Information Cascades: Topic Detection & Tracking

Social Computing

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Lecture Topics

- Topic Detection
- Topic Tracking
- Early Prediction

Matrix Factorization for Topic Detection

Topic Detection

Tweets

Computer technology: 2-Tone L.E.D. to Simplify Screens

Stock Market: A Better Deal For Investors Isn't Simple. Large Sale 03/02

The Shape of Cinema, Transformed At the Click of a Mouse. Movie production.

The three big Internet portals begin to distinguish among themselves as shopping malls

Topic Detection

Topics

Computer	**0.02**
Technology	**0.03**
System	**0.04**
Internet	**0.01**
...	

Sale	**0.02**
Product	**0.03**
Market	**0.02**
Consumer	**0.04**
...	

Film	**0.05**
Movie	**0.04**
Theater	**0.02**
Production	**0.04**
...	

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A **topic** is a distribution over words

Topic Detection

TF/IDF

Topics		Tweets	Assignments

Computer 0.02
Technology 0.03
System 0.04
Internet 0.01
...

Sale 0.02
Product 0.03
Market 0.02
Consumer 0.04
...

Film 0.05
Movie 0.04
Theater 0.02
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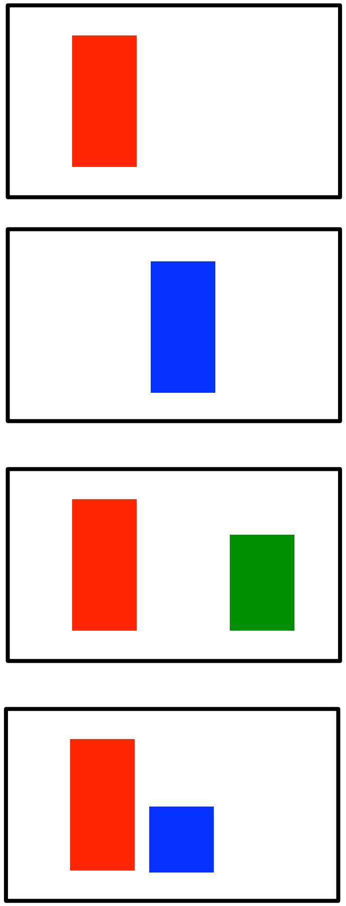


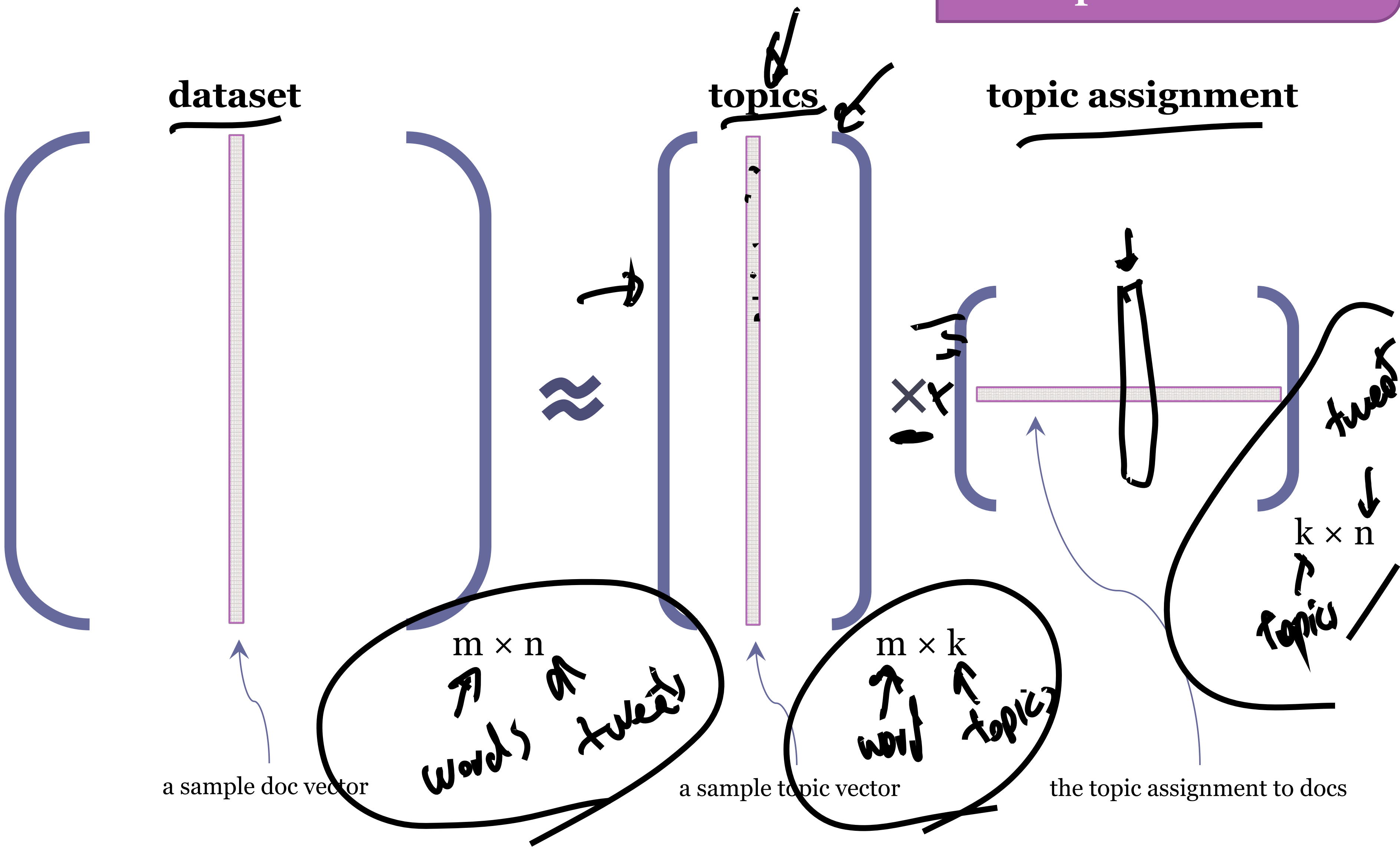
A **topic** is a distribution over words
A **tweet** is a mixture of topics / distribution over topics

Topic Detection

- Different learning techniques
- Matrix factorization methods
  - LU decomposition
  - Singular Value Decomposition(SVD)
  - Probabilistic Matrix Factorization(PMF)
  - (Online) Non-negative Matrix Factorization(NMF)
  - Etc.

Topic Detection - NMF

m: # **terms** in the dataset
n: # **docs** in the dataset
k: # **topics** in the dataset



Topic Detection - NMF

m: # **terms** in the dataset
n: # **docs** in the dataset
k: # **topics** in the dataset

$$\underset{m \times n}{\overset{\textbf{dataset}}{\begin{pmatrix} & & \\ & S & \\ & & \end{pmatrix}}} \approx \underset{m \times k}{\overset{\textbf{topics}}{\begin{pmatrix} \\ D \\ \\ \end{pmatrix}}} \times \underset{k \times n}{\overset{\textbf{topic assignment}}{\begin{pmatrix} & X & \end{pmatrix}}}$$

Topic Detection - NMF

m: # **terms** in the dataset
n: # **docs** in the dataset
k: # **topics** in the dataset

