Canonical Trends

Detecting Trends in Web Data

Felix Bießmann,
Jens-Michalis Papaioannou,
Mikio Braun, Andreas Harth

Berlin Institute of Technology
Department Machine Learning

Karlsruhe Institute of Technology

Temporal Dynamics of Web Data

Web content is copied, repeated or rephrased (Trends/Memes)

This temporal structure contains important information

Growing interest in **temporal dynamics of graphs**

Understanding dynamic graphs [Leskovec et al, KDD, 2005]
Causal Inference [Lozano and Sindhwani, NIPS 2010]
Diffusion of information [Gomez Rodriguez et al, ICML 2011/2012]

Canonical Trend Analysis

- Idea: Predict future features from past features

- Finds trends with **highest impact on network**
- Finds web sources that precede/follow trends
- Based on simple algebra, no density estimation involved

Examples:

- Music trends on Last.fm [Biessmann et al, AAAI Workshop, 2010]
- Trends in News Articles [Biessmann et al, ICML 2012]
- Spatio-temporal retweet responses to news [Biessmann et al, MLSP 2012]
- Twitter retweet dynamics [Biessmann et al, Nips Workshop 2012]

Canonical Trend Analysis For News Articles

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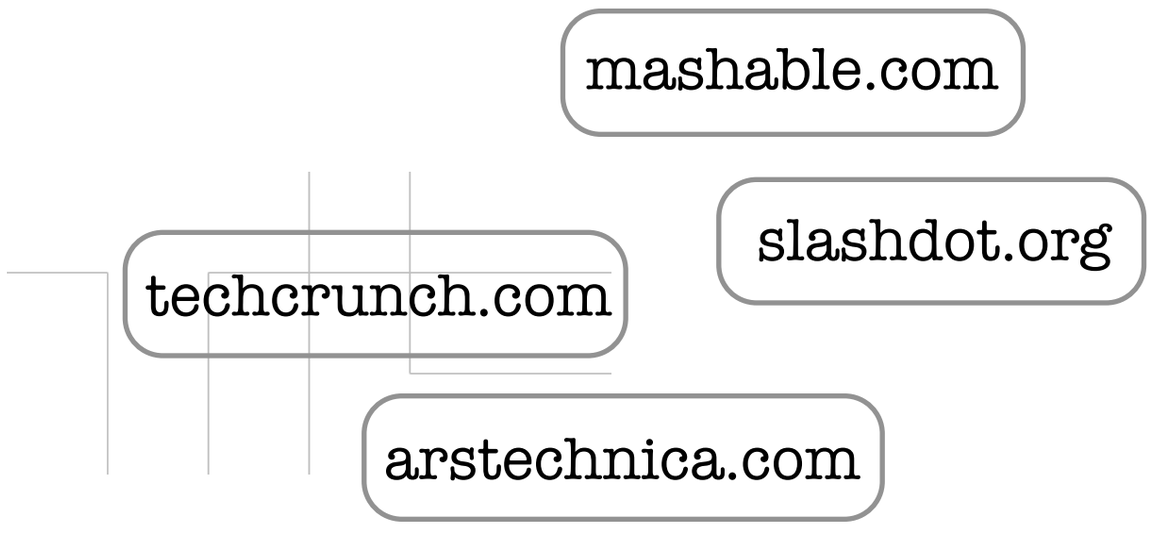

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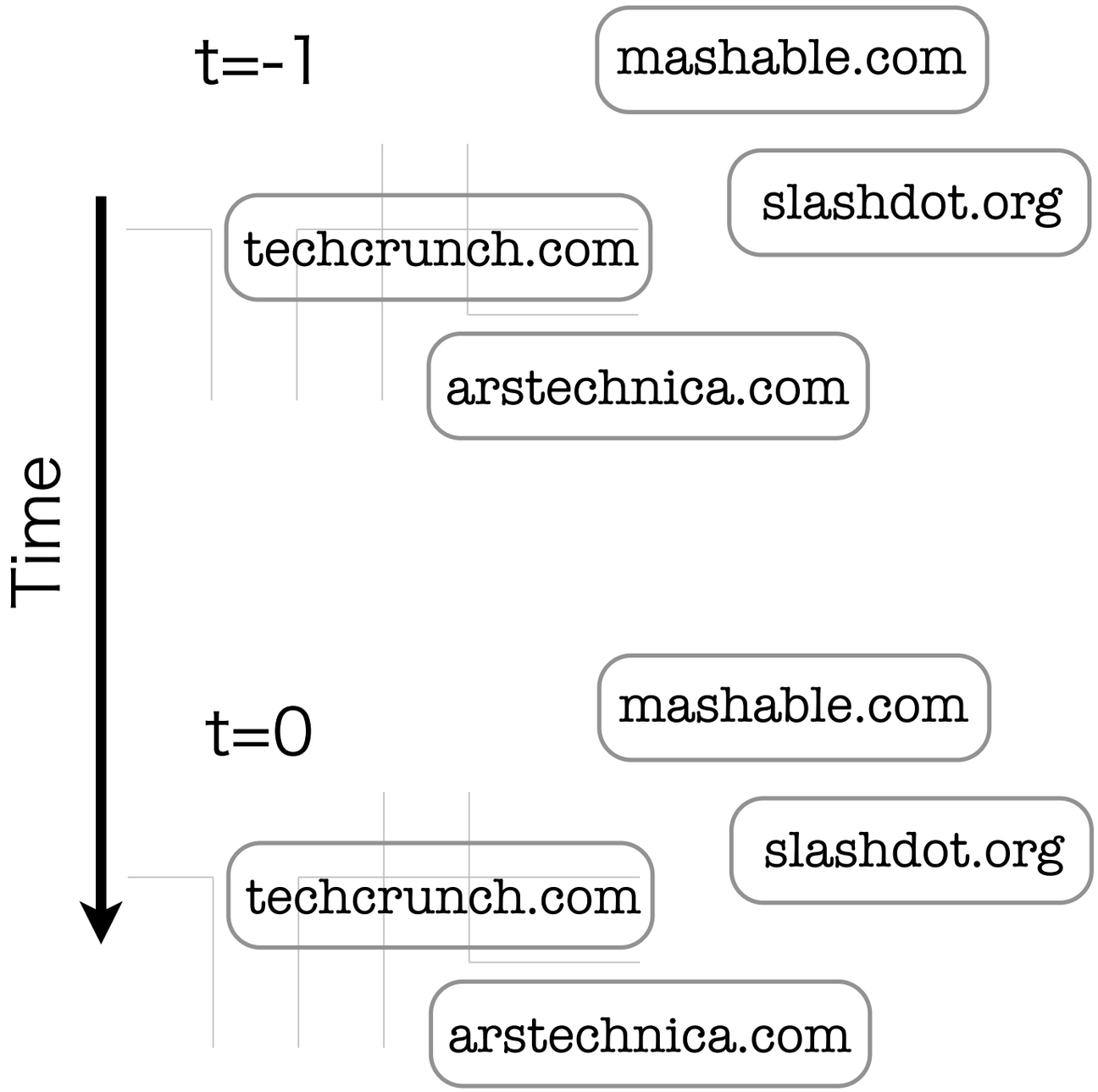

