# MediaMeter: A Global Monitor for Online News Coverage

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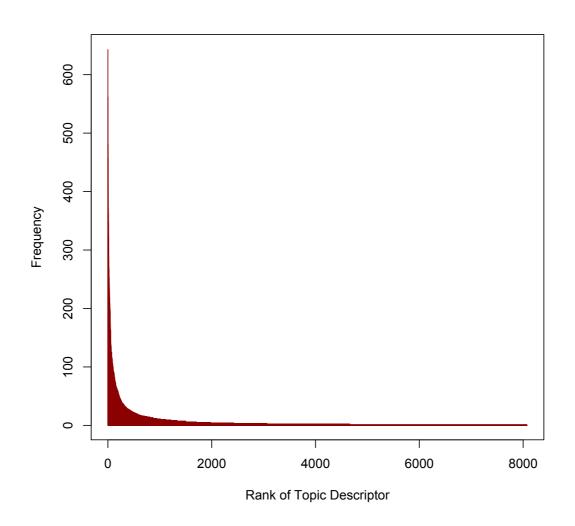
What we are aiming at

Finding novel topics in news streams

So far not much success in the literature (extraction, machine learning)

## Problem

Frequencies of (manually assigned) topic descriptors that appeared in the New York Times from June to December, 2013.



### **Statistics**

1	$\leq 2$	$\leq 5$	$\leq 10$
42.3%	62.0%	78.9%	87.4%

Frequency > 10 : 12.6%

SVM cannot handle a huge taxonomy (Liu, 2005)

The number of unique topics in NYT over 6 months exceeds 8,000.

# Approach

# Memory Based Topic Label Generation

WikiLabel

How it works: Overview

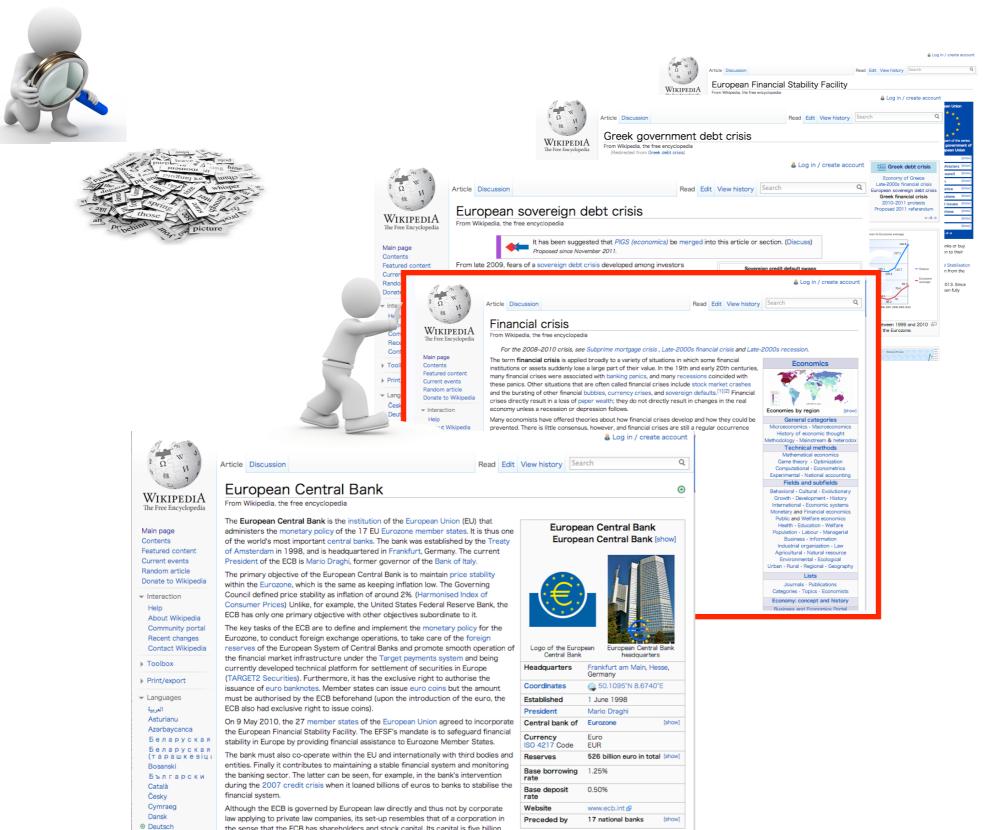
- 1. Look up Wikipedia to find pages most relevant to a news story
- 2. Generate label candidates from page titles
- 3. Pick those that are deemed most fit to represent the content