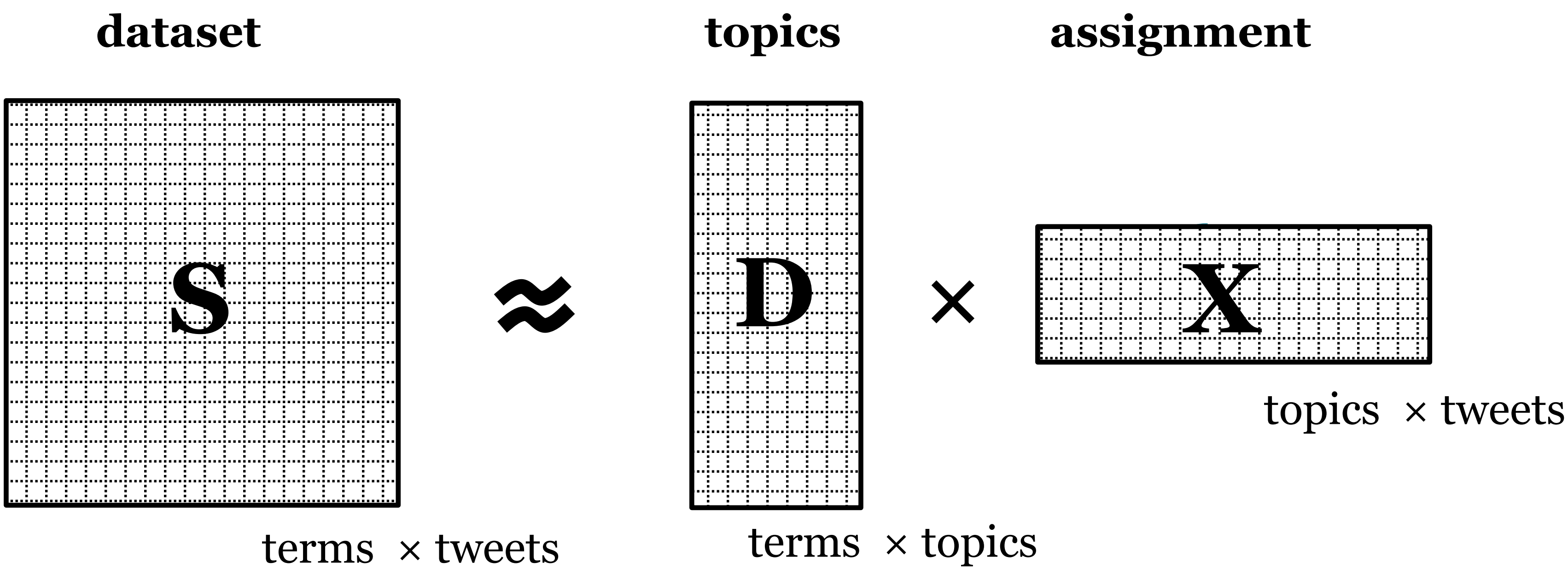
dataset		topics		topic assignment
$\mathbf{S}_{m \times n}$	$\approx$	$\mathbf{D}_{m \times k}$	$\times$	$\mathbf{X}_{k \times n}$

α

$$(\mathbf{D}, \mathbf{X}) = \mathbf{arg\,min}_{\,\mathbf{D},\mathbf{X}} \left\| \mathbf{S} - \mathbf{D}\mathbf{X} \right\|_F^2 + \lambda \left\| \mathbf{X} \right\|_1$$

s.t. $\mathbf{X} \geq \mathbf{0}$, $\mathbf{D} \geq \mathbf{0}$, $\|\boldsymbol{d_i}\| = \mathbf{1}$ *for* $i = \{1,\ldots k\}$

Topic Detection - NMF



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$$\text{s.t. } \mathbf{X} \geq \mathbf{0}, \mathbf{D} \geq \mathbf{0}, \|\boldsymbol{d}_i\| = \mathbf{1} \textit{ for } i = \{1,\ldots k\}$$

Source: Paatero and Tapper, 1994; Lee and Seung, 1999; Chih-Jen Lin, 2007

Topic Detection - NMF

$$(\mathbf{D}, \mathbf{X}) = \mathbf{arg\,min}_{\mathbf{D},\mathbf{X}} \left\| \mathbf{S} - \mathbf{D}\mathbf{X} \right\|_F^2 + \lambda \left\| \mathbf{X} \right\|_1$$

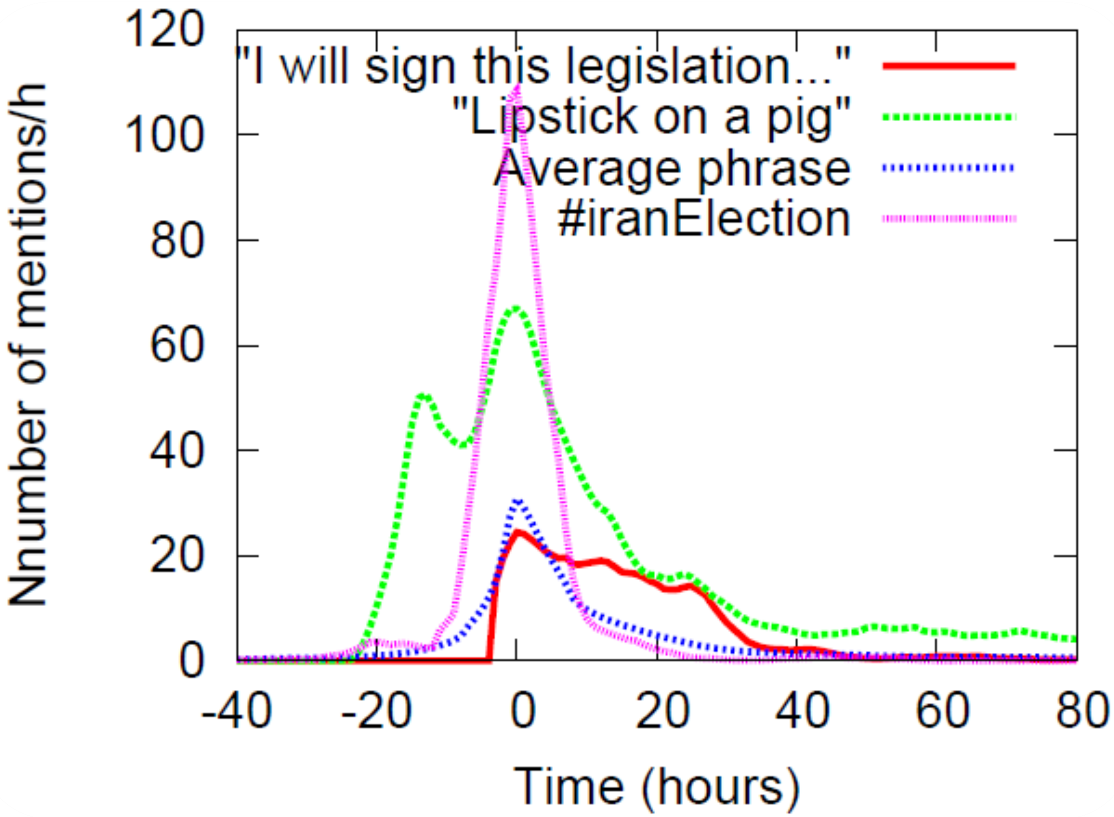
s.t. $\mathbf{X} \geq \mathbf{0}$, $\mathbf{D} \geq \mathbf{0}$, $\|\boldsymbol{d}_i\| = \mathbf{1}$ *for* $i = \{1,\ldots k\}$

- Non-convex optimization problem.
  - many local optimum.
- But, if one of the variables, either **D** or **X**, is known, optimization wrt the other will be convex.
  - Solution:
    - Iteratively optimize the objective function
      - Alternatively optimize wrt **D** and **X** while holding the other fixed!