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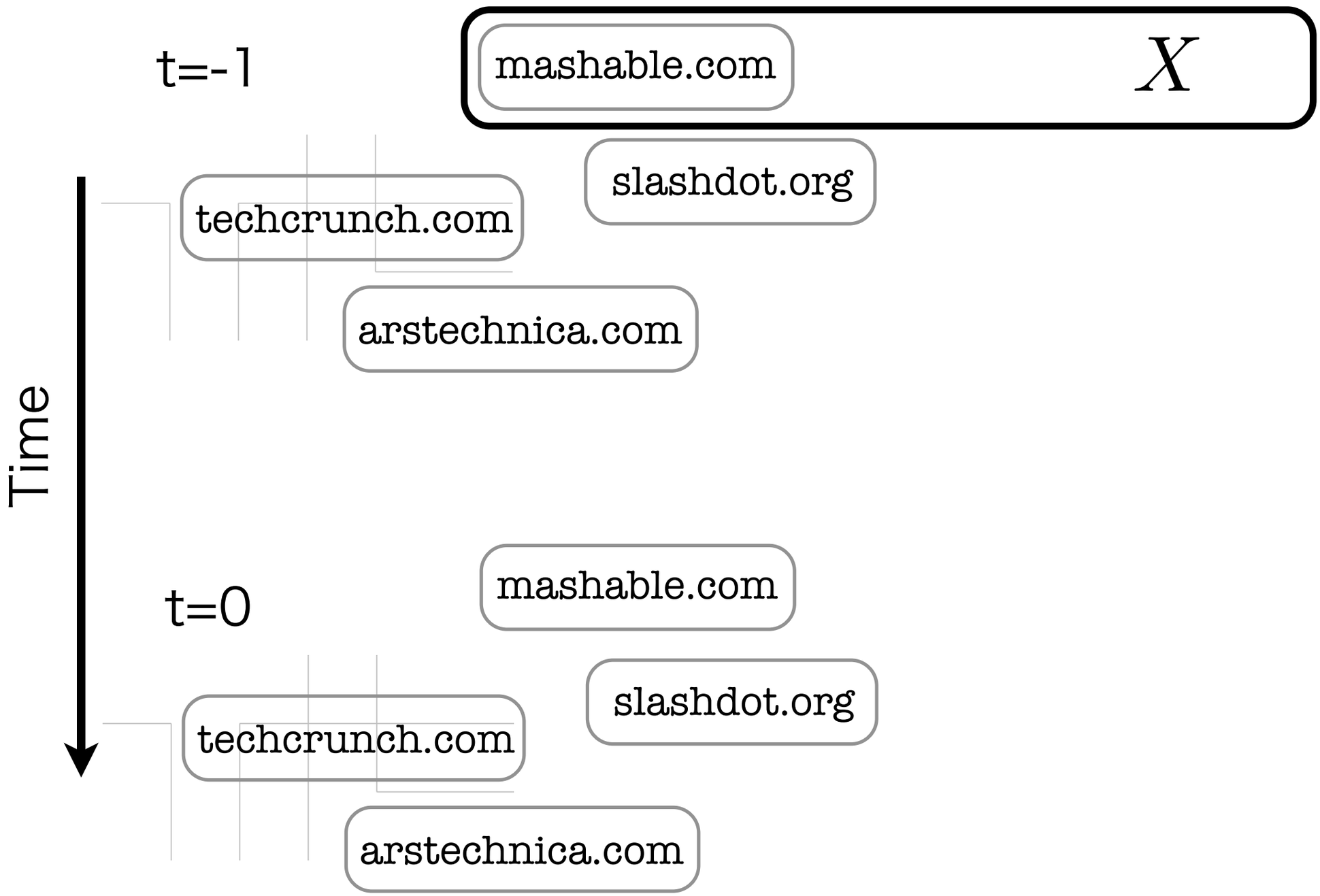

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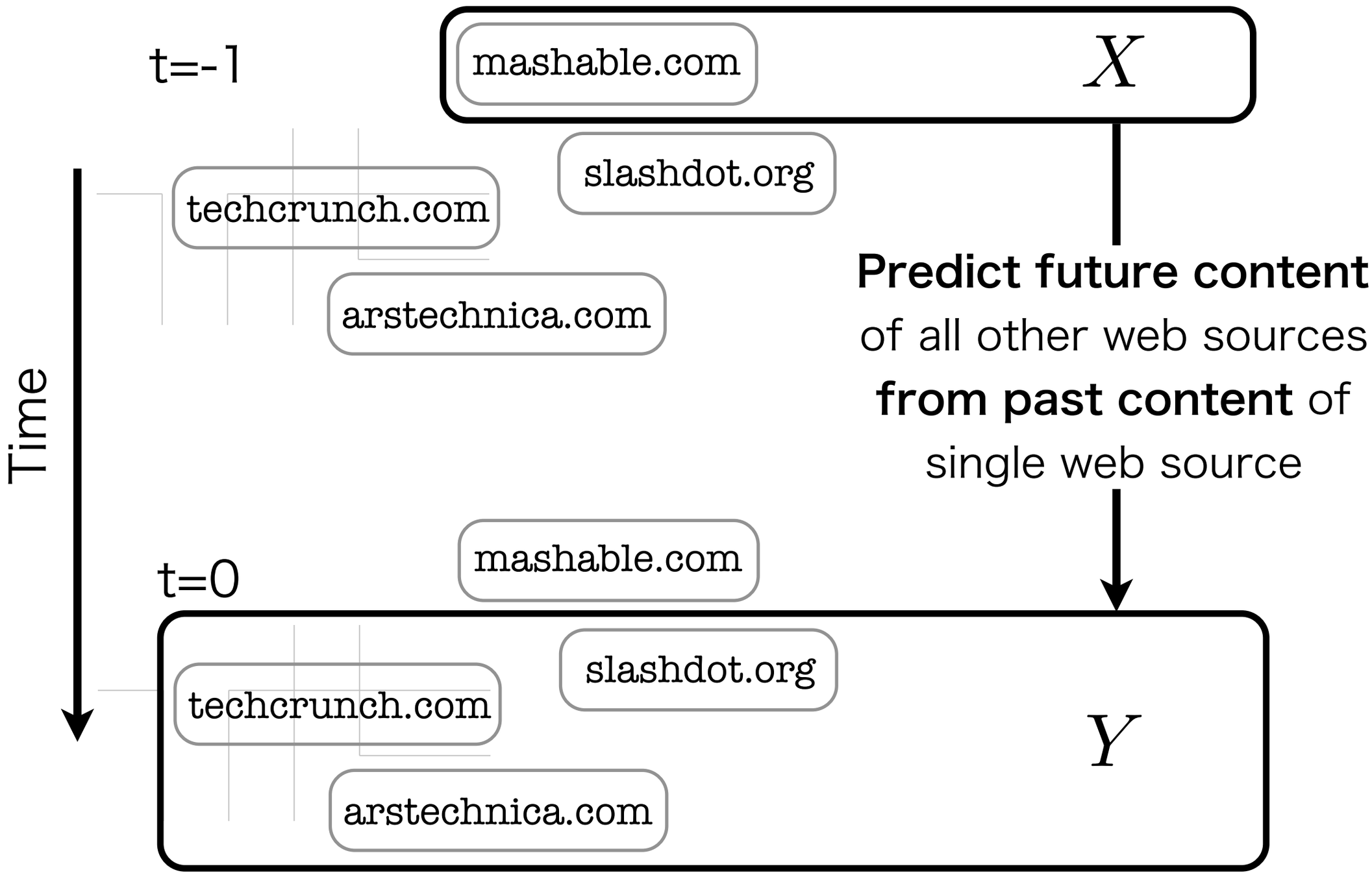

Canonical Trend Analysis For News Articles

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- Which are the main news trends?

