

# **Scalable Detection of Emerging Topics and Geo-spatial Events in Large Textual Streams**

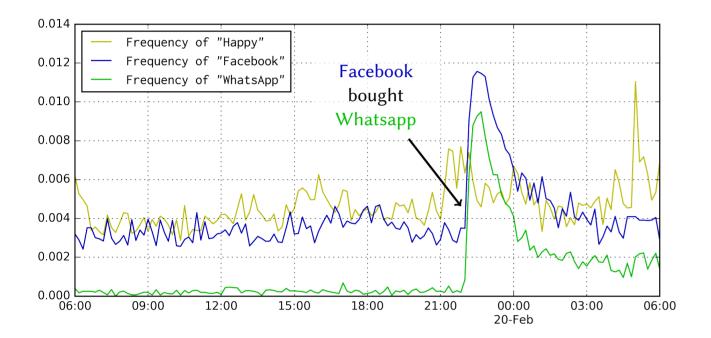


#### **Erich Schubert**<sup>1,2</sup> Michael Weiler<sup>1</sup> Hans-Peter Kriegel<sup>1</sup>

<sup>1</sup> Lehr- und Forschungseinheit Datenbanksysteme, Ludwig-Maximilians-Universität München <sup>2</sup> Lehrstuhl für Datenbanksysteme, Ruprecht-Karls-Universität Heidelberg {schube,weiler,kriegel}@dbs.ifi.lmu.de

# **Objective and Summary**

- Scalable: able to process years of news and Twitter
- Detection: topics and keywords should not need to be defined beforehand
- Emerging: significant increase (c.f. "Trending Topics")
- Topics: not every single message, but groups of related messages are of interest
- Geo-spatial Events: observe locality and able to detect geographic change and differences



# **Change Model and Implementation**

For every word, word-word-, or word-location-pair (w, l)we use a z-score-like significance:

$$z_t(w, l) := \frac{f_t(w, l) - \max \{ \text{EWMA}[f(w, l)], \beta \}}{\sqrt{\text{EWMVar}[f(w, l)]} + \beta}$$

where

- Observed frequency of pair (w, l) $f_t(w, l)$
- Exponentially-weighted moving average EWMA
- EWMVar Exponentially-weighted moving variance
- Laplace-style smoothing term (for rare words) В

Because we cannot afford to store and maintain all EWMA[f(w, l)] values, we employ a Bloom-filter-like hashing strategy to estimate them efficiently.

#### **Bloom-filter / Heavy Hitters**

Counting Bloom filters increment each hash bucket. When estimating counts, the minimum found in the buckets is used as estimate. Here, h = 3 buckets are used:

### **Top Events in News 2014 (Chronological)**

2014-03-08 Malaysia Airlines MH-370 missing in South China Sea 2014-04-17 Russia-Ukraine crisis escalates 2014-04-28 Soccer World Cup coverage: team lineups 2014-07-17 Malaysian Airlines MH-17 shot down over Ukraine 2014-07-18 Russian blamed for 298 dead in airline downing 2014-07-20 Israel shelling Gaza causes 40+ casualties in a day 2014-08-30 EU increases sanctions against Russia 2014-10-22 Ottawa parliament shooting 2014-11-05 U.S. mid-term elections 2014-12-17 U.S. and Cuba relations improve unexpectedly

#### **Top Events in Twitter (2014)**

Score	Date	Keywords	Explanation		
174	03-06	boosi releas jail	Rapper Lil Boosie released from		
			jail early		
154	05-28	rip author poet inspir	Civil rights activist Dr. Maya		
		angelou maya peac dr	Angelou died		
127	05-12	elev jayz attack jay	Solange, Jay Z and Beyonce ele-		
		solang beyonc	vator incident		
98	03-03	ellen degener host selfi	Ellen's Oscar Selfie and Pizza		
		pizza			
76	05-22	ewok	Band 5SOS changed its Twitter		
			name to "Ewok Village"		

# **Key Ideas of our Solution**

- From statistics: control charts for change detection.
- From computational linguistics: Analyze word cooccurrences for more meaningful results.
- From mathematics: Exponentially weighted moving averages for streaming operation.
- From databases: Hashing and Count-Min sketches for scalability to large data.
- From data mining: Clustering of word pairs into simple "topics" based on cooccurrences.
- From visualization: Word-cloud like visualization, but incorporating the relationships of words.
- Integrate geographic information by mapping coordinates to tokens similar to text.
- The *big* challenge is scalability to millions of word pairs, at thousands of Tweets per second!

