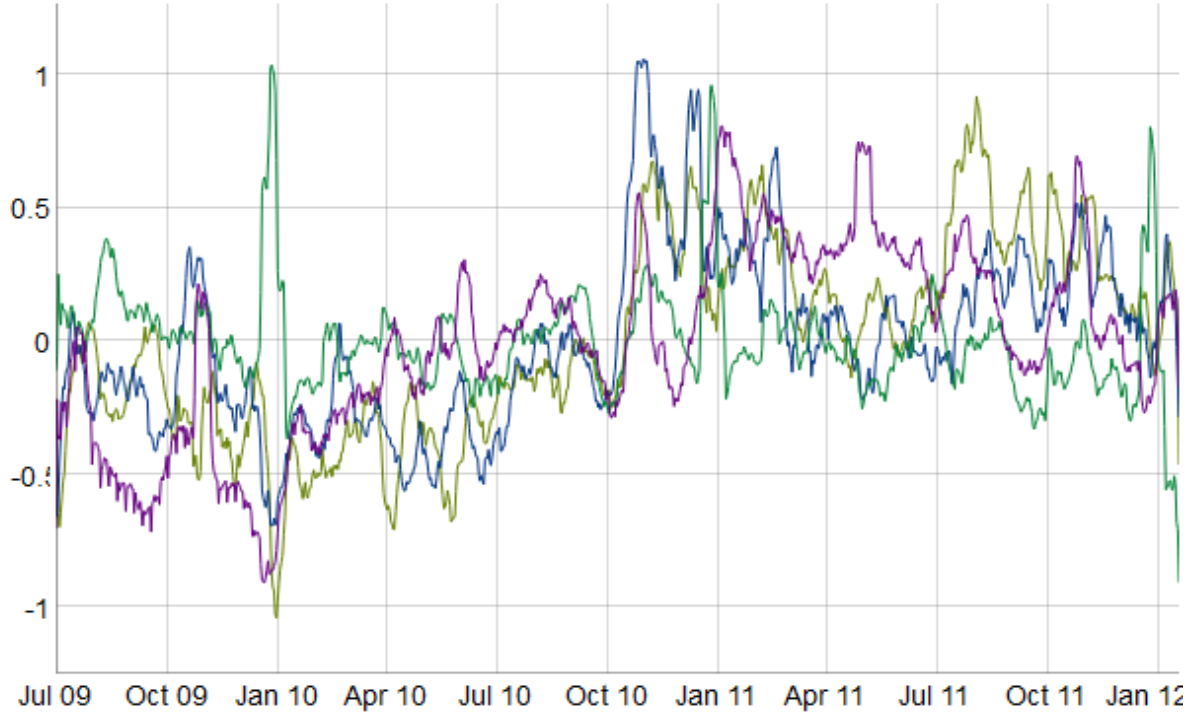


Animation of Mood Changes

Mood Changes in UK Twitter Content 2009-2012

Intelligent Systems Laboratory - University of Bristol

09/11/2011



Face Visualisation Tool: courtesy of http://grimace-project.net/

Demos

celebwatch. .enm.bris.ac.uk

foundintranslation.enm.bris.ac.uk

geopatterns.enm.bris.ac.uk/epidemics

electionwatch.enm.bris.ac.uk

media**patterns**.enm.bris.ac.uk

MediaPatterns

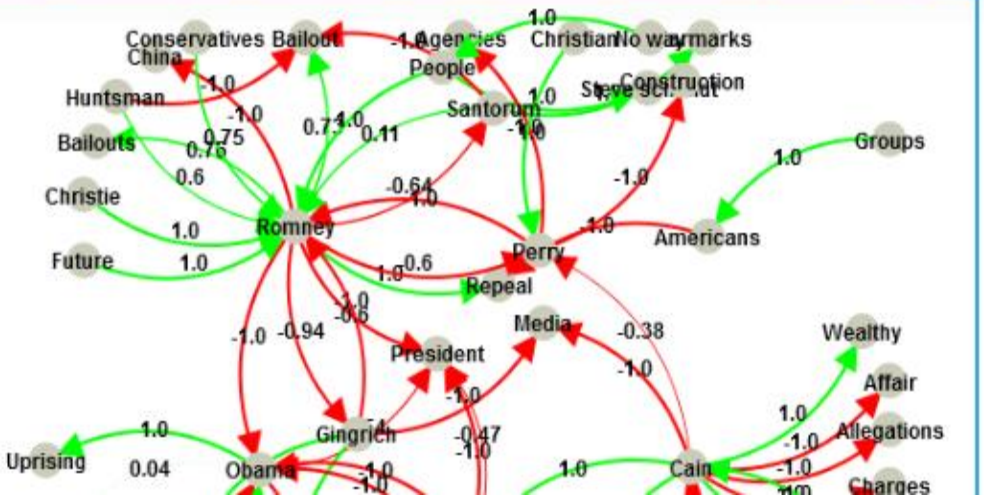
Election Watch'12

Election Watch automatically monitors political discourse about the 2012 USA Presidential Election in 719 US and International news outlets. The information displayed is based on processing 82084 articles. More