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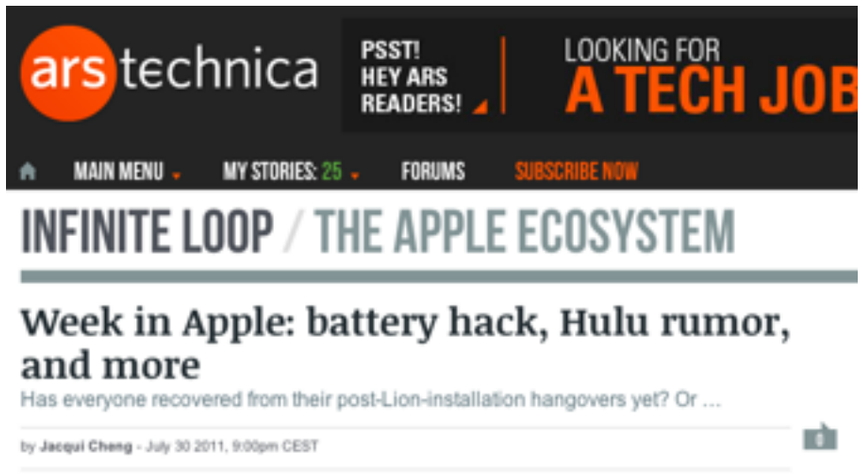
Canonical Trend Analysis For Social Networks



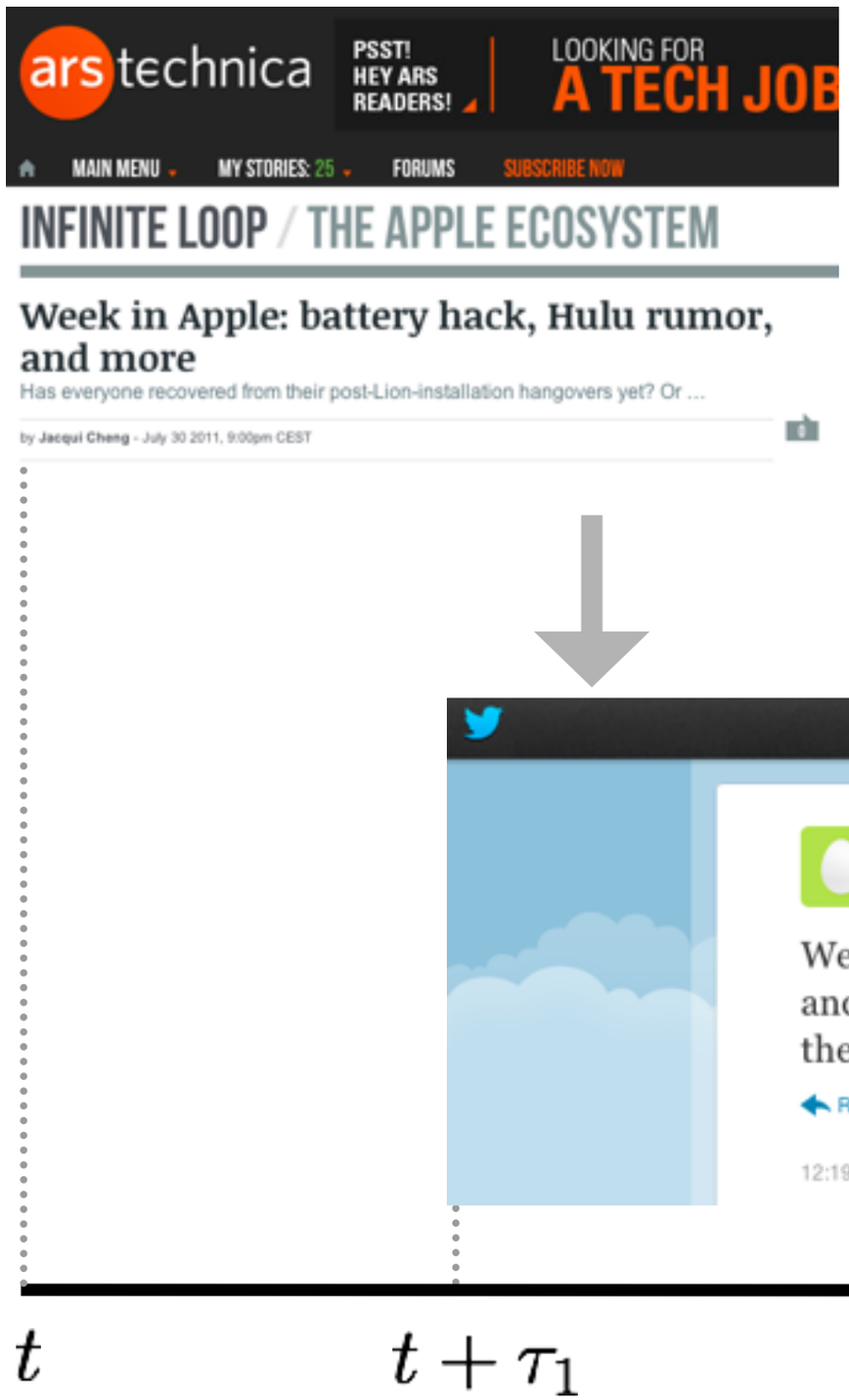
Some **news web site X** publishes some content ...

Canonical Trend Analysis For Social Networks

Some **news web site X** publishes some content ...

... which is **retweeted**

Canonical Trend Analysis For Social Networks



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Canonical Trend Analysis For Social Networks

Some **news web site X** publishes some content ...