## **Tracking all Cooccurences**

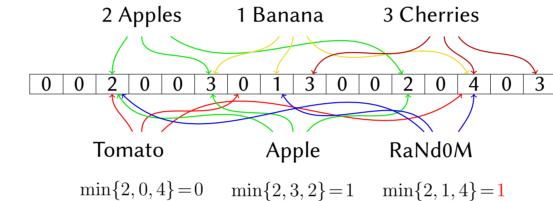
#### Word combinations are interesting:

- "Facebook" bought "WhatsApp"
- Edward "Snowden" traveled to "Moscow"
- "Putin", "Obama" and "Merkel" their interactions are more interesting than their frequency

#### Why not the most popular terms?

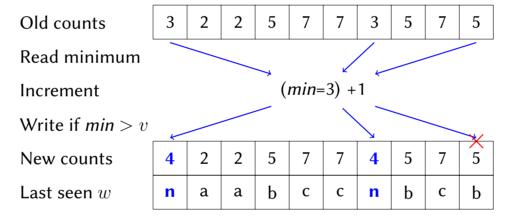
- "@justinbieber" is always popular on Twitter
- Domain specific stopwords (e.g. "follow", "RT")
- Cultural-, language- and geographic differences
- Why word pairs and not just words?

islamic\_state Iraq Syria

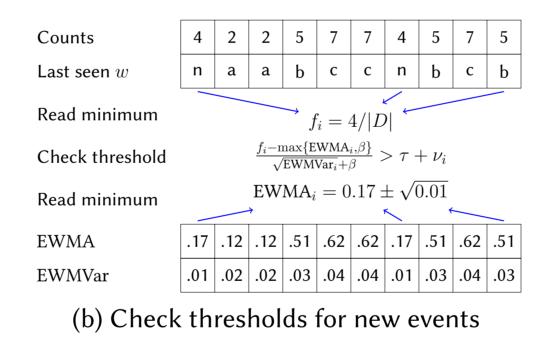


Counting Bloom filters never understimate, but if a term has h hash collisions with more frequent terms, it may overestimate the true frequency.

#### Hash Table Maintenance



(a) Count-min sketch update (new token: n)



Counts	4	2	2	5	7	7	4	5	7	5
Old EWMA	.17	.12	.12	.51	.62	.62	.17	.51	.62	.51
Old EWMVar	.01	.02	.02	.03	.04	.04	.01	.03	.04	.03
								$\downarrow$		
$\Delta \leftarrow x/ D  - \text{EWMA}$										
	$EWMA \leftarrow EWMA + \alpha \cdot \Delta$									
	$EWMVar \leftarrow (1 - \alpha) \cdot (EWMVar + \alpha \cdot$					$-\alpha \cdot$	$\Delta^2$ )			
New EWMA	.28	.16	.16	.50	.66	.66	.28	.50	.66	.50
New EWMVar	.02	.01	.01	.02	.02	.02	.02	.02	.02	.02

76 03-21 bracket mercer duke

63 04-07 geldof dead rip peach

73 05-24 ronaldo bale gareth

60 05-05 shovel

Mercer surprise win over Duke in March Madness Champions league final Peaches Geldof died of heroin 61 04-15 moon eclips lunar blood Blood moon (lunar eclipse) Viral video: "shovel girl fight"

#### **Data Set for SPOTHOT Experiments (2016)**

New geography-oriented data collection:

- 5-6 million geo-tagged tweets per day (no retweets!)
- Estimated 1/3rd of all geo-tagged tweets
- September 10, 2014 to February 19, 2015
- Over 1.1 billion tweets

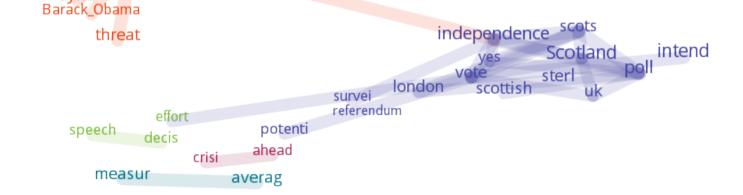
#### Selected top geographies:

Region	Mil.	Share	Region	Mil.	Share
United States	287.7	25.4%	London	7.6	0.67%
Brazil	165.6	14.6%	New York City	7.5	0.66%
Argentina	73.6	6.5%	Tokyo	7.4	0.66%
Indonesia	72.0	6.4%	÷		
Turkey	59.3	5.2%	Germany	3.5	0.31%
Japan	52.4	4.6%	÷		
United Kingdom	49.3	4.4%	Berlin	0.5	0.05%
:			:		

## **Experiment: Most Significant Events**

The most significant words each in its most significant location only:

	0			0
$\sigma$	Time	Word	Location	Explanation
2001.8	2014-10-29 00:59	#voteluantvz	Brazil	Brazilian Music Award 2014
727.8	2014-09-23 02:21	allahımsenbüyüksün	Denizli (Turkey)	Portmanteau used in spam wave
550.1	2015-02-02 01:32	Missy_Elliott	United States of America	Super Bowl Halftime Show
413.5	2014-09-18 21:29	#gala1gh15	Spain	Spanish Big Brother Launch
412.2	2014-11-11 19:29	#murrayftw	Italy	Teen idol triggered follow spree
293.8	2014-10-21 12:05	#tarıkgüneşttyapıyor	Marmara Region	Hashtag used in spam wave
271.2	2015-02-02 02:28	#masterchefgranfinal	Chile	MasterChef Chile final
268.1	2015-01-30 19:28	سباركيز #	Saudi Arabia	Amusement park "Sparky's"
257.7	2014-11-16 21:44	gemma	United Kingdom	Gemma Collins at jungle camp opening
249.1	2014-10-08 02:56	rosmeri	Argentina	Rosmery González joined Bailando 2014
223.1	2015-01-21 18:51	otortfv	Central Anatolia Region	Keyword used in spam wave
212.7	2014-09-11 18:58	#catalansvote9n	Catalonia	Catalan referendum requests
208.4	2014-12-02 20:00	#cengizhangençtürk	Northern Borders Region	Hashtag used in spam wave
205.3	2015-01-04 15:56	hairul	Malaysia	Hairul Azreen, Fear Factor Malaysia
198.7	2014-12-31 15:49	あけましておめでとうございます	Japan	New Year in Japan
198.5	2015-01-10 20:19	ВК	<b>Russian Federation</b>	"Russian Facebook" VK unavailable
179.7	2014-10-04 16:28	#hormonestheseries2	Thailand	Hormones: The Series Season 2
174.7	2014-11-28 21:29	chespirito	Mexico	Comedian "Chespirito" died
160.9	2014-09-21 21:27	#ss5	Portugal	Secret Story 5 Portugal launch
157.3	2014-09-24 01:57	maluma	Colombia	Maluma on The Voice Kids Colombia



Pairs allow the discovery of interactions and structure.

#### Integrating Geographic Information

We map geographic data to tokens

 $\rightarrow$  {Symbol, ...} (longitude, latitude)

#### such that nearby locations produce the same symbol. Example tokenization of a Tweet:

Presenting	g a	novel	event	detection	method	at	#SSDBM2016	in	Budapest	:-)
present		novel	event_	detection	method		#ssdbm2016	Q1	781:Budap	est i)
(stem)	(stop	)	(e	ntity)		(stop)	(normalized)	(stop)	(entity)	(norm.)
47.5323	19.05	530								

#### (!geo0!46!18)(!geo1!48!18)(!geo2!48!20)

(Overlapping grid cells) (!geo!Budapest)(!geo!Budapesti\_kistérség)(!geo!Közép-Magyarország)(!geo!Hungary (Hierarchical semantic location information)

(c) Vectorized statistics table update

# **Experiments**

### **Data Set for SigniTrend Experiments (2014)**

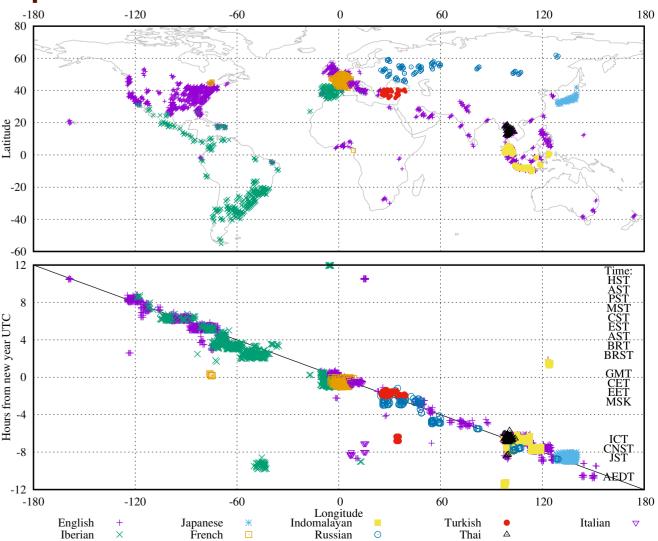
News: articles from 2013 of Reuters and Bloomberg news. Twitter: 114 days of the 1% Twitter sample, originally 279 million tweets before filtering duplicates, retweets, and non-English tweets.

StackOverflow: dump of the main programming Q&A site for years 2010 to 2013.

Data set	Documents	Paragraphs	Unique Words	Total Words	Unique Pairs	Total Pairs
News	424,704	5,867,457	300,141	56,661,782	71,289,359	660,430,059
Twitter	94,127,149	94,127,149	25,581,022	245,140,695	179,105,233	473,871,456
StackOverflow	5,932,320	30,423,831	2,040,932	138,205,636	91,460,397	545,570,530

#### Data set statistics (after stopword removal)

#### **Experiment: New Year Around the World**



E. Schubert, M. Weiler, and H.-P. Kriegel. "SigniTrend: Scalable Detection of Emerging Topics in Textual Streams by Hashed Significance Thresholds". In: Proc. KDD. 2014, pp. 871-880 E. Schubert, M. Weiler, and H.-P. Kriegel. "SPOTHOT: Scalable Detection of Geo-spatial Events in Large Textual Streams". In: Proc. SSDBM. 2016, 8:1-8:12