

Evolutionary Hierarchical Dirichlet Processes for Multiple Correlated Time-varying Corpora

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Outline

- Motivation
- Preliminaries
- Evolutionary HDP
- Experiments
 - Synthetic data
 - Finance related online document collections
- Conclusions

Motivation

- Mining cluster evolution patterns in multiple correlated time-varying corpora



Markets end lower

News: World braces for insurer AIG's crash

Congress wrestles with Wall Street bailout package

Obama, McCain debate economic, foreign policy...

Blogs: Financial crash: A system in chaos

Preparing for a Financial Crisis

Bailout people, not banks

Message boards: Do I have to tell my landlord I lost my job?

Is Obama a US citizen

Canceling my shopping

An example of online textual data from three corpora: news, blogs, and message boards.

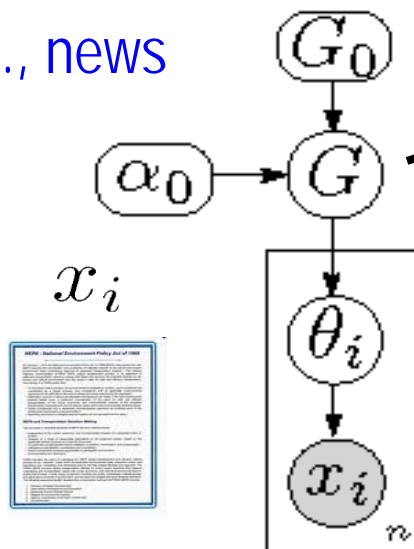
Motivation (Cont')

- Patterns to discovery
 - Clusters within each corpus at each epoch
 - Shared clusters among different corpora
 - Evolving of clusters within a corpus and across corpora overtime
- Challenges
 - Single integrated model
 - Commonality & diversity
 - Time dependencies
 - Cluster numbers
- Previous works
 - Multiple corpora
 - Time-varying corpus, evolutionary clustering

Preliminaries

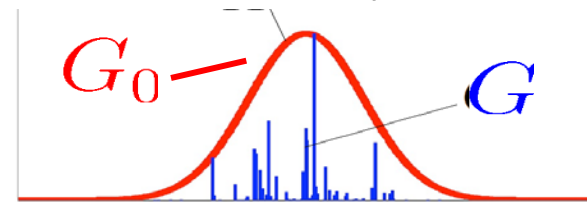
- Dirichlet process mixture models (DPM)
 - DPM: (prior) infinite mixture model which can automatically determine the component number by placing a Dirichlet process (DP) prior for a mixture model

A text corpus, e.g., news



The DP prior

$$G \sim \text{DP}(\alpha_0, G_0)$$

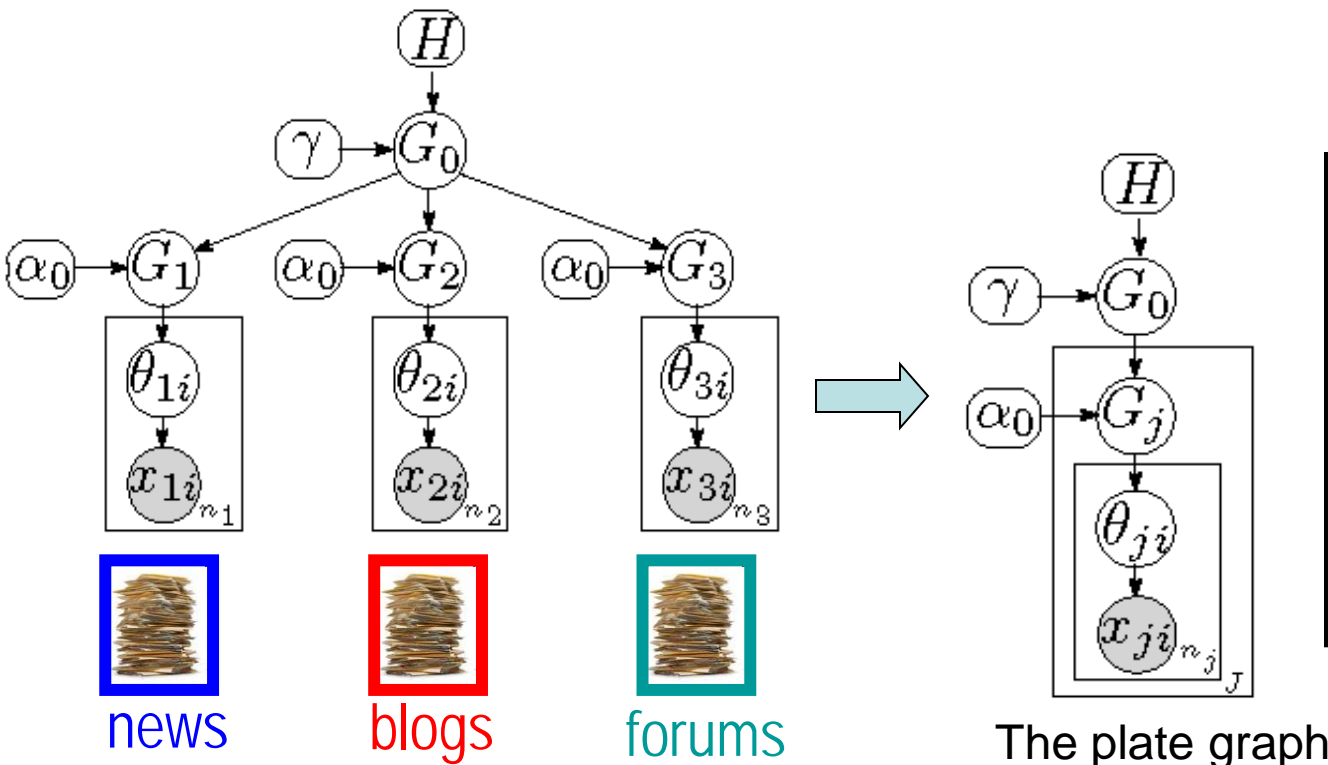


$\theta_i \in \{\text{politics, market, companies, ...}\}$

$$\theta_i \sim G, x_i \sim F(x|\theta_i)$$

Preliminaries (Cont')