... which is **retweeted**

... at different locations Y

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Canonical Trend Analysis

For each web source $f \in \{1, 2, \ldots, F\}$ extract

Feature time series

$$x_f(t) \in \mathbb{R}^W \quad t = \{0, 1, \ldots, T\}$$

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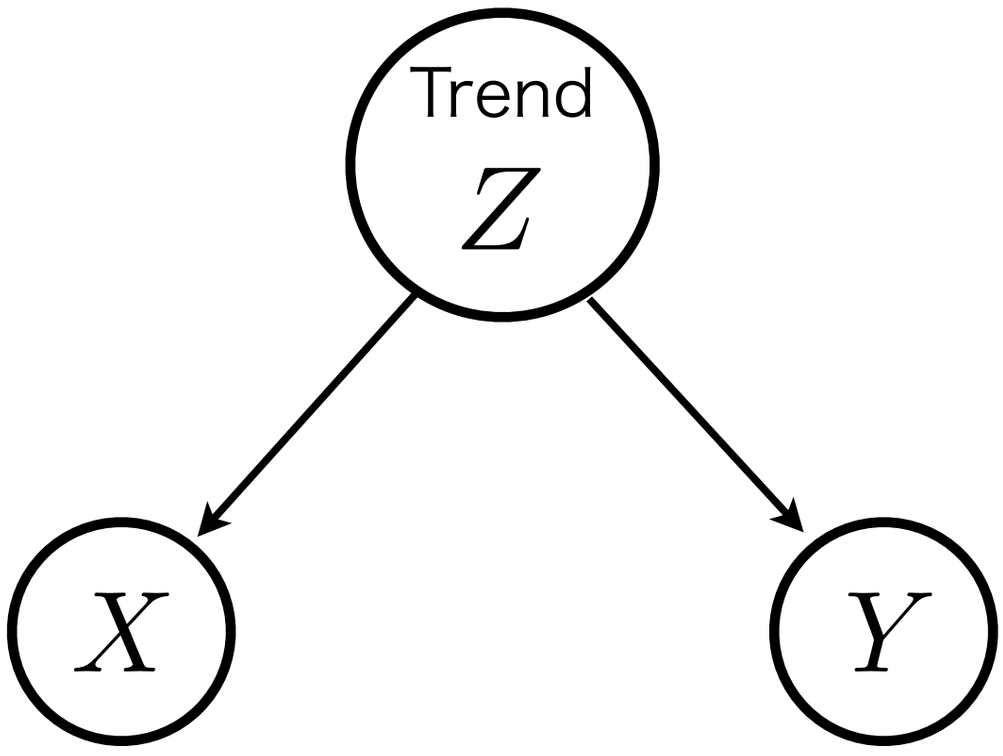
Feature time series of **all other nodes**

$$Y_f = 1/(F - 1) \sum_{f' \neq f} X_{f'} \in \mathbb{R}^{W \times T}$$


Trend
Z

Canonical Trends



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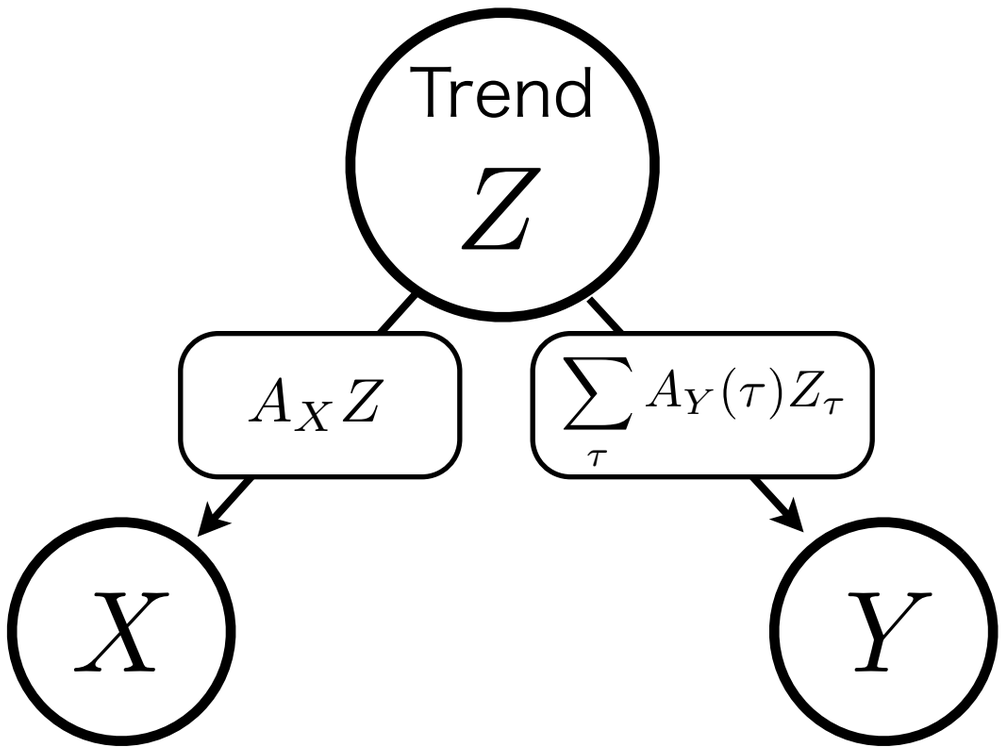

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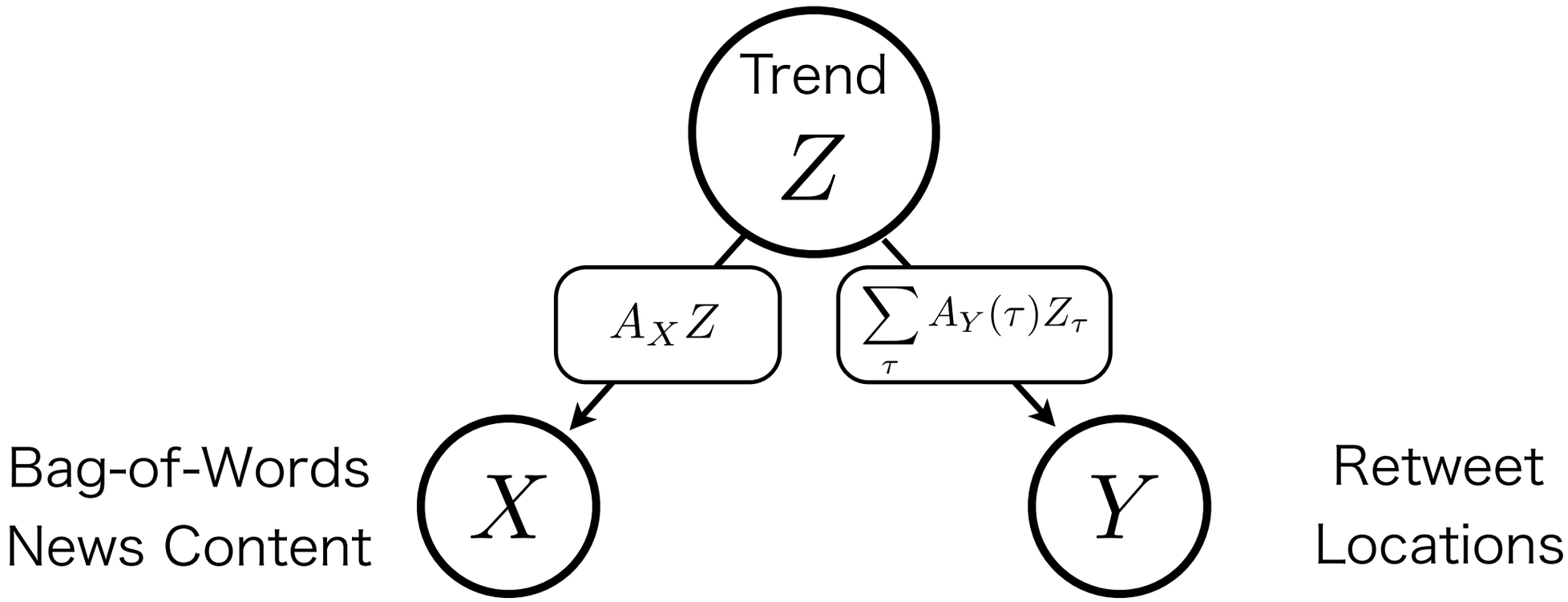