# WikiLabel: Concept Generation with Wikipedia





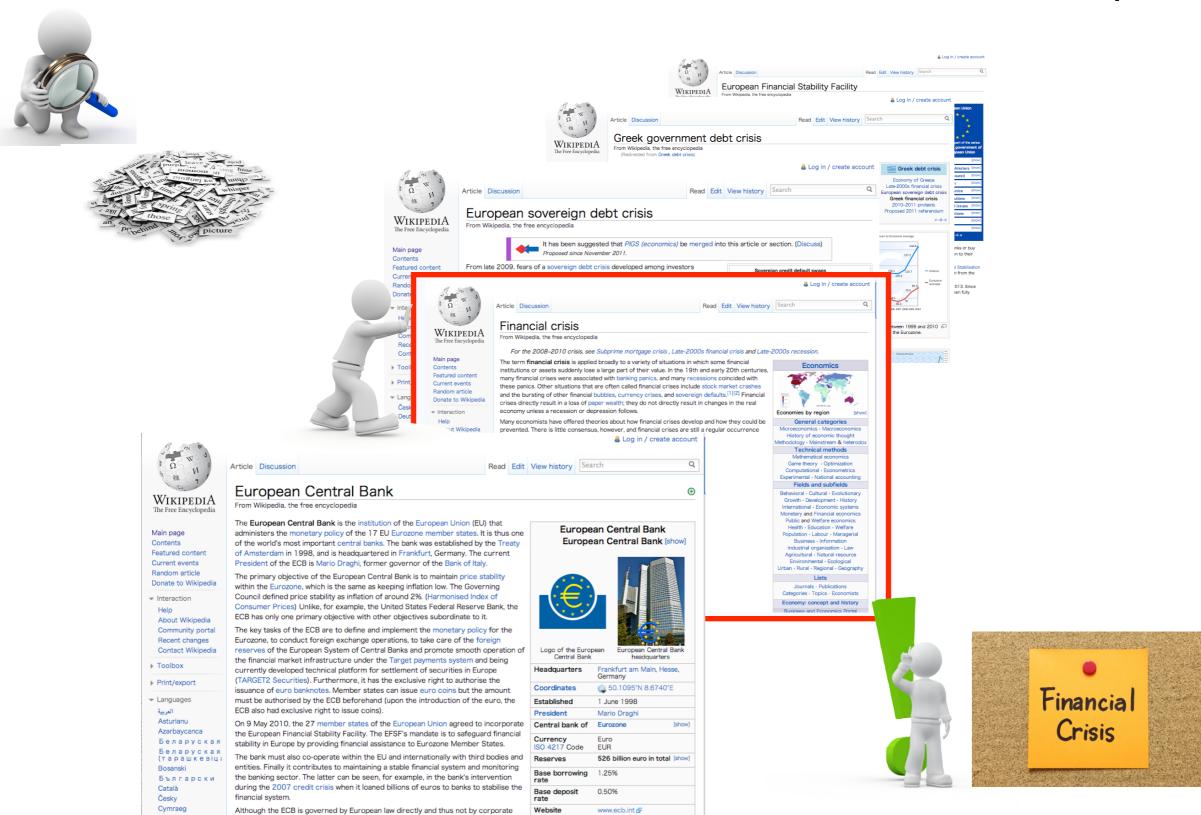
### WikiLabel: Concept Generation with Wikipedia



the sense that the ECB has shareholders and stock capital. Its capital is five billion

euro which is held by the national central banks of the member states as shareholders. The initial capital allocation key was determined in 1998 on the basis of the states' population and GDP, but the key is adjustable. Shares in the ECB are not transferable and cannot be