- HDP mixture model: to model multiple corpora to enable them sharing components
 - Multiple DPMs sharing a same DP prior

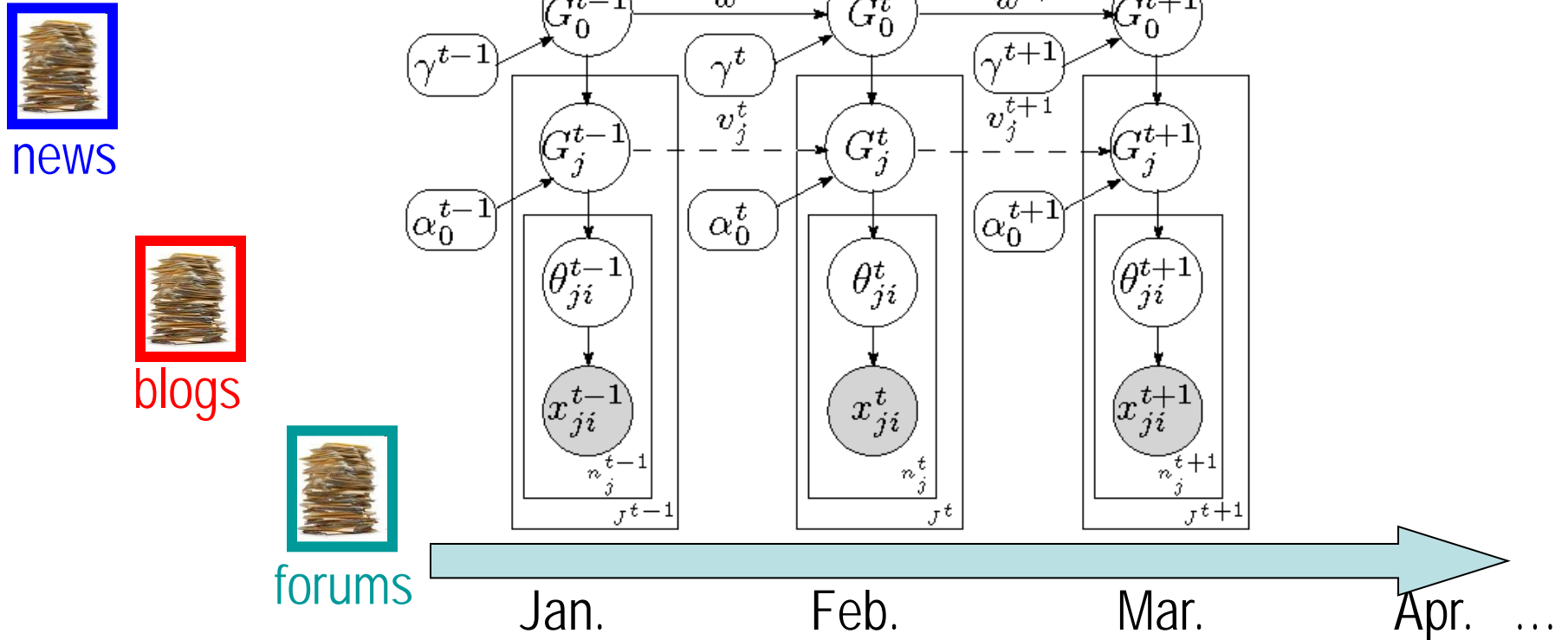


HDP: Multiple DPMs sharing a same DP prior with its parameter drawn from another DP