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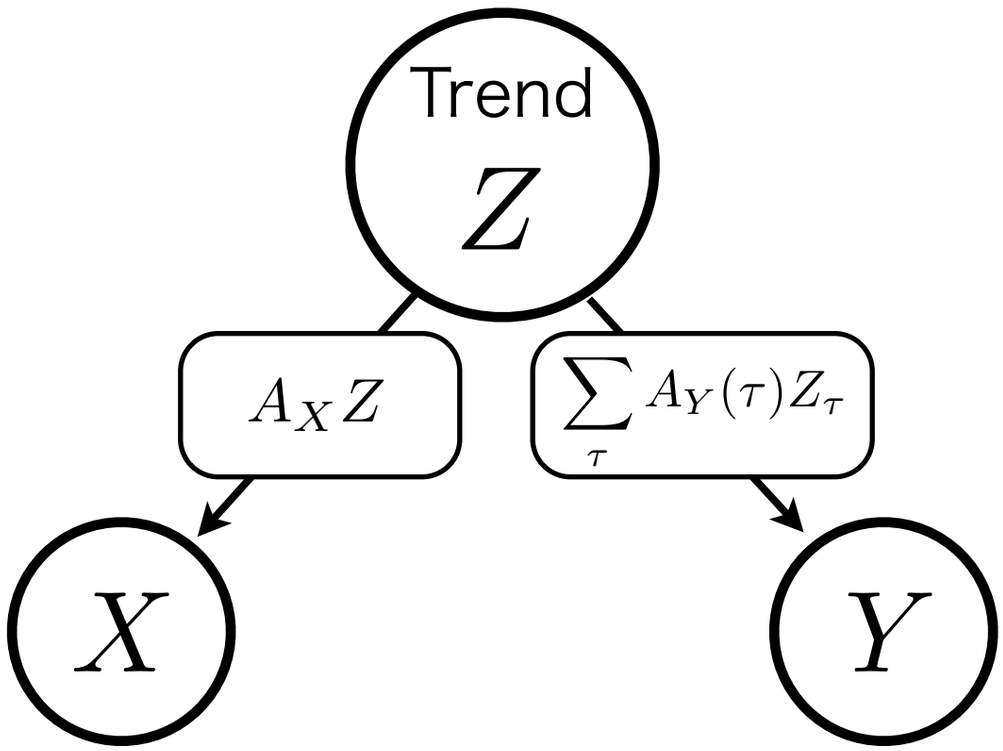

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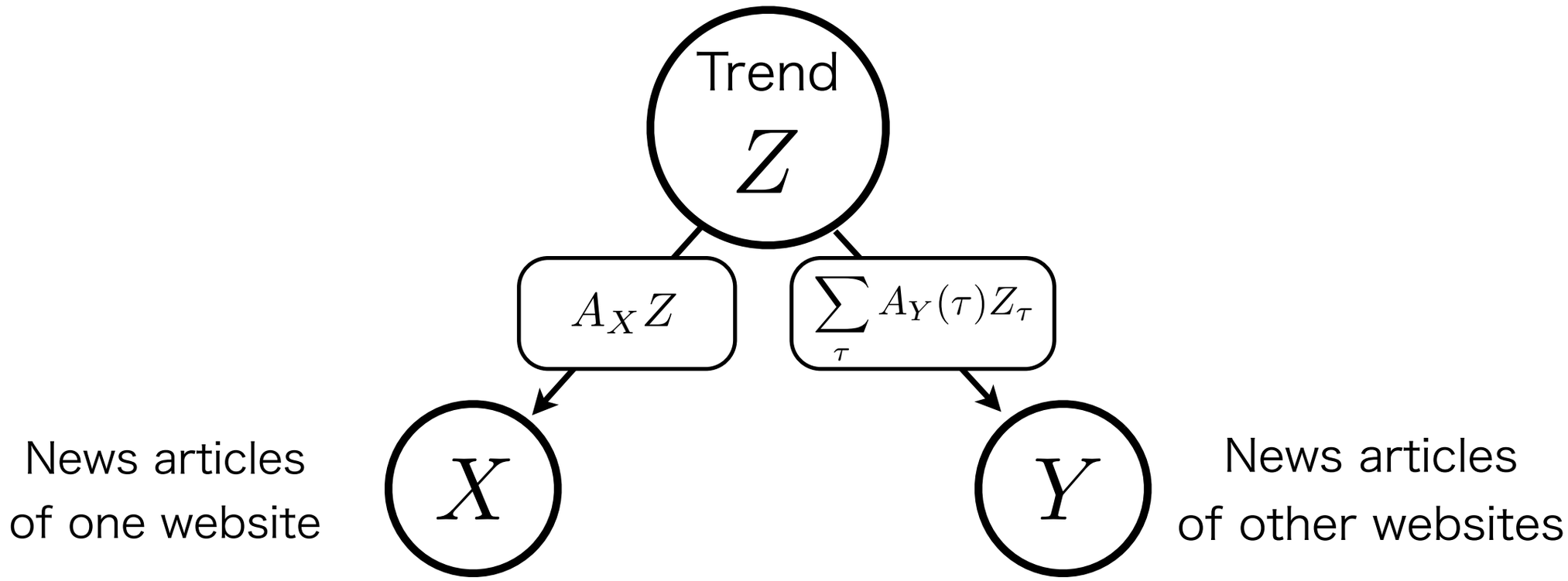

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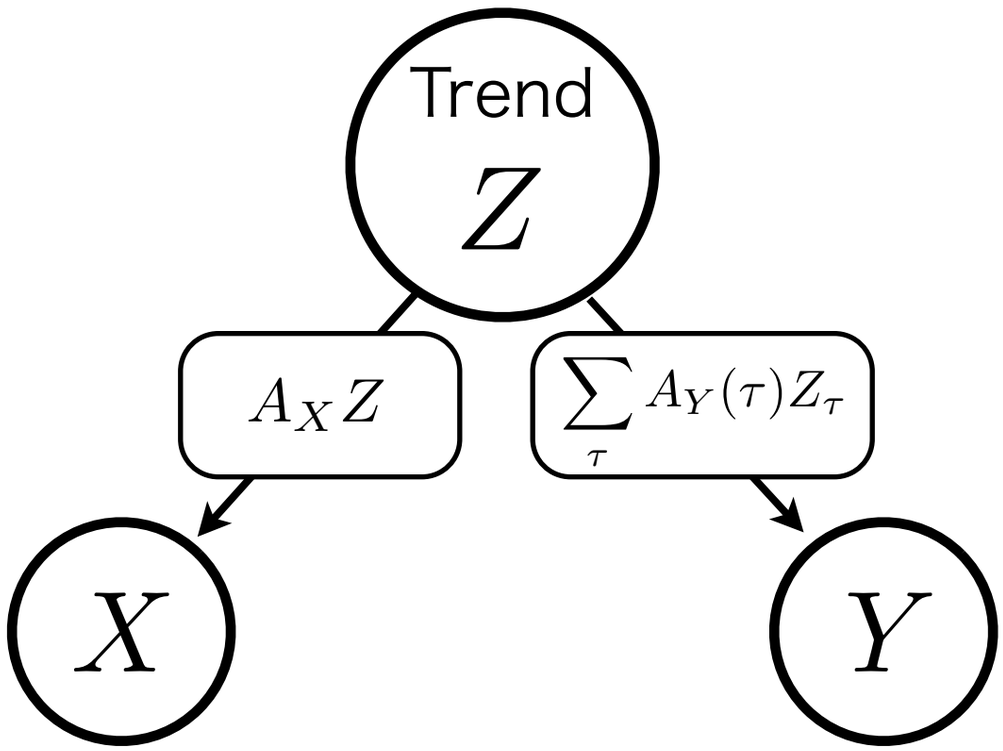