# WikiLabel: Concept Generation with Wikipedia



17 national banks

Dansk

Deutsch

law applying to private law companies, its set-up resembles that of a corporation in

the sense that the ECB has shareholders and stock capital. Its capital is five billion

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#### **Mechanics**

$$l_{ec{ heta}}^* = rg \max_{l:p[l] \in \mathcal{U}} Prox(p[l])(ec{ heta}|_N),$$
 news story Concept Dictionary

$$Prox(p[l], \vec{\theta}|_{N}) = \lambda Sr(p[l], \vec{\theta}|_{N}) + (1 - \lambda)Lo(l, \vec{\theta})$$

content similarity relevance of label

$$Sr(\mathbf{r}, \mathbf{q}) = \left(1 + \sum_{t}^{N} (\mathbf{q}(t) - \mathbf{r}(t))^{2}\right)^{-1}$$

$$Lo(l, \mathbf{v}) = \frac{\sum_{i}^{|l|} I(l[i], \mathbf{v})}{|l|} - 1$$

$$I(w, v) = \begin{cases} 1 & \text{if } w \in v \\ 0 & \text{otherwise.} \end{cases}$$

What if Wikipedia does not know the event ....

Use sentence compression to generalize

### Example

#### 2009 detention of American hikers by Iran

detention

detention by Iran

detention of hikers

detention of hikers by Iran

detention of American hikers by Iran

2009 detention

2009 detention by Iran

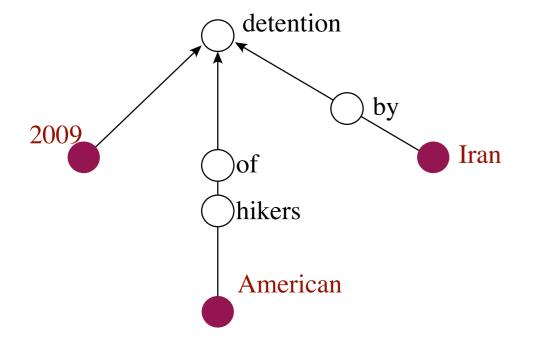
2009 detention of hikers

2009 detention of hikers by Iran

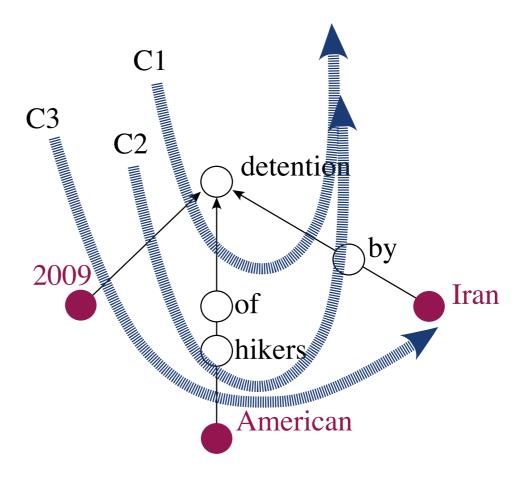
2009 detention of American hikers by Iran