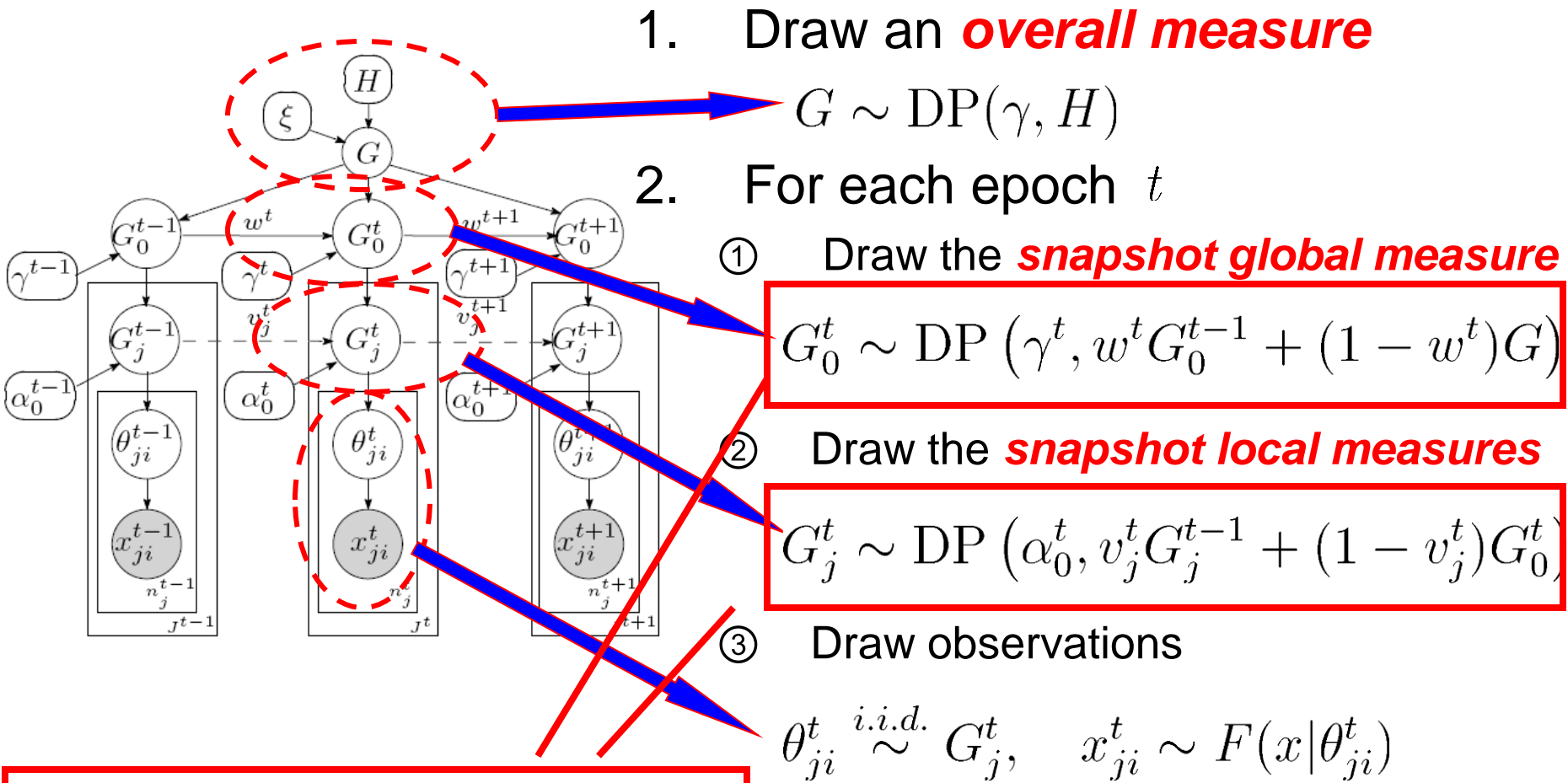
The plate graph

Evolutionary HDP

- Modeling multiple time varying corpora



Evolutionary HDP (Cont')



The time dependency model

The time dependency model

G : plays as a bookkeeper of all the components
(the common taste)

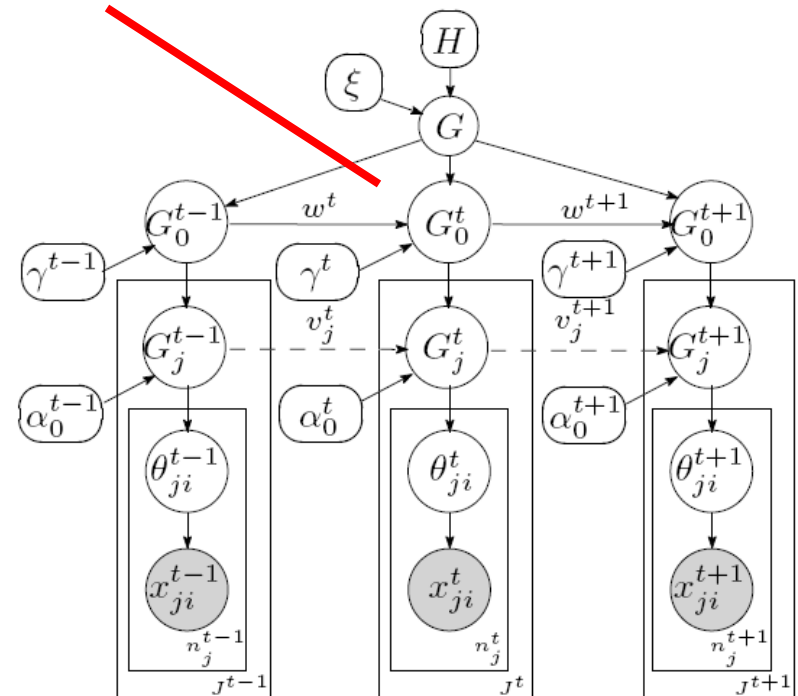
$$G_0^t \sim \text{DP}(\gamma^t, w^t G_0^{t-1} + (1 - w^t)G)$$

A part of the atoms of G_0^t are drawn from the previous one G_0^{t-1} while others are drawn from G

Some are inherited from the previous, and some are newly from the common taste.

$$G_j^t \sim \text{DP}(\alpha_0^t, v_j^t G_j^{t-1} + (1 - v_j^t)G_0^t)$$

Similarly...



More...