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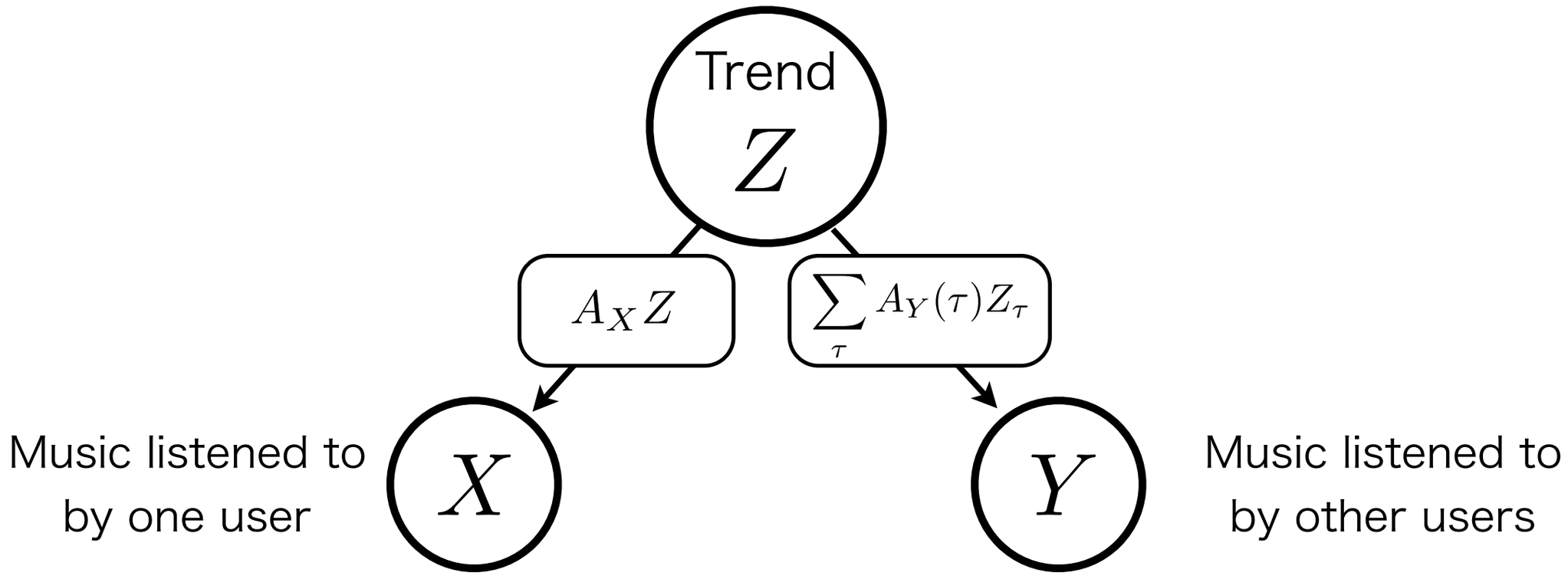

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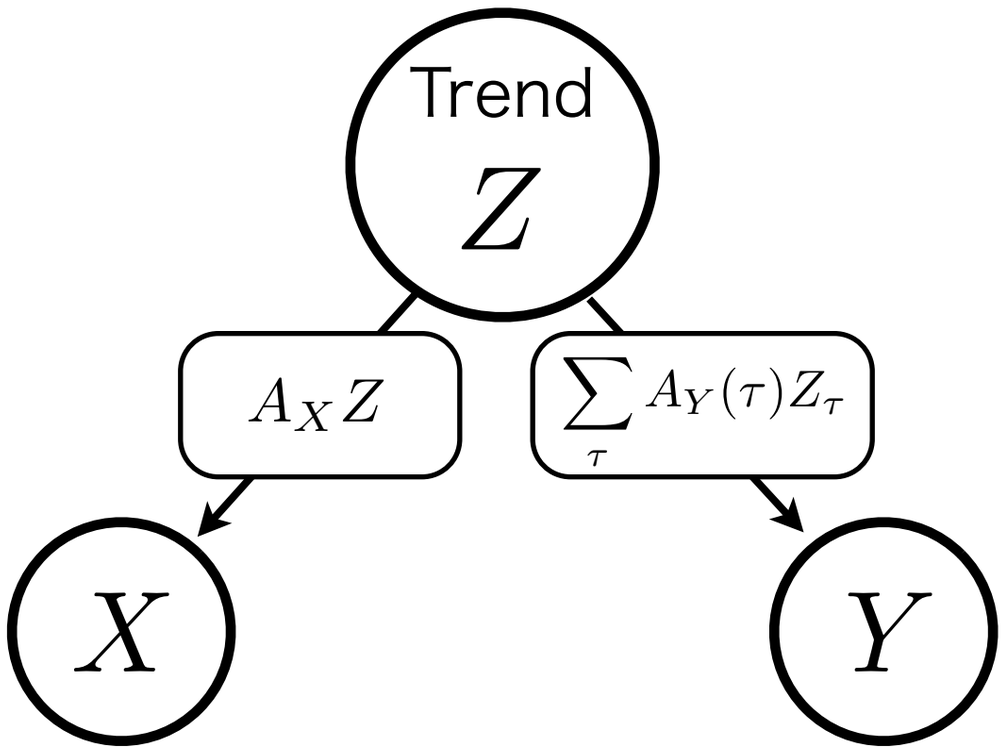