Making it shorter makes it more general

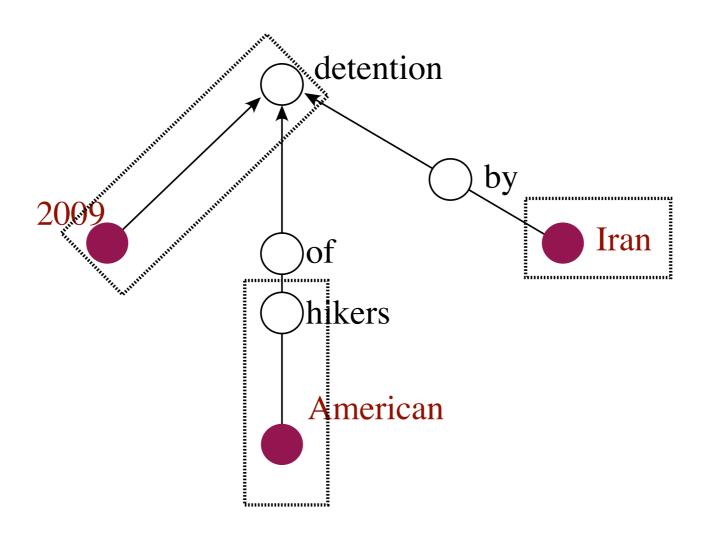
# Dependency pruning

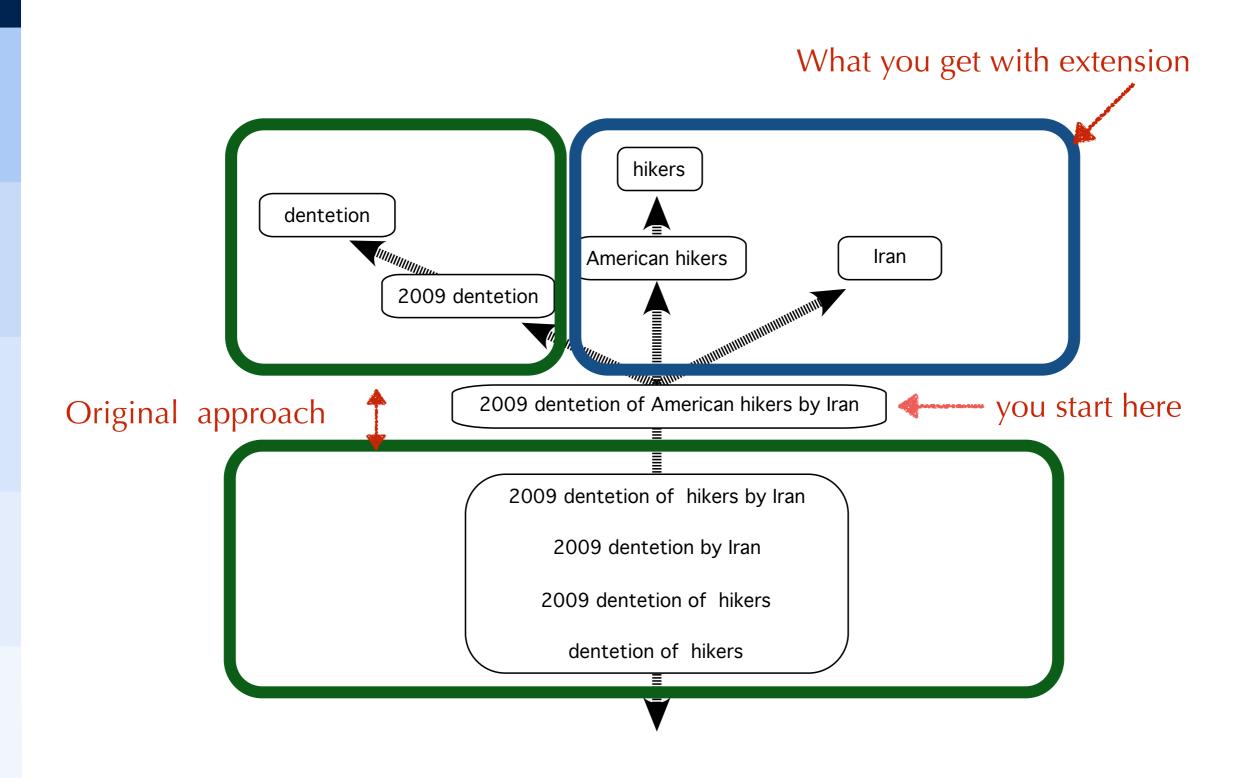






# Use every NP in the title as a resource

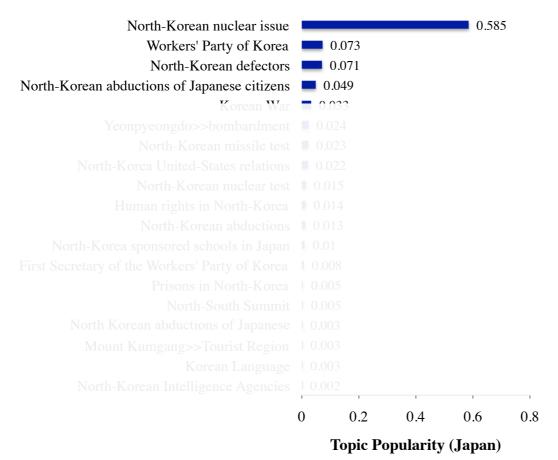


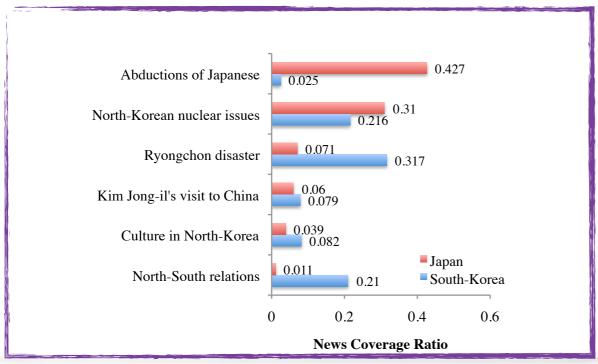


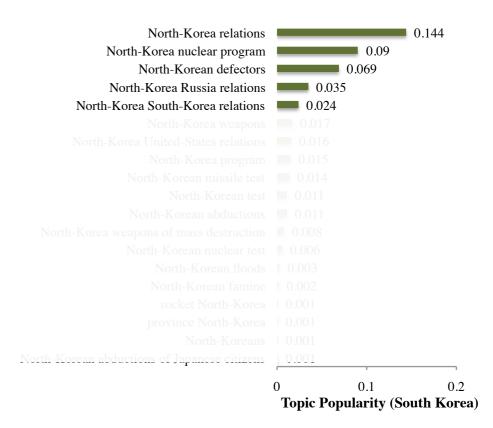
# Testing it out in the field

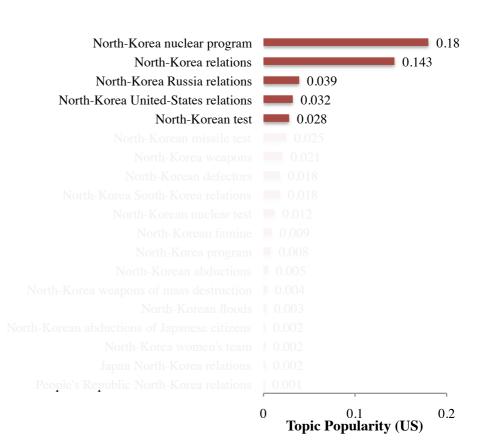
COUNTRY	MEDIA OUTLETS	#outlets	#stories
US/UK	THE NEW YORK TIMES, YAHOO, CNN,	9	2,230 (239,844)
	MSNBC, FOX, WASHINGTON POST, ABC,		
	BBC, REUTERS		
SOUTH-KOREA	JOONGANG ILBO (English edition),	2	2,271(19,008)
	CHOSUN ILBO (English edition)		
JAPAN	ASAHI, JCAST, JIJI.COM, MAINICHI,	11	2,815 (259,364)
	NHK, NIKKEI, SANKEI, TBS, TOKYO, TV-		
	ASAHI, YOMIURI		