Topic Tracking

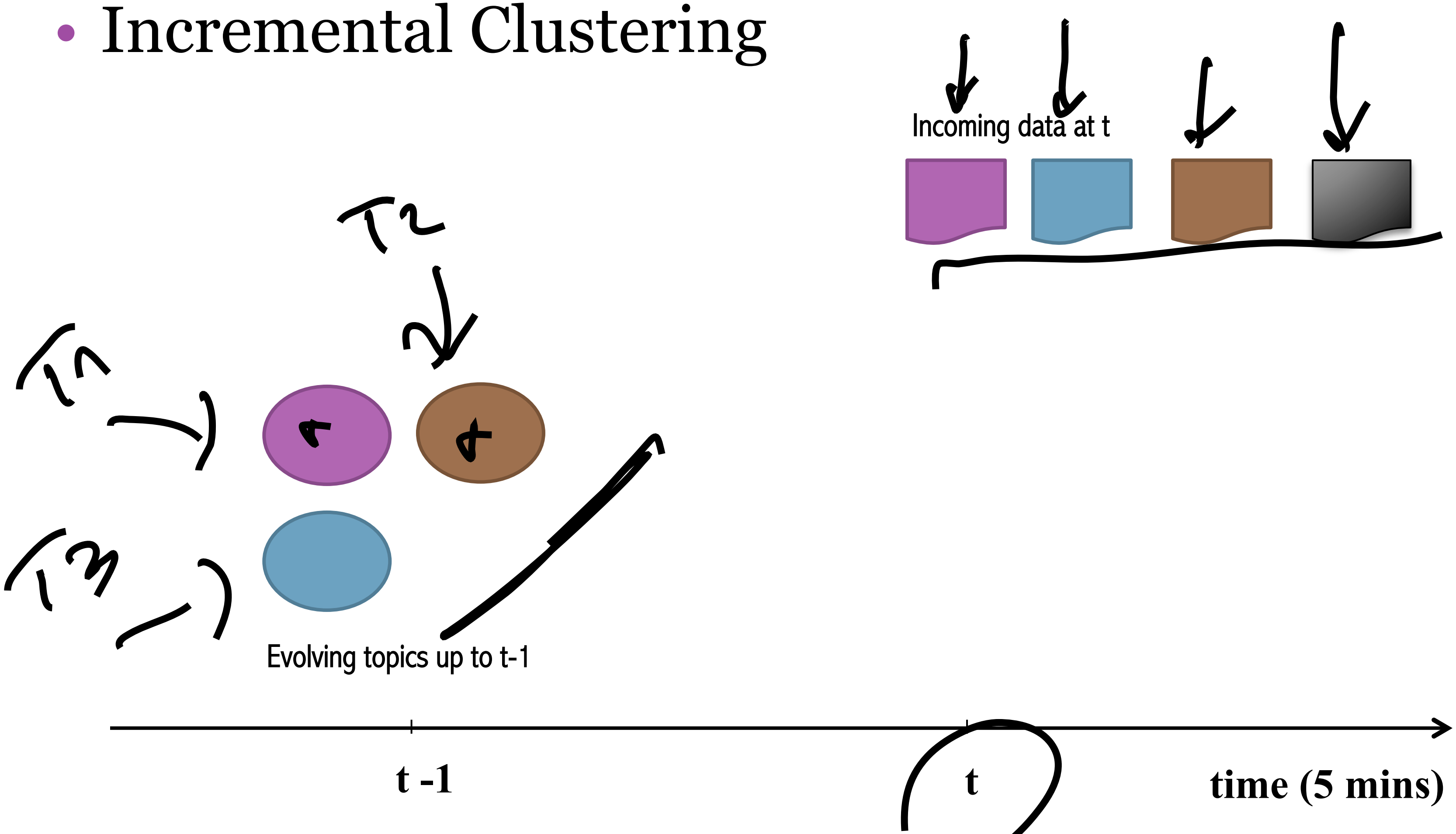
Topic Tracking

- Smooth evolution of topics through time



Topic Tracking

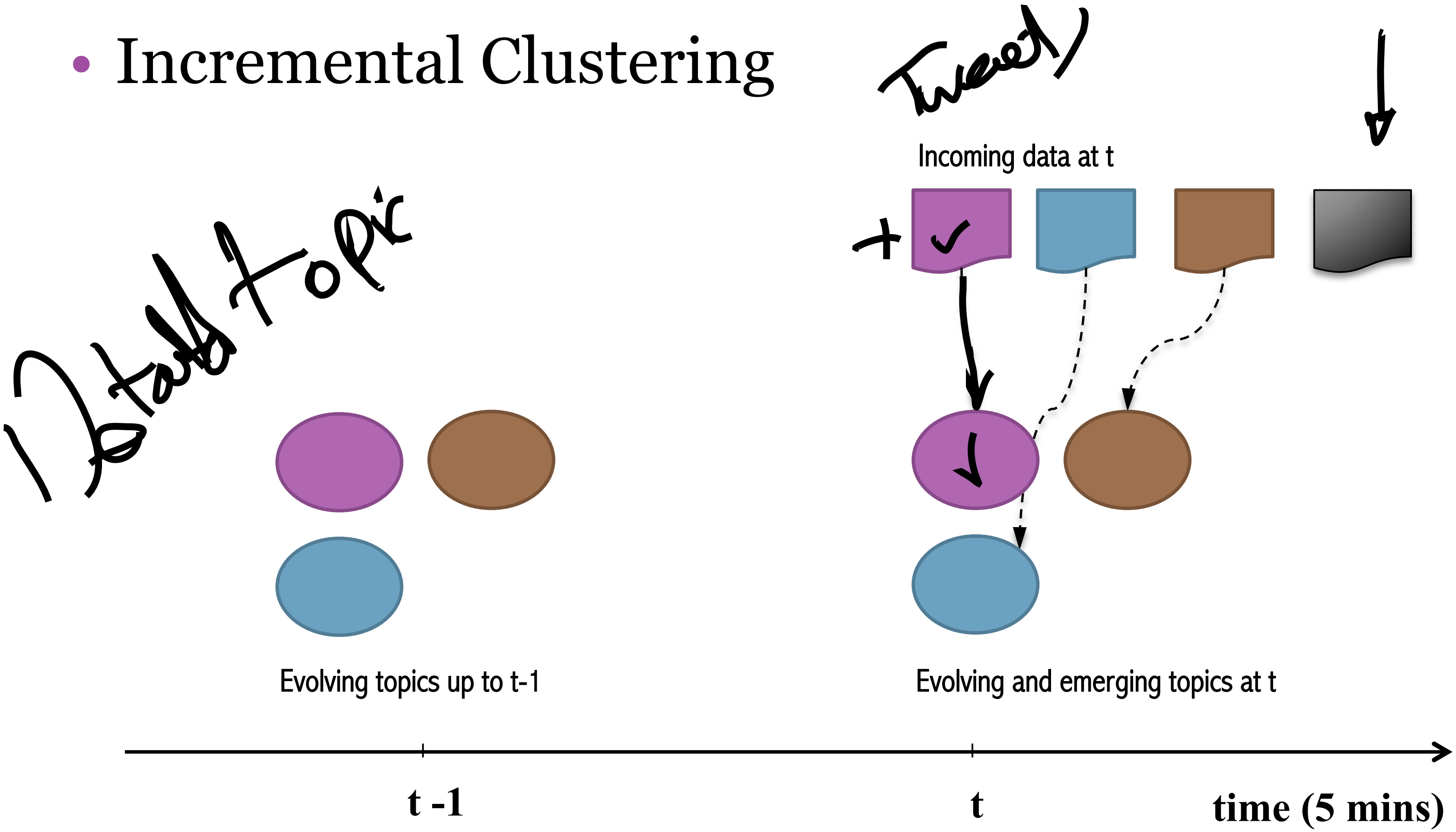
- Incremental Clustering



Evolving topic: a previously identified topic.
Emerging topic: new topics

Topic Tracking

- Incremental Clustering



Evolving topic: a previously identified topic.
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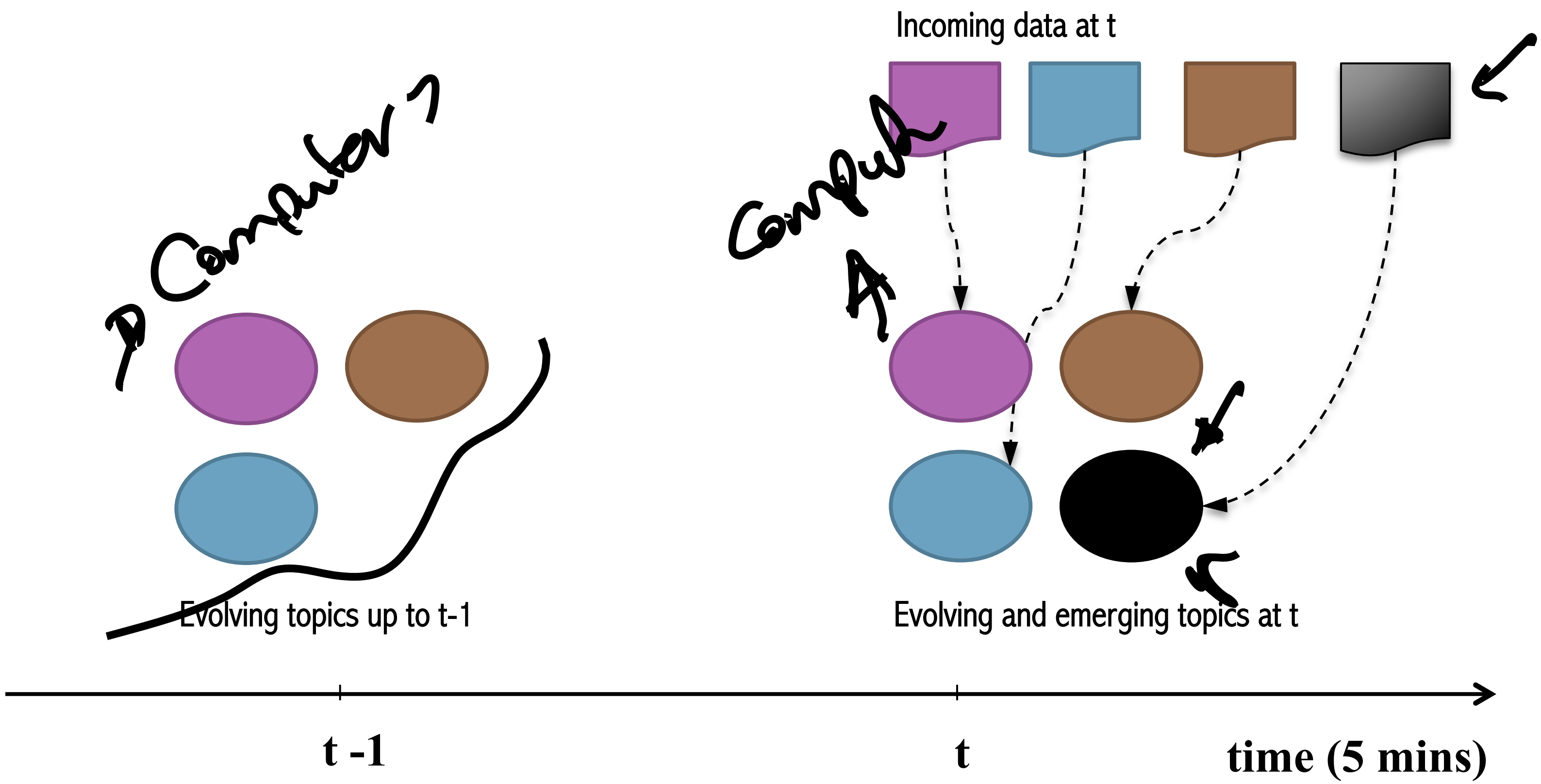
Topic Tracking

- Incremental Clustering



Evolving topic: a previously identified topic.
Emerging topic: new topics

Topic Tracking

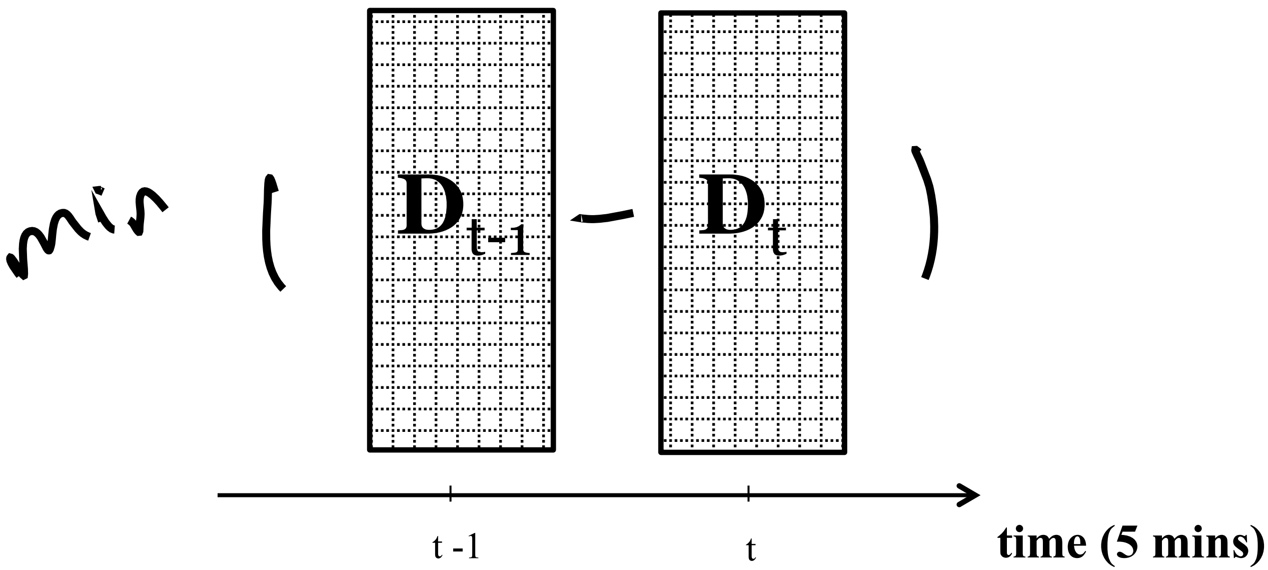
- Incremental Clustering for Topic Discovery

  - Compute similarity btw each incoming tweet and each cluster center.
  - If the maximum similarity value is greater than τ , assign the tweet to the cluster and update cluster center.
  - Otherwise, generate a new cluster and cluster center.
  - *faster* approach: Minhash or LSH

Input: tweet sets D, topic cluster set C, cluster cente