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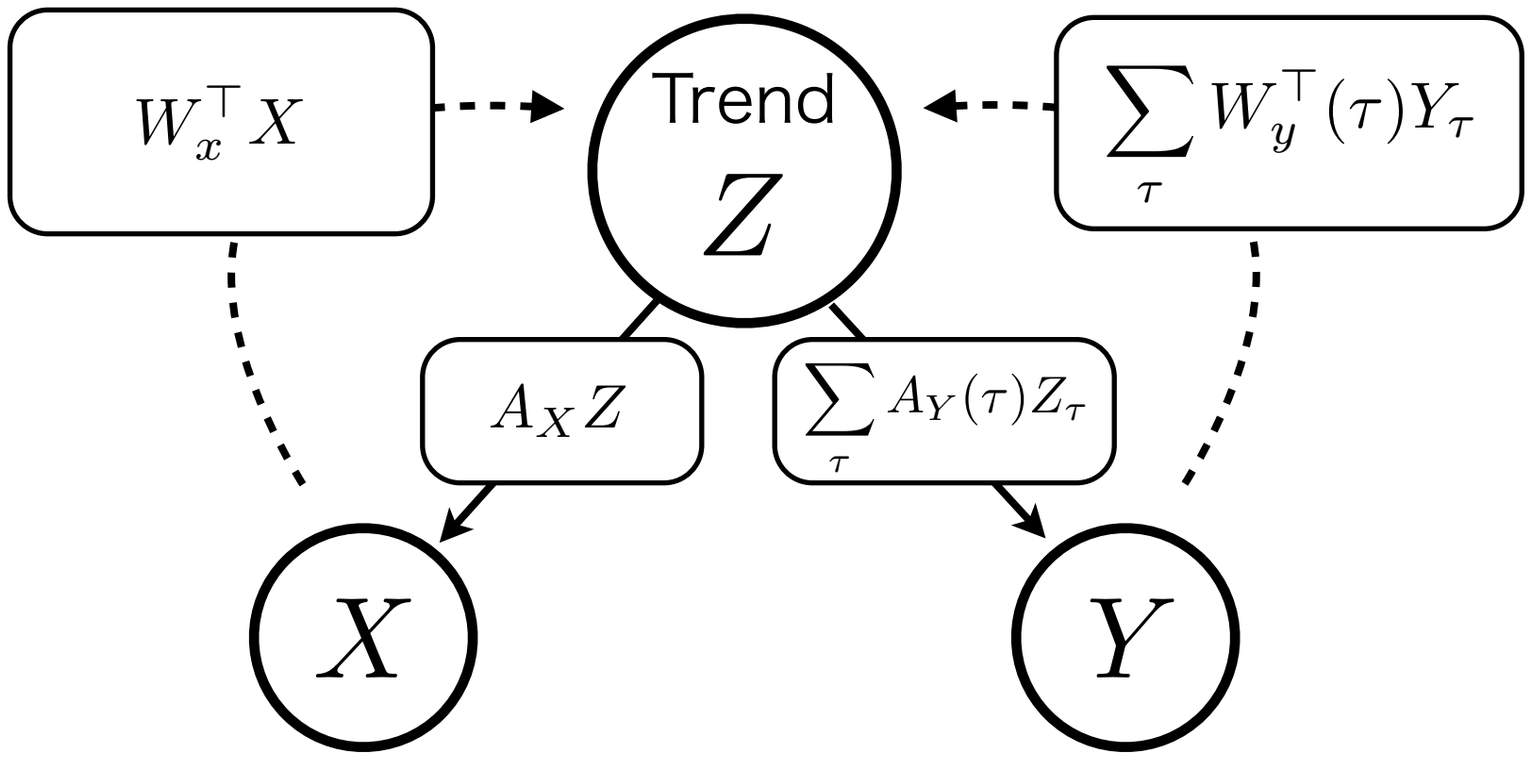
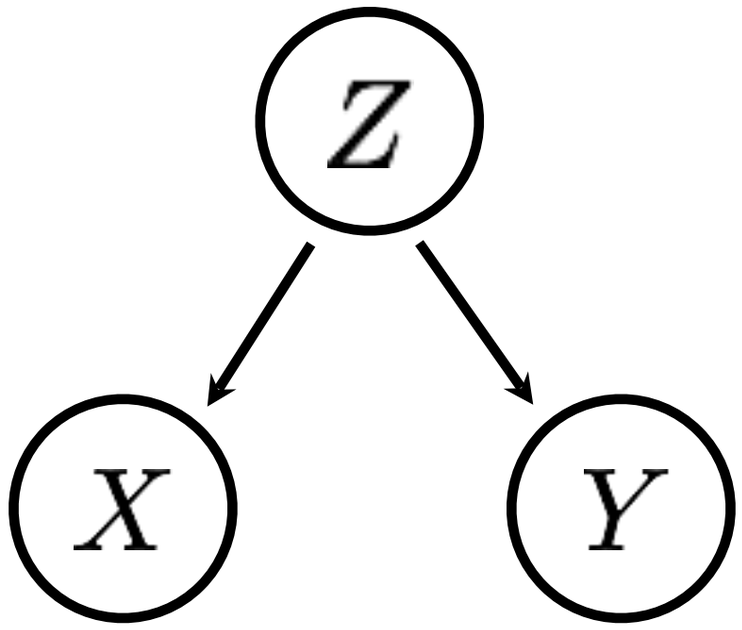


Canonical Correlation Analysis



Latent Variable
(Trend)

Features
(e.g. Bag of Words, User actions, edge histograms, ...)

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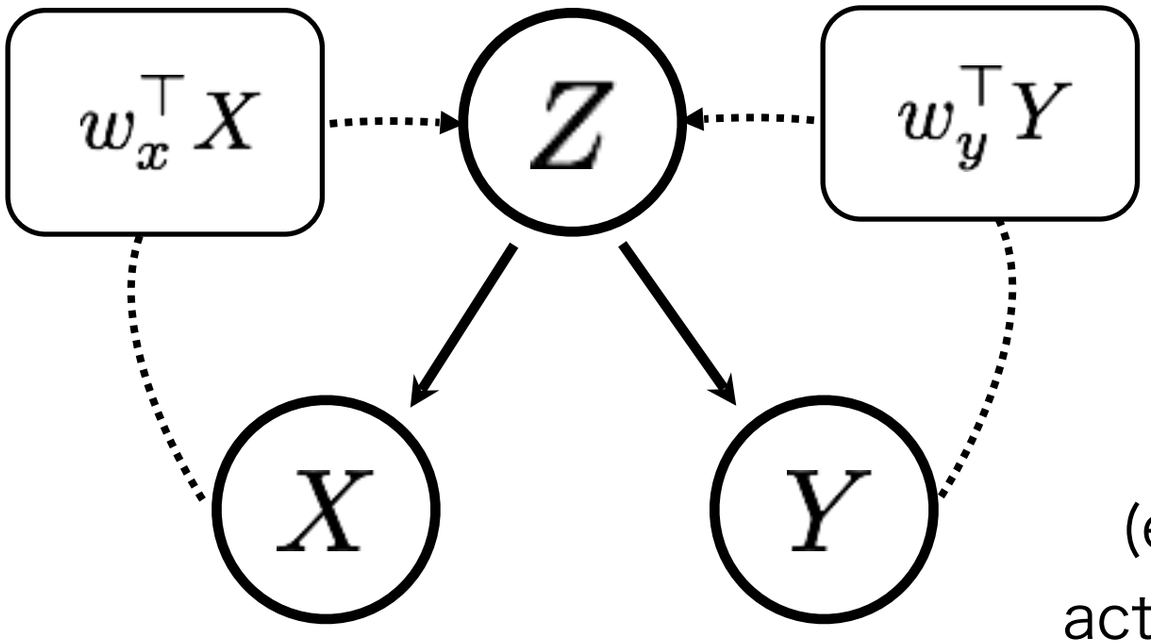