#### North-Korean Agenda







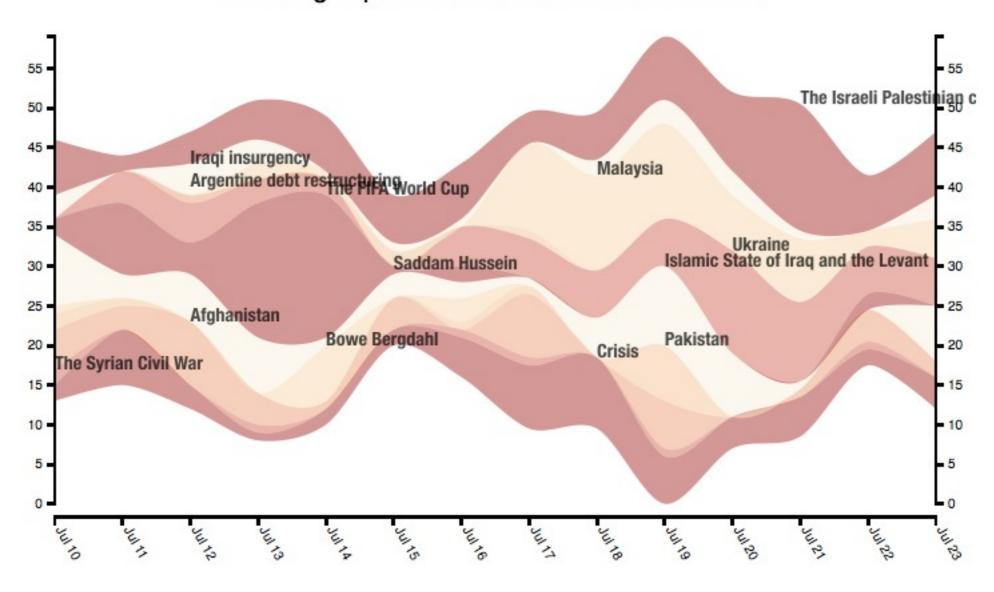


# **Human Evaluation**

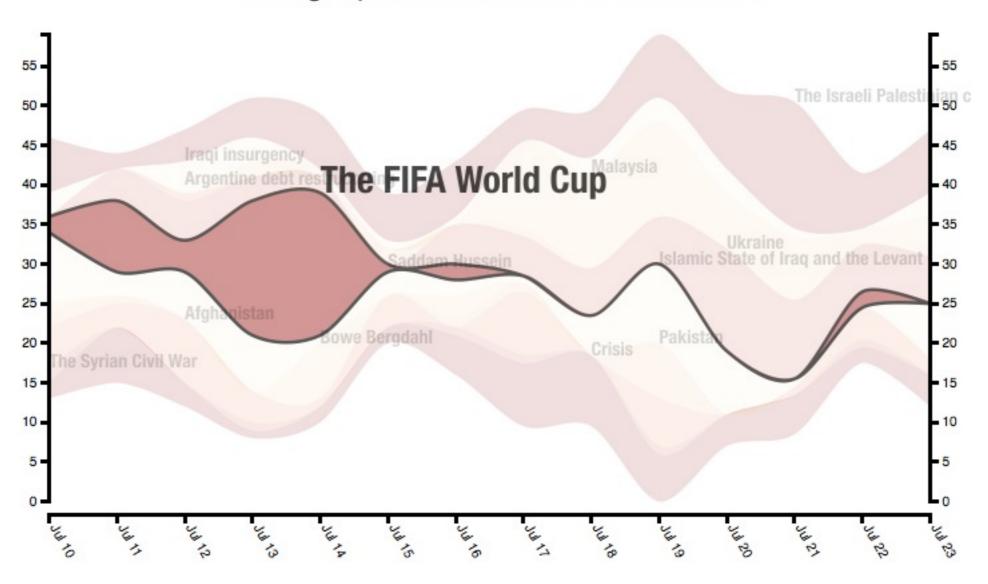
RATING	EXPLANATION
5	Title is one of major topics in Article. Article gives a particular
	attention to Title.
$\parallel$ 4	Part of Article deals with Title. Article makes a clear reference
	to Title.
3	Part of Title has some relevance to a dominant theme of Article.
	Example: Title 'European Tax System' is partially relevant to
	an article discussing US Tax System.
2	Article makes a reference to part of Title.
1	Title has no relevance to Article, in whatever way.