set $Center$, and threshold τ.
Output: update topic clusters C, and update cluster centers $Center$.
Process:
if $C = \emptyset$ **then**
    random select N tweets from D and add into C and $Center$.
end if
initialize max, tmp_C, tmp_{center}.
for $d_i \in D$ **do**
    for $center_j \in Center$ **do**
        compute Cosine Similarity sim between $center_j$ and d_i.
        if $sim > max$ **then**
            $max = sim$, $tmp_C = C_j$, $tmp_{center} = center_j$.
        end if
    end for
    if $max > \tau$ **then**
        distribute d_i to cluster tmp_C, and update tmp_{center}.
    else
        new cluster and centroid and add to C and $Center$.
    end if
end for
return C and $Center$.

Topic Tracking

- **Key Idea**: Temporal Coherence, smooth evolution

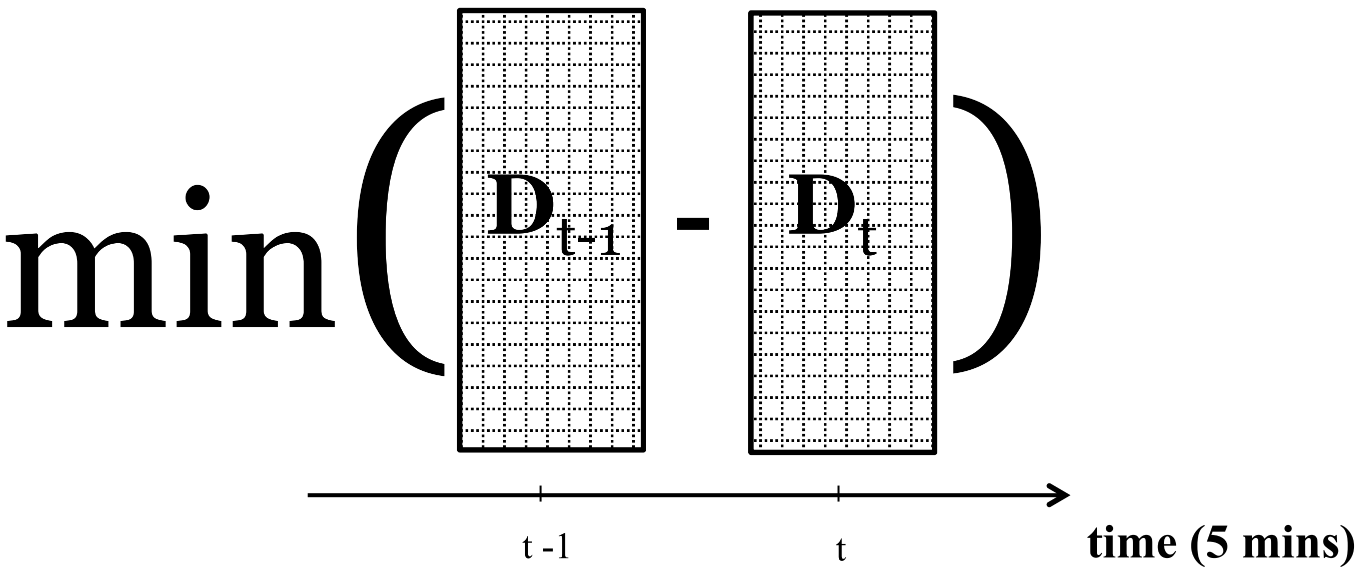


D at *t* to be a smooth evolution of **D** at *t-1*

No dramatic change in distribution over words for the same **evolving** topic in consecutive time stamps.
The nature of the topic remains the same.