Actor Spectrum

- Obama
- Perry
- Gingrich
- President
- Democrats
- China
- Santorum
- Muct
- Uprising
- Harry Reid
- Bailouts
- Bailout
- Christie
- Future
- Repeal

Triplet Graph | Actor Space | Actor Bias | Map | Timeline | Bar Chart | Activity Map



Relations

- Gingrich Oppose Romney
- Romney Oppose Gingrich
- Romney Endorse Bailout
- Romney Oppose Obama
- Romney Oppose Santorum
- Santorum Endorse Romney
- Romney Endorse Bailouts
- Romney Oppose President
- Obama Oppose Republicans
- Mitt Romney Oppose President
- Republicans Oppose Obama
- Obama Oppose President
- Conservatives Endorse Romney
- Cain Oppose Allegations

Turchi, M., Flaounas, I., Ali, O., Bie, T.D., Snowsill, T., Cristianini, N.: Found in translation. In: Machine Learning and Knowledge Discovery in Databases, European Conference (ECML/PKDD). Lecture Notes in Computer Science, vol. 5782, pp. 746–749. Springer, Bled, Slovenia (2009)

Meme Watch | What's on our minds?

Home About People

Top memes (2010-08-26)

|< Prev Next >|

- the anniversary
- checkpoint
- powerful
- north korean leader kim jong
- michael enright

|<	<	Aug 2010	>	>|	
S	M	T	W	T	F	S
1	2	3	4	5	6	7
8	9	10	11	12	13	14
15	16	17	18	19	20	21
22	23	24	25	26	27	28
29	30	31	1	2	3	4

In the news (103)

North Korean leader reported to be in China

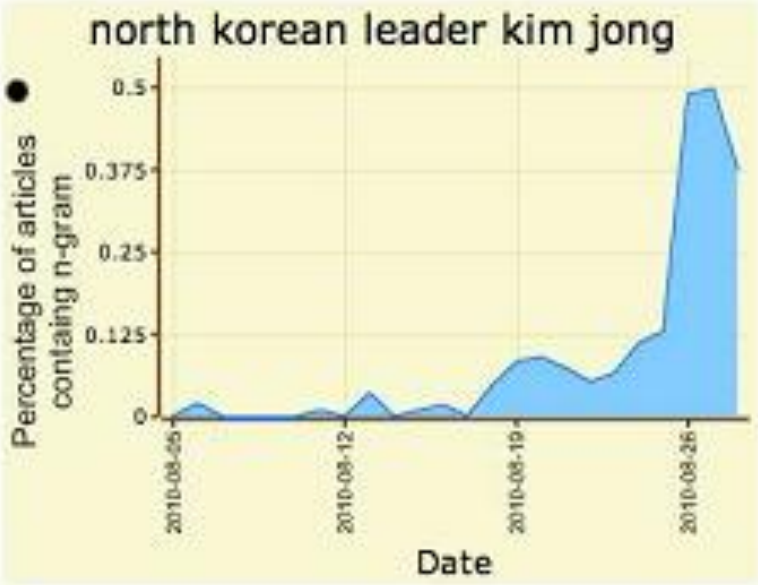
[2010-08-26 06:00:12] North Korean leader Kim Jong Il is visiting China, the South Korean JoongAng...

Kim Jong-Il may be visiting China: S.Korea official

[2010-08-26 06:00:25] North Korean leader Kim Jong-Il may have left for China Thursday in what would...

N.Korea's Kim Jong-il 'in China'

Meme timelines



Cluster details [–][?]

kim jong | jong | leader kim jong | il | jong - | kim jong - | leader kim | kim jong - il | jong - il | korean leader

north korean leader | - il | north korean | korean leader kim jong | korean leader kim | north korean leader kim

leader kim jong - il | leader kim jong - | to china | succession | kim 's | kim ' | jilin | that kim | korea 's | korea

Snowsill, T., Flaounas, I., Bie, T.D., Cristianini, N.: Detecting events in a million new york times articles. In: Machine Learning and Knowledge Discovery in Databases, European Conference (ECML/PKDD). pp. 615–618. Barcelona, Spain

Celebrity Watch

celebwatch.enm.bris.ac.uk

Celebrity Watch

Celebrity Watch
... the World's hottest celebrity gossip, tracking 11325 Celebrities in 1000 News Outlets!
Read on...