- Different perspectives to the model (necessary to lead to the sampling scheme)
- Gibbs sampling to infer the model

(Detailing and boring. If you are interested in, we're appreciated if you would like to read the paper instead)

Experiments

- Synthetic data
- Real financial related web text collections

Experiments on synthetic data

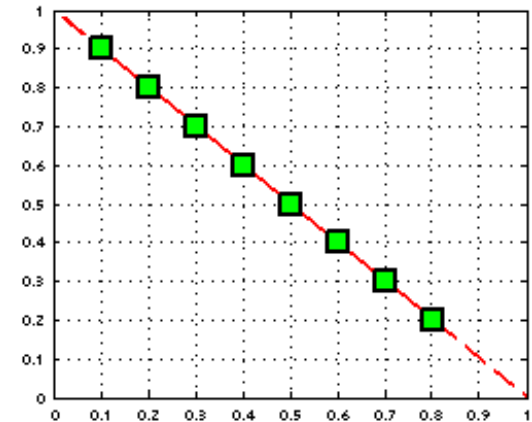
$$p_j^t(x) = \sum_{\tau=1}^3 \frac{1}{3} \text{Multinomial} \left(x; \phi_{k_{j\tau}^t} \right)$$

2-dimensional multinomial

Table 1: Synthetic data set.

Global components (dishes)								
k	1	2	3	4	5	6	7	8
$\phi_{k,1}$	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8

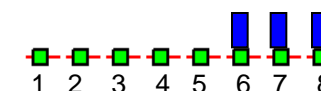
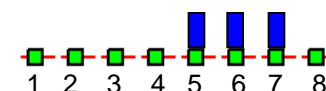
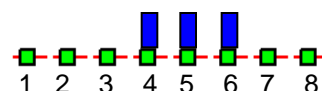
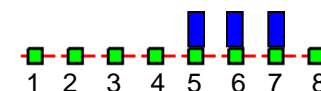
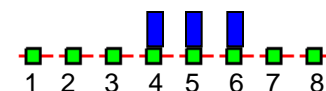
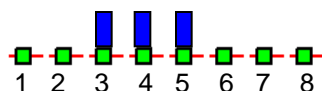
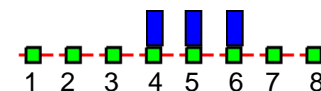
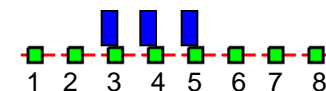
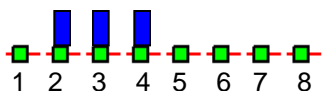
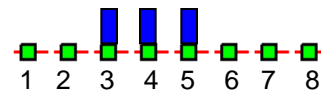
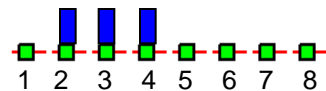
Local components (tables) and corpora sizes						
	Tables ($k_{j1}^t, k_{j2}^t, k_{j3}^t$)			Corpora sizes n_j^t		
	$j=1$	$j=2$	$j=3$	$j=1$	$j=2$	$j=3$
$t=1$	1, 2, 3	2, 3, 4	3, 4, 5	500	300	400
$t=2$	2, 3, 4	3, 4, 5	4, 5, 6	510	320	430
$t=3$	3, 4, 5	4, 5, 6	5, 6, 7	520	320	430
$t=4$	4, 5, 6	5, 6, 7	6, 7, 8	530	340	450



$j = 1$

$j = 2$

$j = 3$



**Three corpora,
four time epochs**

t

Evaluation criteria

- Static criteria

- NMI

- $\log(\textit{perword-perplexity})$ *LogPerp*

$$-\frac{1}{n_{test}} \sum_{t,j,i} \log p(x_{ji,test}^t | Model, X_{train})$$

- Temporal criteria

- Temporal correlations / divergences overtime

- Compared to HDP without considering time dependencies

Better predict ability

Better clustering performance

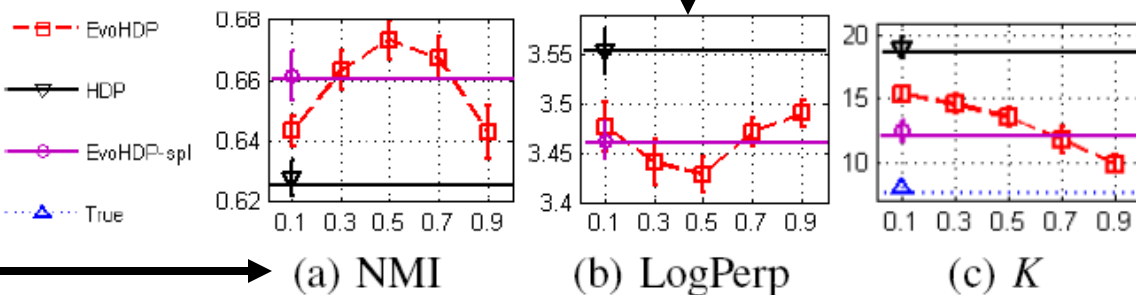


Figure 6: Results on the synthetic data set: static performances, averaged on 10-fold cross validation.