Topic Tracking

- **Key Idea**: Temporal Coherence, smooth evolution



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Topic Tracking

$$\mathcal{L}(\mathbf{D}) = \| \mathbf{S} - \mathbf{D}\mathbf{X} \|_F^2 + \lambda \| \mathbf{X} \|_1 + \mu \| \mathbf{D} - \mathbf{D}^{t-1} \|_F^2$$

$$\mathcal{H}[\mathcal{L}(\mathbf{D})] = \mathbf{X}\mathbf{X}^T + 2\mu \mathbf{I}_k \qquad \mathbf{D}_{i+1} = P\left[\mathbf{D}_i - \alpha_i \nabla_{\mathbf{D}} \mathcal{L}(\mathbf{D})_{[\mathbf{D}_i, \mathbf{X}]}\right]$$

Algorithm 5.2. Computing $\mathbf{D}^t$ and $\mathbf{X}^t$ at time t, see TL in Figure 4

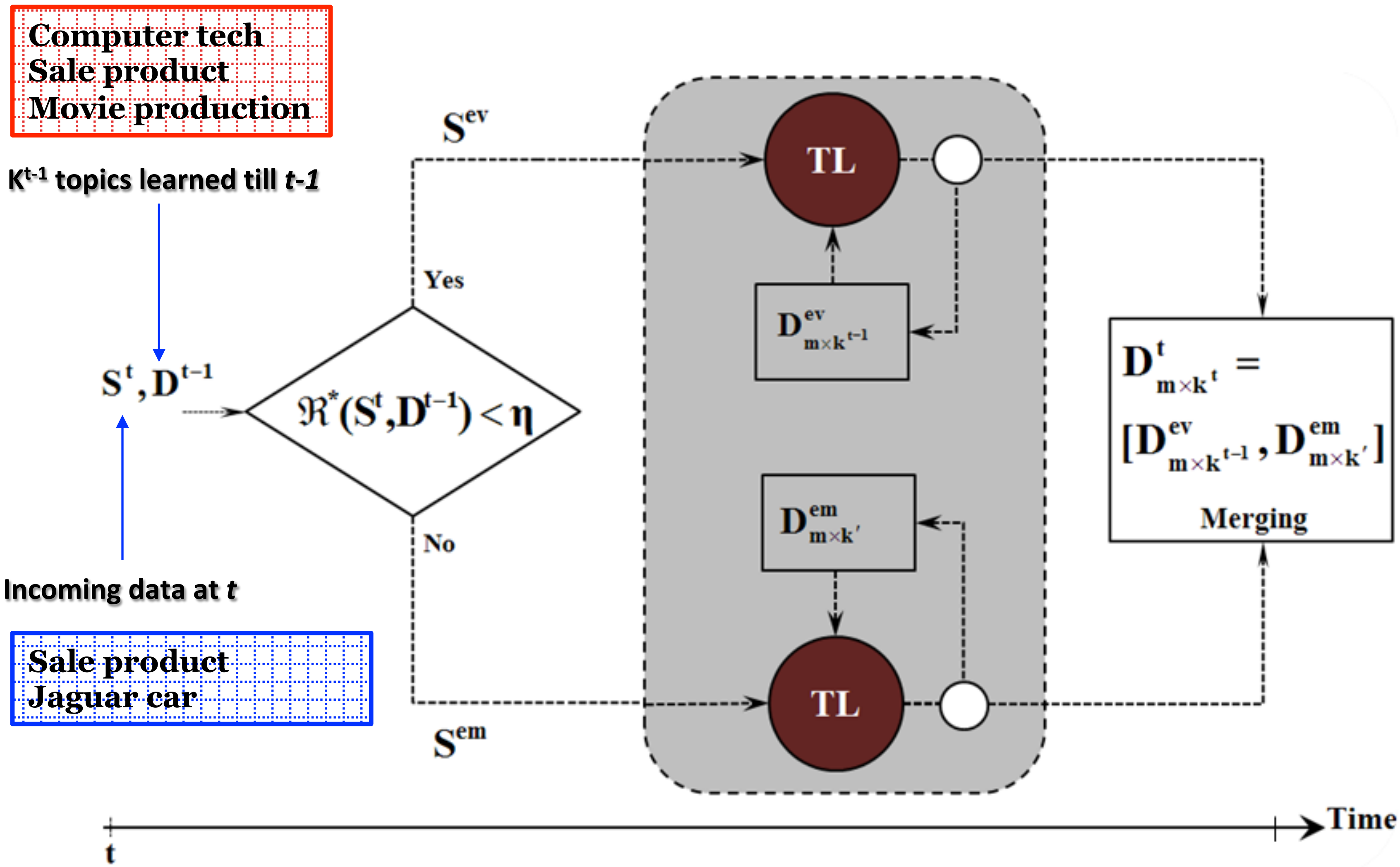
Input: $\mathbf{S}^t$, $\mathbf{D}^{t-1}$, itr: number of iterations