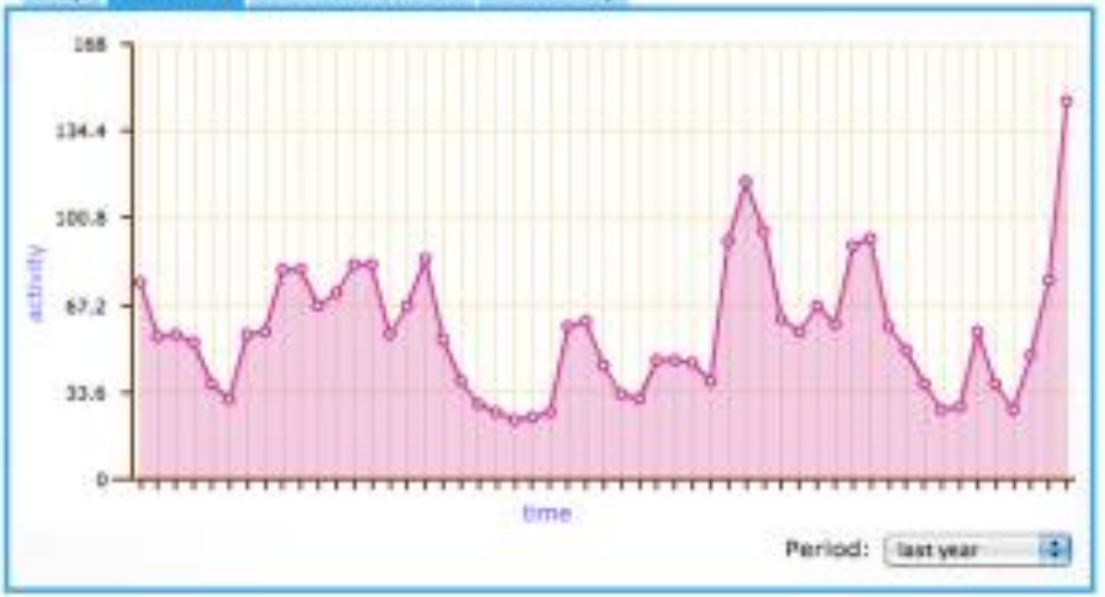
Mariah Carey Activity

0 1 2 3 4 5 6 7 8 9

PASCAL

BRT

Map | Timeline | Social Network | Text Only



Mariah Carey (27)

Inside Mariah Carey's baby shower!

9 Mar 2011 17:21:59 GMT

On March 6, Mariah Carey and Nick Cannon gathered an intimate group of friends and family at the rooftop Conservatory Grill at the Montage hotel to celebrate the arrival of their twin boy and girl, due in late April or early May. Read more on Inside Mariah Carey's baby shower!...
Read more...

Mariah Carey Dishes On Her Baby Shower!

9 Mar 2011 21:19:57 GMT

MARIAH Carey says her baby shower is the first one she's ever been to. The superstar singer — who's expecting twins with husband Nick Cannon — gathered an intimate group of friends and family at the [illegible] Montage hotel to celebrate

Search

Search

Hot Today

- Mariah Carey (27)
- Nelly Furtado (13)
- Collins (20)
- Mark Cuban (7)
- Carey (14)
- George Michael (12)
- Jon Cryer (55)
- Till (5)
- John Stamos (24)
- Chuck Lorre (72)
- Phil Collins (22)
- Tyson (17)
- Mike Tyson (18)
- Alexander McQueen (8)
- Johnny Depp (11)
- Vanessa Hudgens (3)
- Tom Izzo (1)
- Matt Damon (8)
- Leslie Moonves (3)
- Webster (10)