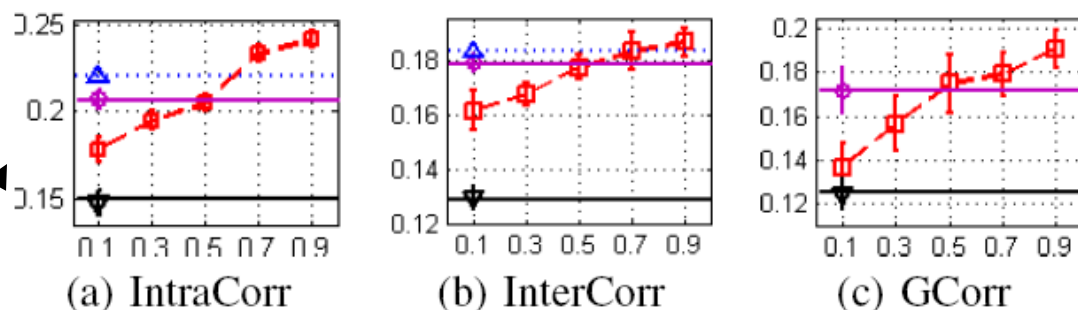


Figure 7: Results on the synthetic data set: temporal correlations, averaged on 10-fold cross validation.

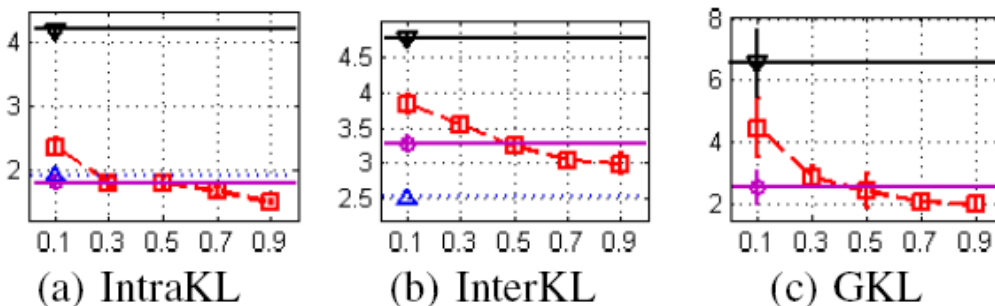
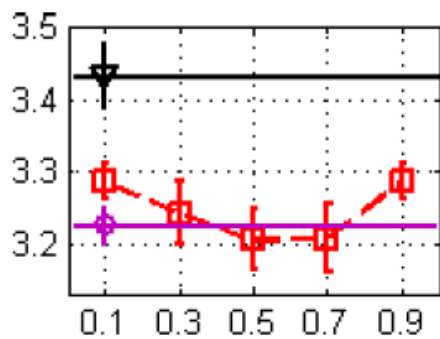


Figure 8: Results on the synthetic data set: temporal divergences, averaged on 10-fold cross validation.

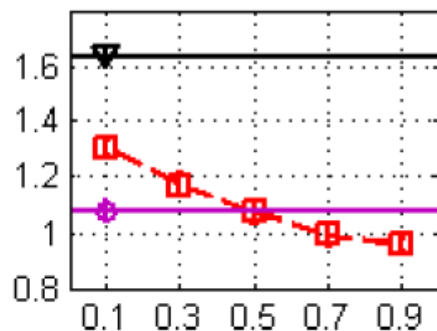
Stronger correlation overtime

Experiments on Real Data

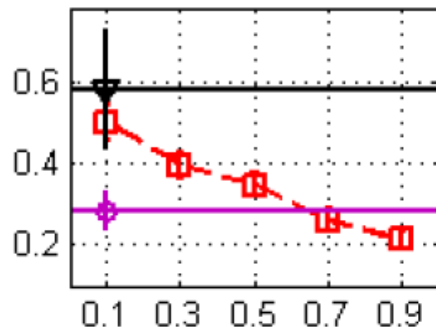
- 103,986 text articles queried from a search engine *Boardreader*.
- Financial related. Queries: 20 financial companies' names, e.g., “AIG insurance”, “Bank of America”, etc.
- Three types. News, blogs, message boards.
- 6 months, Jul. 2008 – Dec. 2008
- Dictionary size $W = 77,999$