Output: $\mathbf{D}^t$, $\mathbf{X}^t$

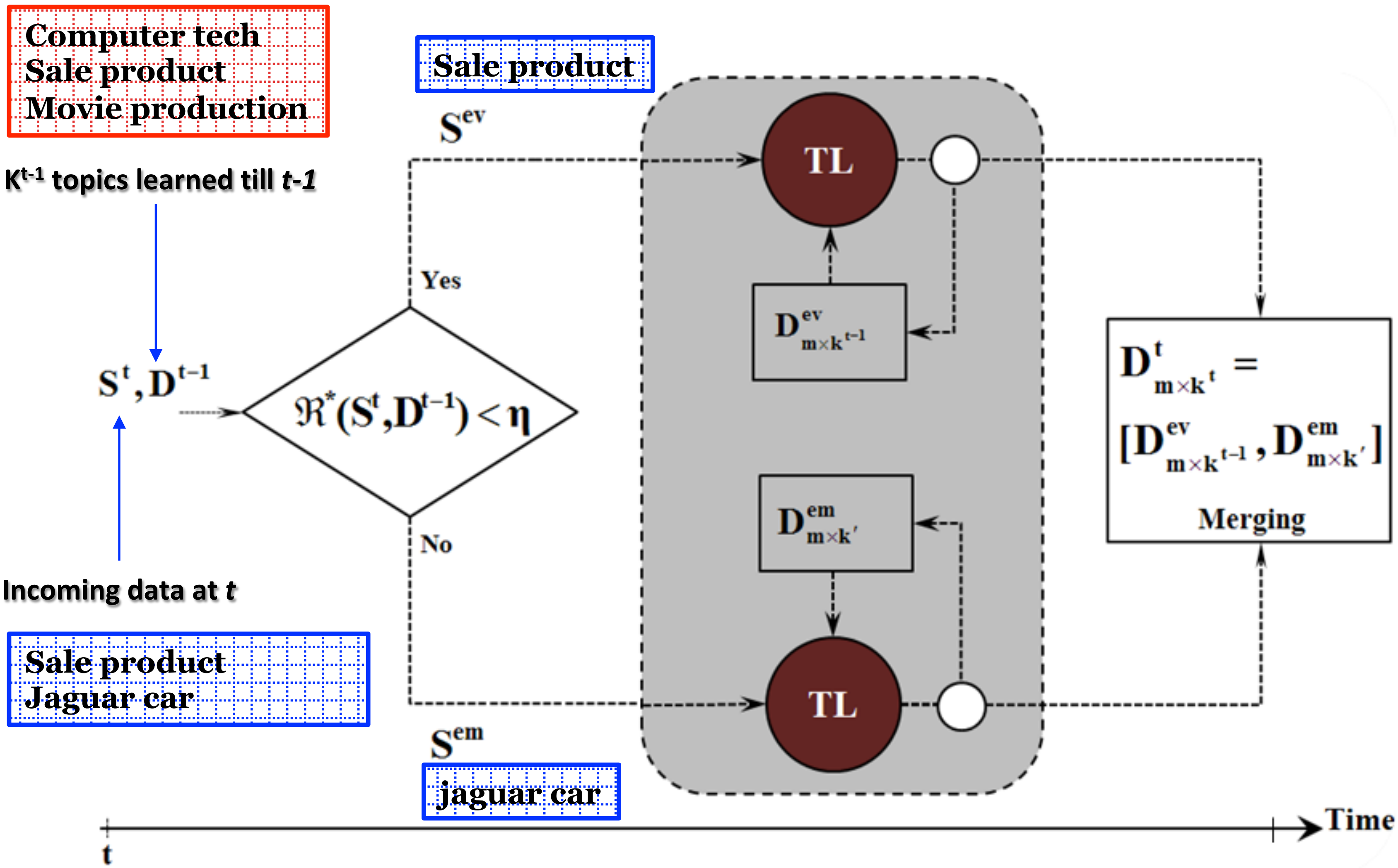
1. Compute $\mathbf{X}^t$ using $\mathbf{S}^t$ and $\mathbf{D}^{t-1}$
2. $\mathbf{D}_0^t = \mathbf{D}^{t-1}$
3. for i=1 : itr do
4. compute $\nabla_{\mathbf{D}} \mathcal{L}(\mathbf{D}_{\mathbf{i-1}}^{\mathbf{t}})$
5. $\mathbf{U} = \nabla_{\mathbf{D}} \mathcal{L}(\mathbf{D}_{\mathbf{i-1}}^{\mathbf{t}}) diag^{-1}\left(\mathcal{H}[\mathcal{L}(\mathbf{D})]_{[\mathbf{X}^{\mathbf{t}}]}\right) + \mathbf{D}_{\mathbf{i-1}}^{\mathbf{t}}$
6. $\mathbf{D}_{\mathbf{i}}^{\mathbf{t}} = max(\mathbf{0}, \mathbf{U})$
7. end for

[1] Julien Mairal, Francis Bach, Jean Ponce, Guillermo Sapiro: *Online Learning for Matrix Factorization and Sparse Coding*. Journal of Machine Learning Research 11: 19-60 (2010)

Temporal Coherence

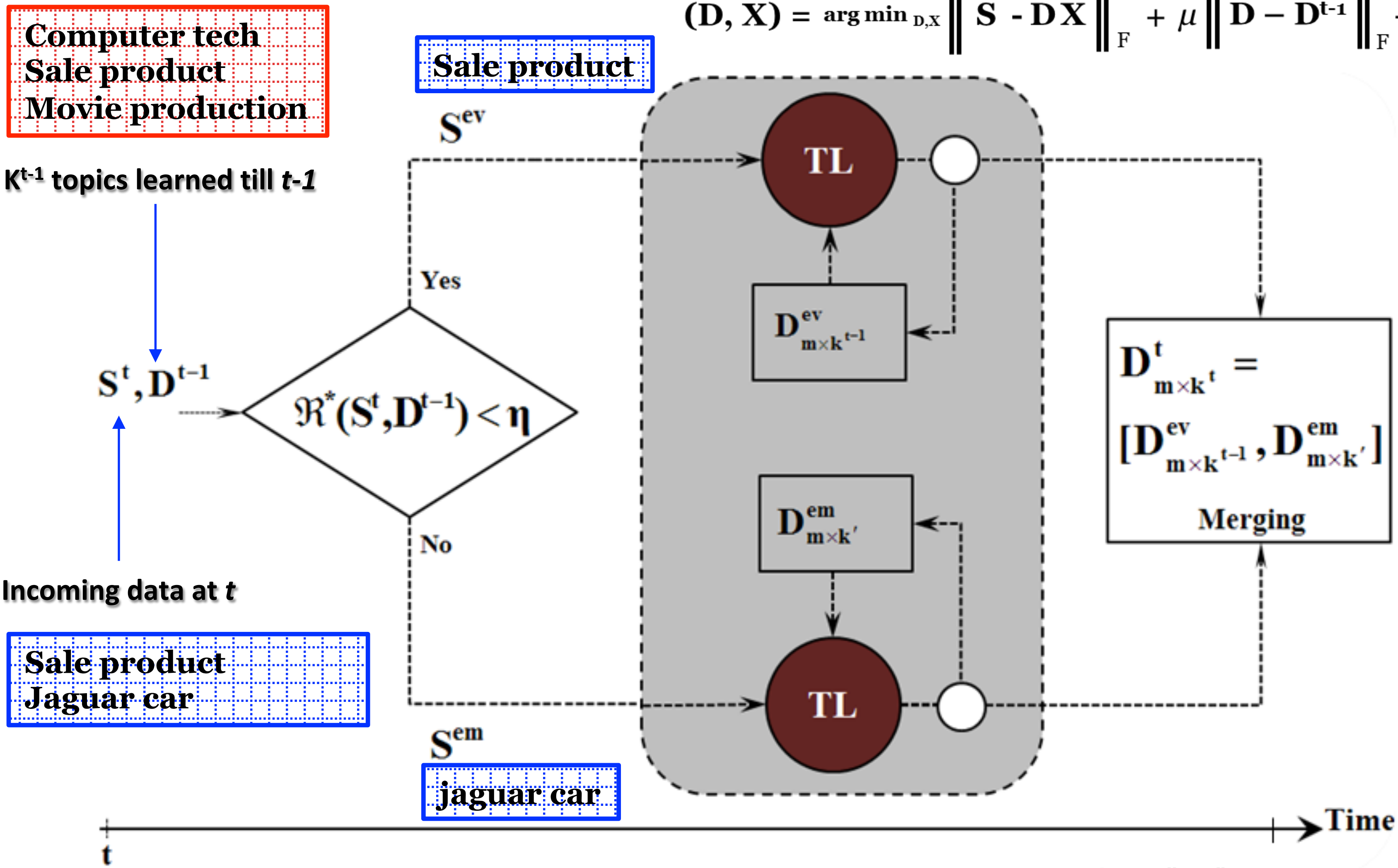


Temporal Coherence



Temporal Coherence

$$(D, X) = \arg\min_{D,X} \left\| S - DX \right\|_F^2 + \mu \left\| D - D^{t-1} \right\|_F^2 + \lambda \left\| X \right\|_1$$



$$(D, X) = \arg\min_{D,X} \left\| S - DX \right\|_F^2 + \lambda \left\| X \right\|_1$$