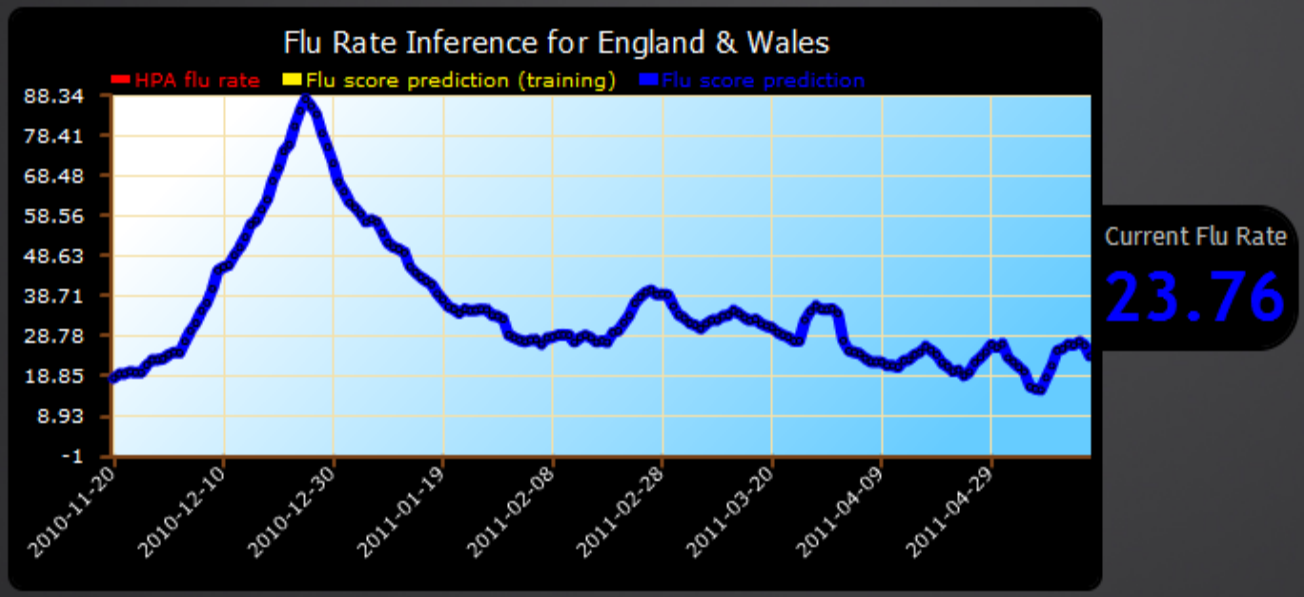
Hot This Month

- Justin Bieber (33)
- Natalie Portman (14)
- Colin Firth (20)
- James Franco (5)
- Britney Spears (54)
- Kim Kardashian (33)
- Michael Jackson (14)
- Perry (54)
- Anne Hathaway (7)
- Christina Aguilera (20)
- Nicole Kidman (8)
- Jennifer Aniston (18)
- Oprah Winfrey (30)

Flu Detector *tracking epidemics on Twitter*

Home | Regional Inferences | Archive | About

Here are the inferred flu rates for England & Wales in the last 6 months based on geolocated Twitter content



Current Flu Rate

23.76

Vertical axis	Inferred flu rate indicating the number of GP consultations per 100,000 citizens where the diagnosis' result was Influenza-like Illness (ILI)
Horizontal axis	Date in yyyy-mm-dd format

Check Regional Flu Inferences:
for the last 6 months
since June 2009

Flu Detector uses the content of Twitter to nowcast flu rates in several UK regions. Inferences are compared with official ILI rates from HPA. Performance evaluation results are available here.

The methodology is described in the following papers:

Tracking the flu pandemic by monitoring the Social Web, Lampos and Cristianini, CIP 2010.

Flu Detector - Tracking Epidemics on Twitter, Lampos, De Bie and Cristianini, ECML PKDD 2010.

Conclusions

- Many diverse case studies, trying to make a single point: standard machine learning technologies can help the social sciences to enter its “big data” (or -omics) phase.

- We started from a single question: can we capture macroscopic scale patterns in the contents of the global media system?
(of the type that a single observer cannot see)

MediaPatterns

Conclusions

- This journey took us to deal with named entity disambiguation, social network analysis, narrative analysis, machine translation, topic detection, sentiment analysis... but also databases, data visualisation, data mining...

- I hope I managed to convey just part of the fun we had (dealing with social scientists, lawyers, psychologists)...

MediaPatterns

Thanks To

Ilias Flaounas, Omar Ali, Elena Hensinger, Bill Lampos, Marco Turchi, Saatviga Sudhahar,
(Intelligent Systems Laboratory, Bristol)

Justin Lewis, Nick Mosdell
(School of Journalism, Cardiff)

Roberto Franzosi
(Emory University)

MediaPatterns.enm.bristol.ac.uk