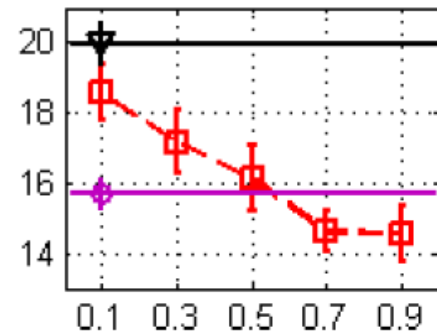
(a) LogPerp



(b) InterKL

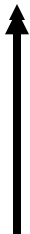


(c) GKL

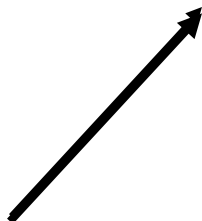


(d) K

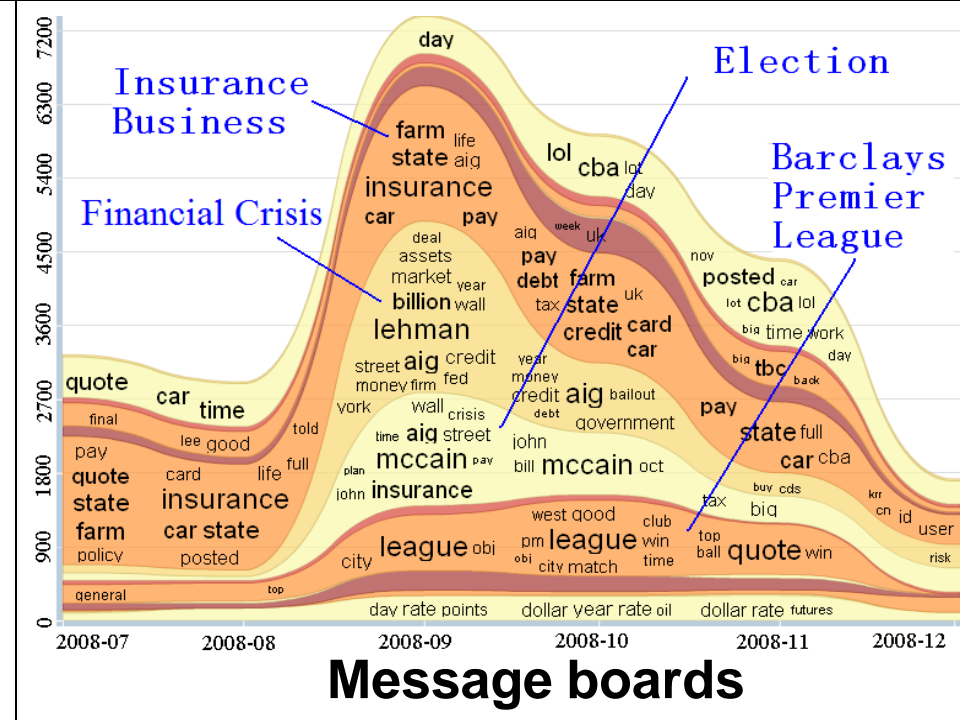
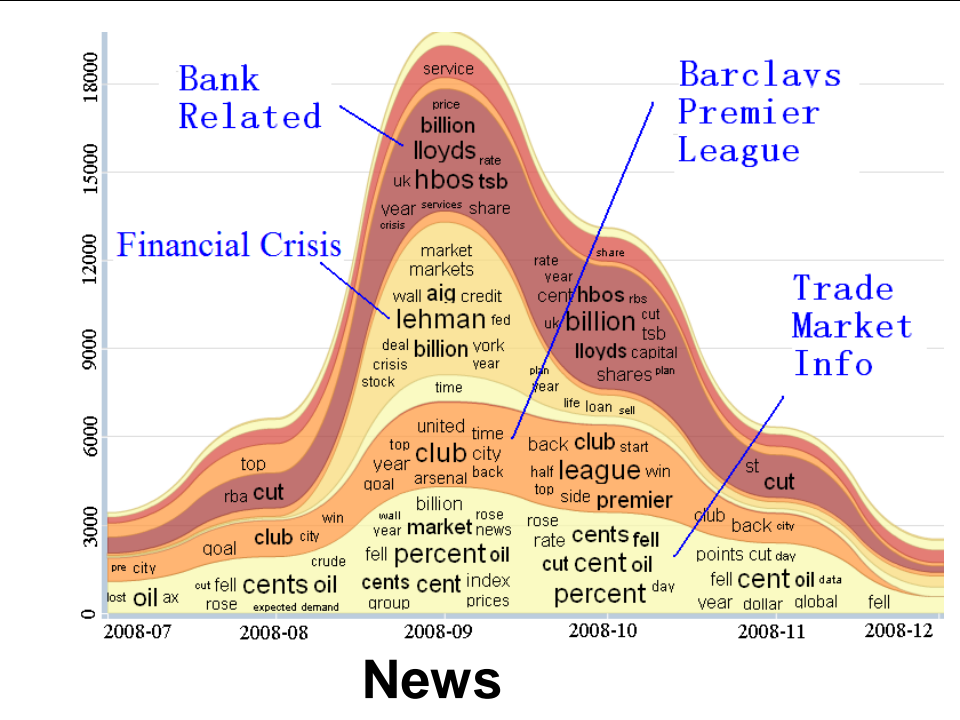
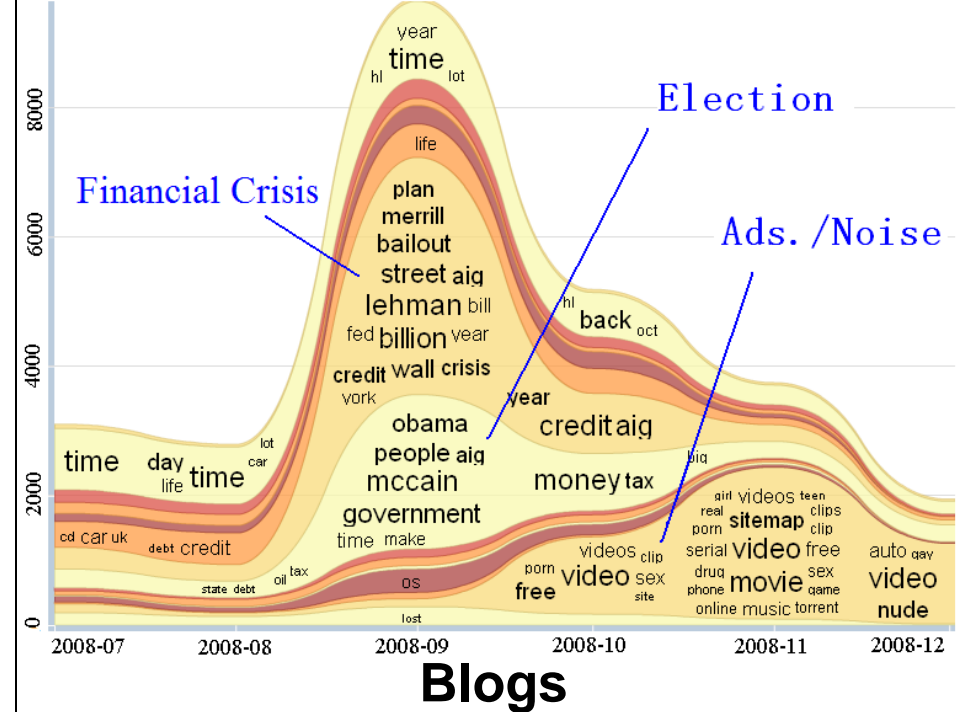
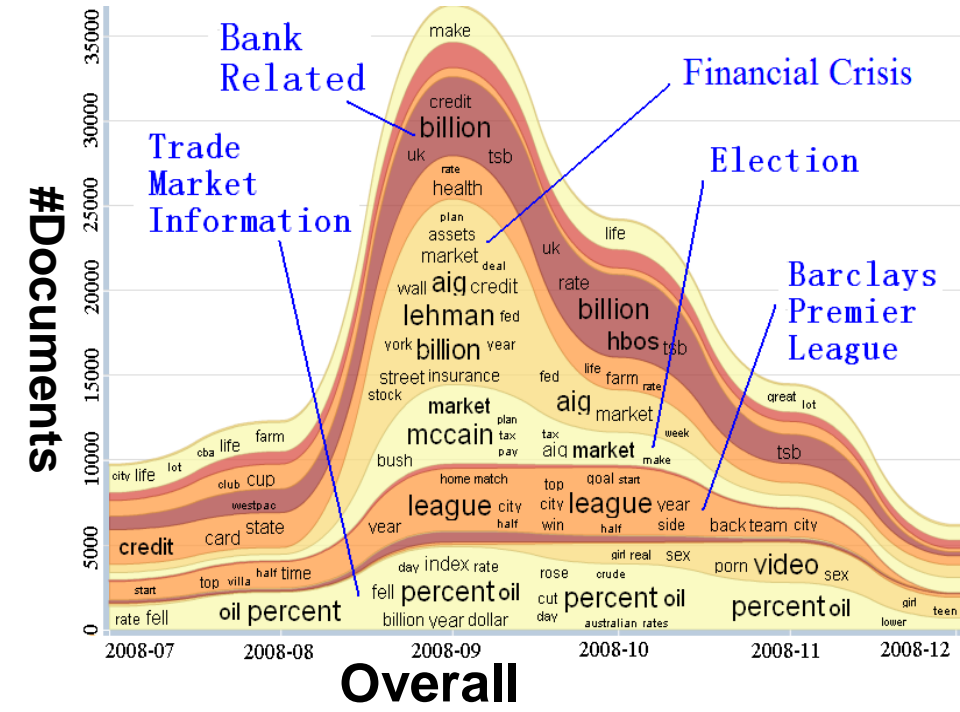
**Better predict
ability**