Emerging Topics

Temporal Coherence

Evolving Topics

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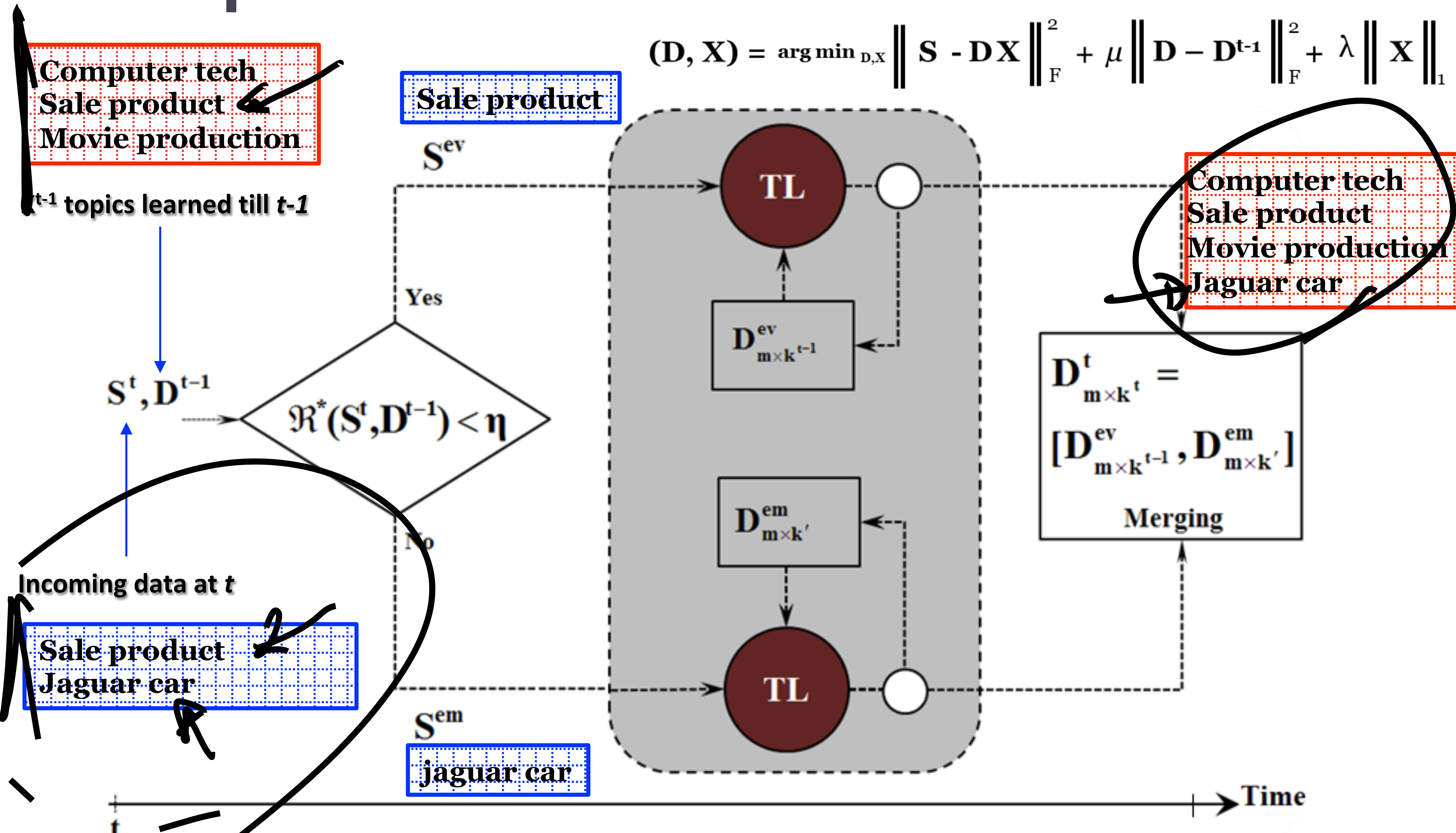


$$(D, X) = \arg\min_{D,X} \left\| S - DX \right\|_F^2 + \lambda \left\| X \right\|_1$$

Emerging Topics

Topic Tracking- Cnt.

- Temporal Coherence constraint for topic learning:
  - $\mathbf{D}^{ev}$ to be a smooth evolution of $\mathbf{D}^{t\text{-}1}$

$$(\mathbf{D}, \mathbf{X}) = \arg\min_{\mathbf{D},\mathbf{X}} \left\| \mathbf{S} - \mathbf{D}\mathbf{X} \right\|_F^2 + \lambda \left\| \mathbf{D} - \mathbf{D}^{\mathbf{t-1}} \right\|_F^2 + \lambda \left\| \mathbf{X} \right\|_1$$

s.t. $\mathbf{X} \geq \mathbf{0}$, $\mathbf{D} \geq \mathbf{0}$, $\|\boldsymbol{d_i}\| = \mathbf{1}$ *for* $i = \{1,\ldots k\}$

- Can be solved efficiently
  - Space: O(n*m), given that m >> k
  - Running time: O(n)

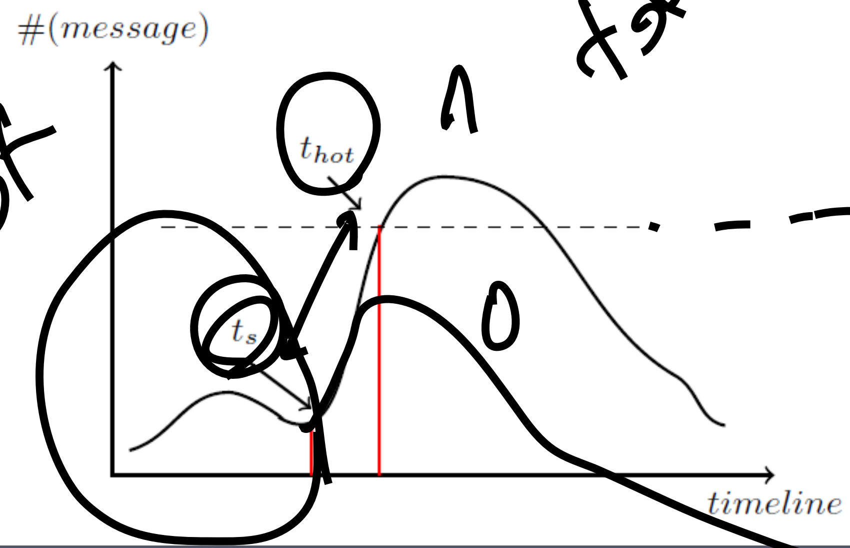
Early Detection of Emerging Topics

Chen, Yan, et al. "Emerging topic detection for organizations from microblogs." SIGIR 2013.

Early Detection of Topics

- Evolution of a hot topic
  - t_s topic detection time
  - t_{hot} the time by which topic becomes major.
    - tweets number exceeds a threshold.
- We aim to predict if an already-detected topic will be major in the near future!

Hot a topic



Early Detection

View 1: rate indicators

- Rate of increase in #users
- Rate of increase in #tweets
- Rate of increase in #re-tweets

View 2: overlap indicators

- Overlap btw users posted about topic and influential users
- Overlap btw topic keywords and top influential keywords

Co-training (Co): Two SVM classifiers trained on the above two orthogonal views of features

Ensemble Learner (En): Ensemble of three classifiers (Decision Tree, SVM, and Naive Bayesian) vote for each unlabeled topic.

Early Detection

- User authority / user influence against the topic
- Tweet authority / derived from topical user auth.

- f_1 is the rate of increase of user number,

$$f_1 = \frac{|U^t|}{\sum_{x=0}^{t} \frac{1}{t-x+1} |U^x|}. \qquad (6)$$

- f_2 is the rate of increase of tweets number,

$$f_2 = \frac{|Tw^t|}{\sum_{x=0}^{t} \frac{1}{t-x+1} |Tw^x|}. \qquad (7)$$

- f_3 is the rate of increase of re-tweets number,

$$f_3 = \frac{|Rtw^t|}{\sum_{x=0}^{t} \frac{1}{t-x+1} |Rtw^x|}. \qquad (8)$$

- f_4 is the overlap between org keyusers and top N influential topic users,

$$f_4 = \frac{\#(ku_{tp} \cap ku)}{\#ku_{tp}}. \qquad (9)$$

- f_5 is the overlap between org keywords and top N influential topic keywords, and

$$f_5 = \frac{\#(kw_{tp} \cap kw)}{\#kw_{tp}}. \qquad (10)$$

- f_6 represents the rate of increase of influence of the accumulated weight of tweets,

$$f_6 = \frac{|A^t|}{\sum_{x=0}^{t} \frac{1}{t-x+1} |A^x|}, \qquad (11)$$

where $A = \frac{\sum_{tw \in Tw_{tp}} auth_{tp}(tw)}{|Tw_{tp}|}$.