LANGUAGE	RATING	#instances
ENGLISH	4.63	97
JAPANESE	4.41	92

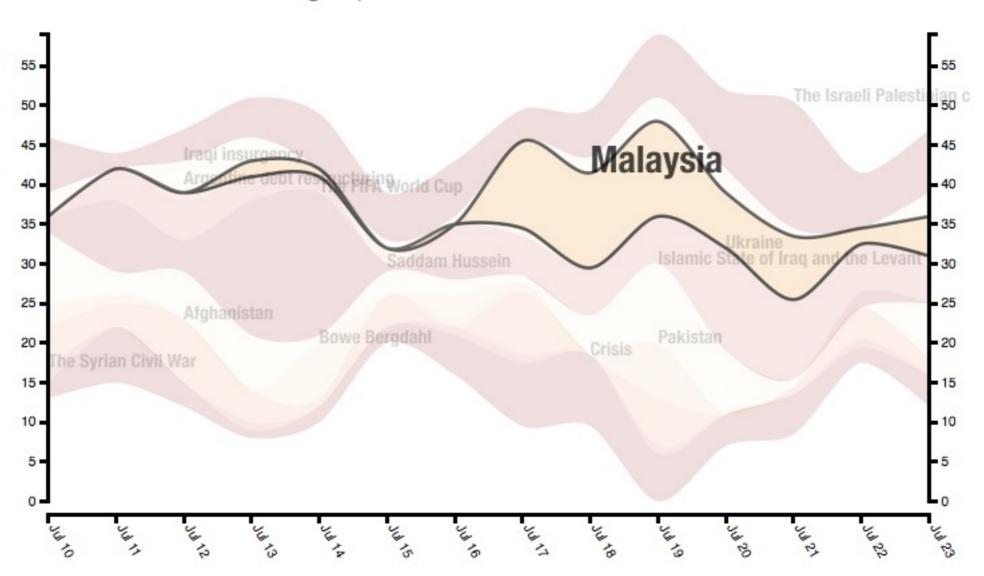
#### Trending Topics in the US Online News Media



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#### **Evaluation Metric: ROUGE-W**

$s_1$	$s_2$	ROUGE-W
The United States of	The United States of America	1
America		
The United States	The United States of America	0.529
States	The United States of America	0.077

$$\mathcal{S}(\mathcal{C}|_k, l) = \frac{1}{k} \sum_{c \in \mathcal{C}|_k} \text{ROUGE-W}(c, l)$$

Results

#### Text Rank vs. WikiLabel

	TRANK	$RM_0$	$RM_1$	$RM_1/X$
NYT	0.000	0.056	0.056	0.069
$\parallel  ext{ TDT } \mid$	0.030	0.042	0.048	$\boldsymbol{0.051}$
FOX*	0.231	0.264	0.264	0.298

New York Times (2013): 19,952

TDT (1994): 15,863

FOX (2015):11,014

Wikipedia (2012)

### Summary

- Talked about topic detection using WikiLabel
- Leveraging Wikipedia
- Generalizing concept with sentence compression
- Use of sentence compression led to a huge improvement, producing performance twice as good as that of TextRank
- Online topic learning seems promising

#### Solution to Problem

Frequencies of (manually assigned) topic descriptors that appeared in the New York Times from June to December, 2013.