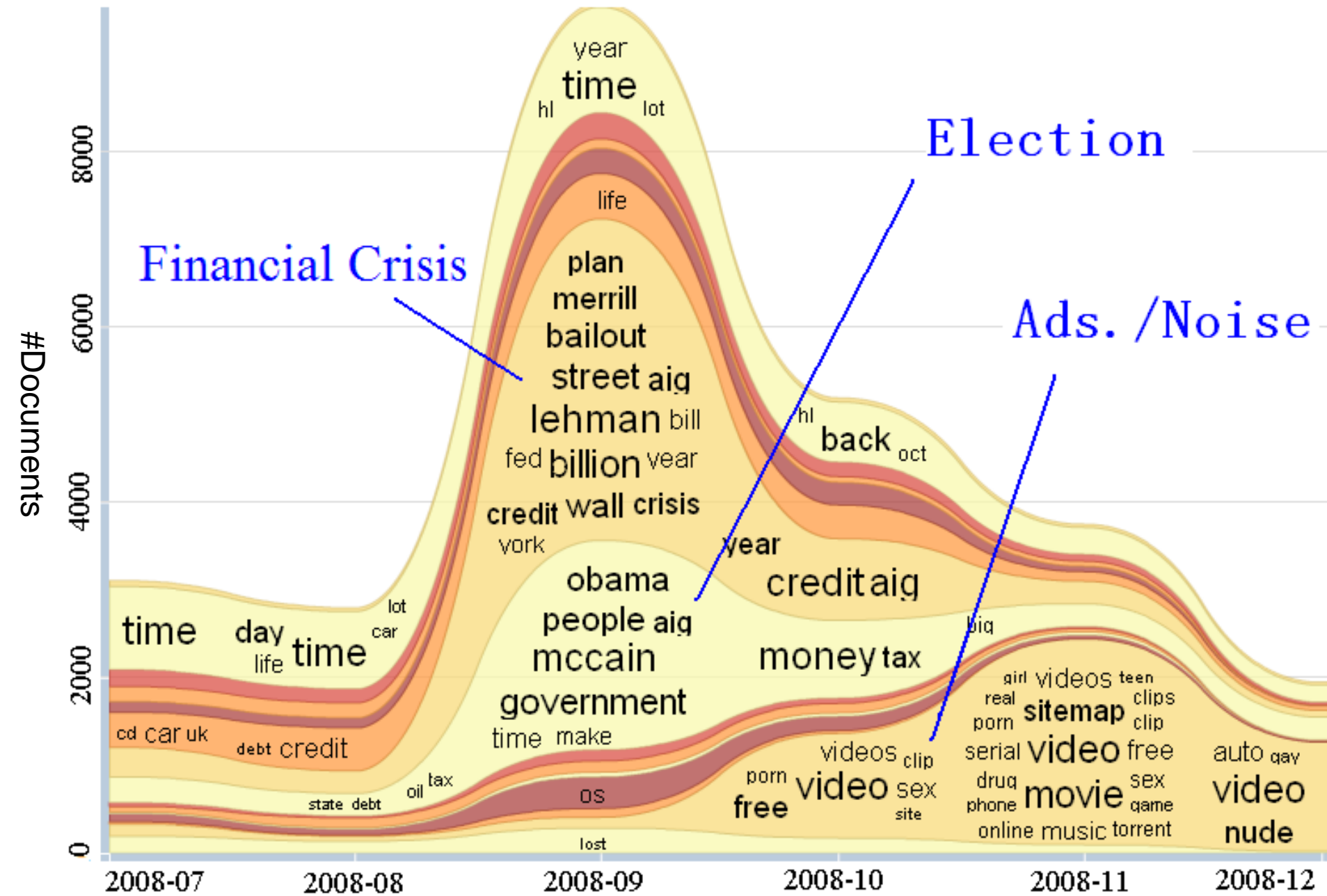
**Stronger correlation
overtime**



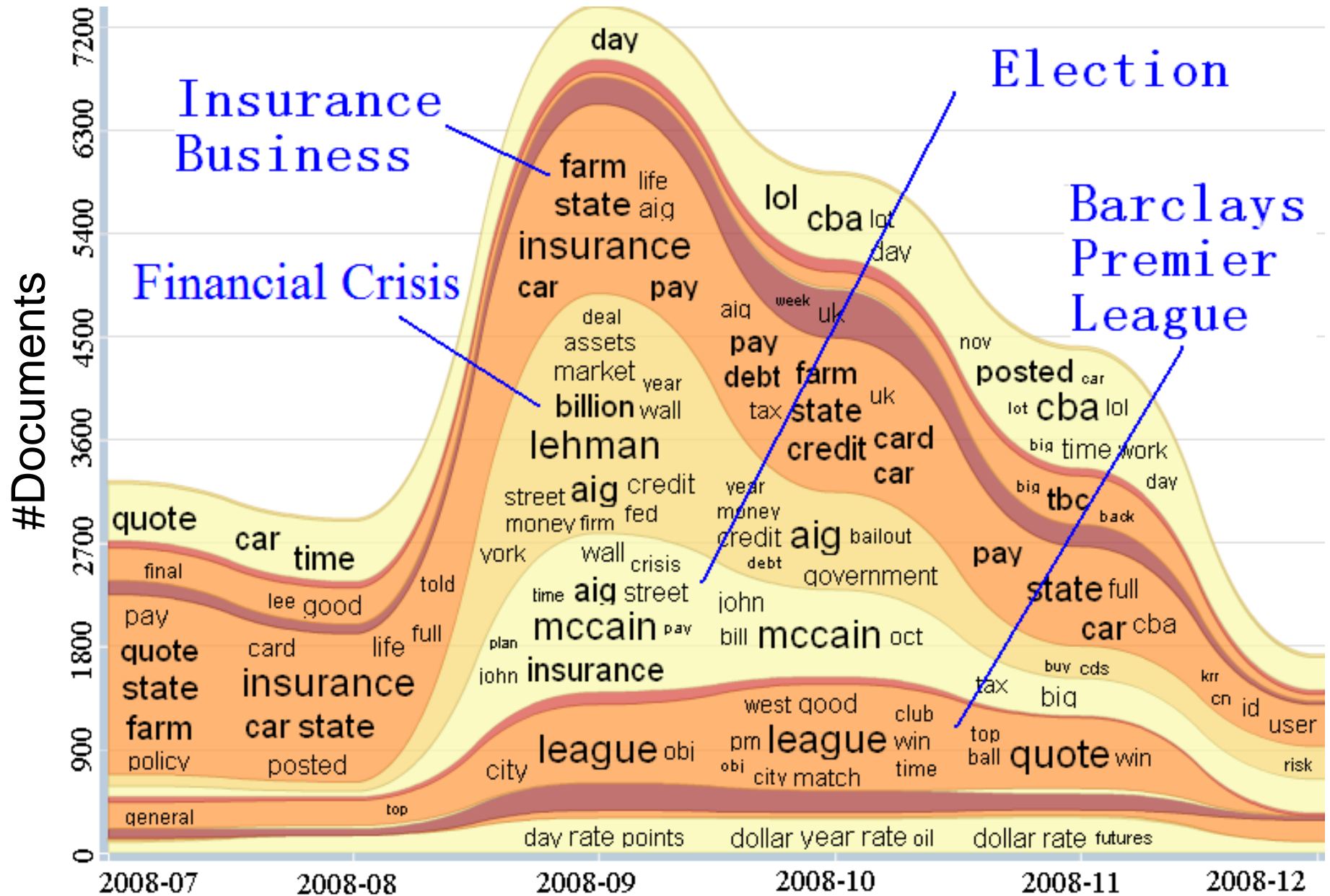
Visualization of clusters utilizing the time-based topic visualization tool TIARA (Liu et al. CIKM'09)



Blogs



Message Boards



Conclusions

- An EvoHDP model to mine cluster evolution patterns from multiple correlated time-varying corpora
- Extension of the original HDP
- Gibbs sampling
- Better predicting ability and stronger correlations across corpora overtime
- Cluster evolution patterns in real financial related web data

Thank You!!!