Evaluation

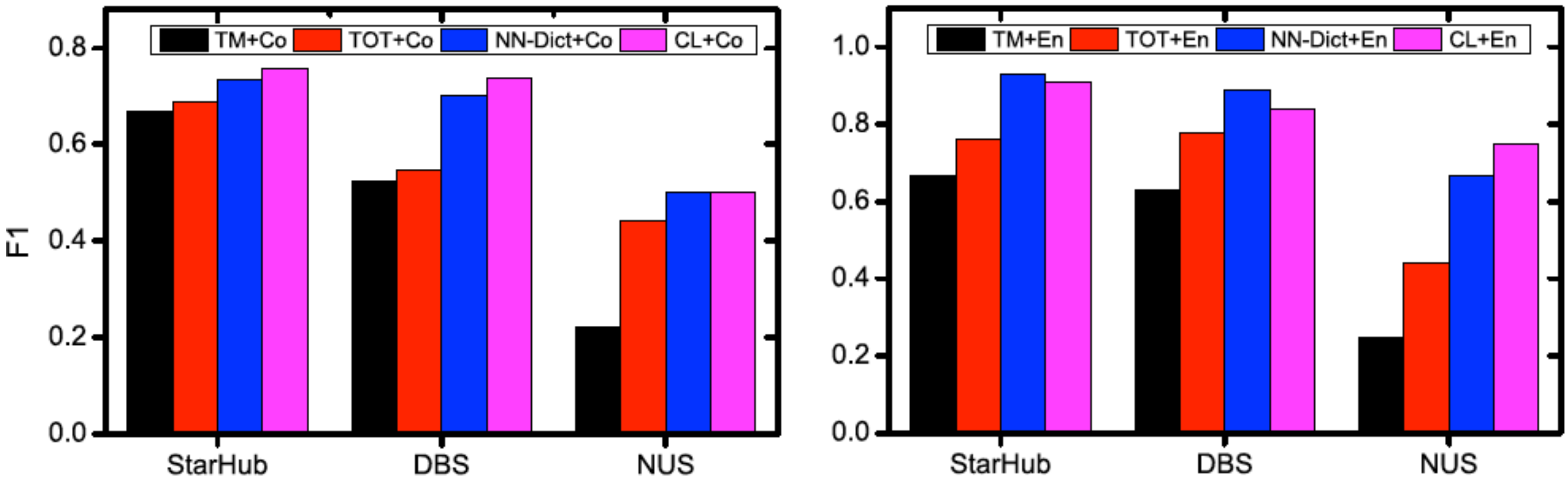


Figure 5: Performance of emerging topic Detection when $T_L = t_{hot}$

CL: Incremental clustering
Co: Co-training
En: Ensemble Learner

Evaluation

Table 2: Performance of emerging topic detection when $T_L = t_{hot}$

Methods	Organization	recall	precision	F_1
CL+En	*StarHub*	**0.93**	**0.87**	**0.90**
CL+TSVM		0.86	0.75	0.80
CL+Semi-NB		0.86	0.71	0.77
CL+En	*DBS*	**0.89**	**0.80**	**0.84**
CL+TSVM		**0.89**	0.73	0.80
CL+Semi-NB		**0.89**	0.67	0.70
CL+En	*NUS*	**1.00**	**0.60**	**0.75**
CL+TSVM		**1.00**	0.50	0.67
CL+Semi-NB		**1.00**	0.42	0.73

CL: Incremental clustering
Co: Co-training
En: Ensemble Learner

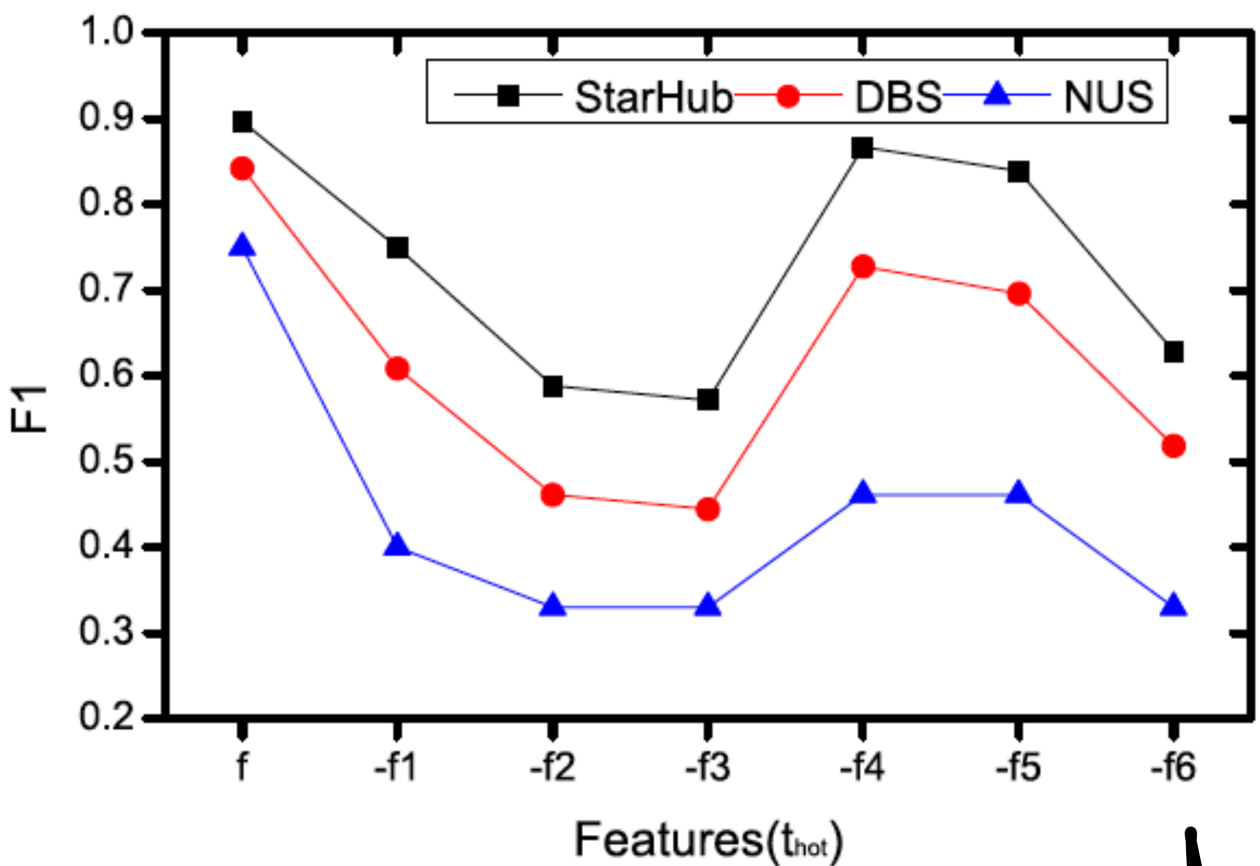
Evaluation

Table 3: Performance of emerging topic detection when $T_L = t_{mid}$

Methods	Organization	recall	precision	F_1
CL+En	*StarHub*	**0.71**	**0.83**	**0.77**
CL+TSVM		**0.71**	0.71	0.71
CL+Semi-NB		**0.71**	0.67	0.69
CL+En	*DBS*	**0.78**	**0.78**	**0.78**
CL+TSVM		**0.78**	0.70	0.74
CL+Semi-NB		**0.78**	0.64	0.70
CL+En	*NUS*	**0.67**	**0.50**	**0.57**
CL+TSVM		**0.67**	0.40	0.50
CL+Semi-NB		**0.67**	0.40	0.50

CL: Incremental clustering
Co: Co-training
En: Ensemble Learner

Evaluation



f2: rate of increase in #tweets
f3: rate of increase in #re-tweets,
f6: overall accumulated influence of tweets

Summary

- Effective NMF model with temporal coherence constraint
  - Improves topic tracking in streaming data.
- Effective framework for early prediction of emerging topics.
  - Rate and overlap features

Reading

- Emerging topic detection for organizations from microblogs. Chen, Y., et al. SIGIR'13.