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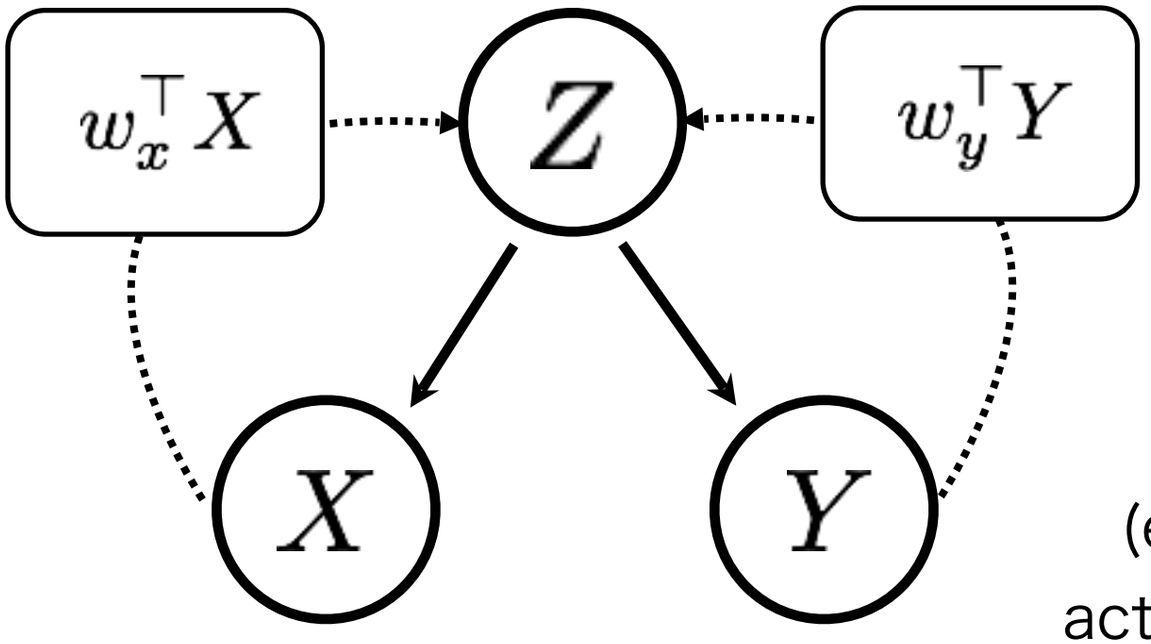

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$$\underset{w_x,\ w_y}{\operatorname{argmax}} \frac{w_x^\top X Y^\top w_y}{\sqrt{w_x^\top X X^\top w_x w_y^\top Y Y^\top w_y}}$$

[Jordan 1875], [Hotelling 1936], [Bach and Jordan 2006]

Canonical Trend Analysis

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Trend

Canonical Trend Analysis

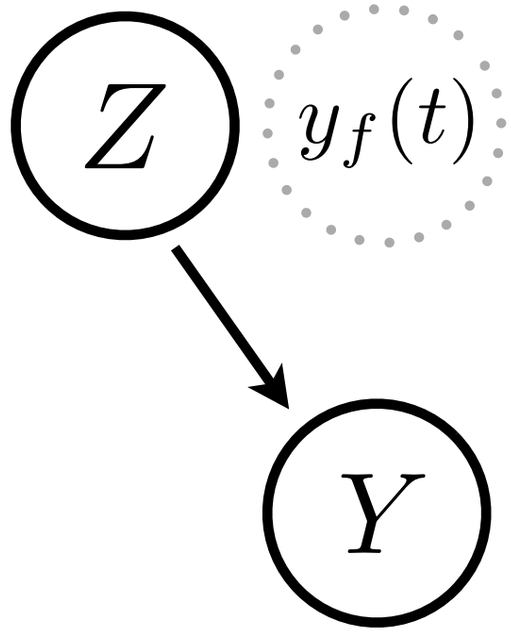
Overall Trend in features of all nodes

$$y_f(t) = w_y^\top Y_f(:, t)$$

Trend

Features

(e.g. Bag of Words)



Canonical Trend Analysis

Overall Trend in features of all nodes

$$y_f(t) = w_y^\top Y_f(:, t)$$

Prediction based on single node features

$$\hat{y}_f(t) = \sum_\tau w_x(\tau)^\top X_f(:, t - \tau)$$

Trend

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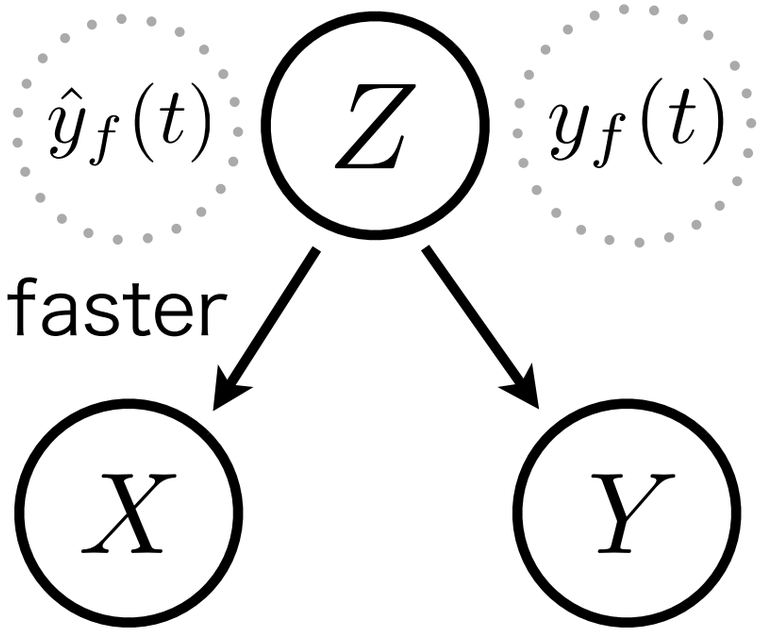

Single Topic Example

Overall Trend in features of all nodes

$$y_f(t) = w_y^\top Y_f(:, t)$$

Prediction based on single node features

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Optimal $w_y \in \mathbb{R}^W$ and $w_x(\tau) \in \mathbb{R}^{W \times N_\tau}$

$$\underset{w_x(\tau), w_y}{\operatorname{argmax}} \operatorname{Corr}(y_f(t), \hat{y}_f(t))$$

Efficient Computation of Canonical Trends

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Temporal Embedding

$$\tilde{X}_f = \begin{bmatrix} X_{f,\tau=-N_\tau} \\ \vdots \\ X_{f,\tau=-1} \end{bmatrix} \in \mathbb{R}^{W N_\tau \times T}$$

- Converts problem into standard CCA problem

  Jordan 1875, Hotelling 1936, Anderson 1999

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(linear) 'Kernel Trick'

$$w_x(\tau) = X_{f,\tau}\alpha$$
$$w_y = Y_f\beta$$

- $2T$ parameters instead of $WN_\tau + W$ parameters
- Very efficient for high-dimensional feature spaces

Fyfe 2000, Fukumizu 2007

Efficient Computation of Canonical Trends

Objective function is maximized in the dual

$$\begin{aligned}\mathrm{Corr}(y(t), \hat{y}(t)) =& \frac{\sum_\tau (w_x(\tau)^\top X_\tau)^\top Y w_y}{\sqrt{\sum_\tau (w_x(\tau)^\top X_\tau X_\tau^\top w_x(\tau)) w_y^\top Y Y^\top w_y}} \\ =& \frac{\alpha^\top K_{\tilde{X}} K_Y \beta}{\sqrt{\alpha^\top K_{\tilde{X}}^2 \alpha \beta^\top K_Y^2 \beta}}\end{aligned}$$

where $K_{\tilde{X}} = \tilde{X}^\top \tilde{X}$, $K_Y = Y^\top Y$ are linear kernels

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Dual coefficients are solution to generalized eigenvalue equation

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Bießmann et al, Machine Learning, 2010

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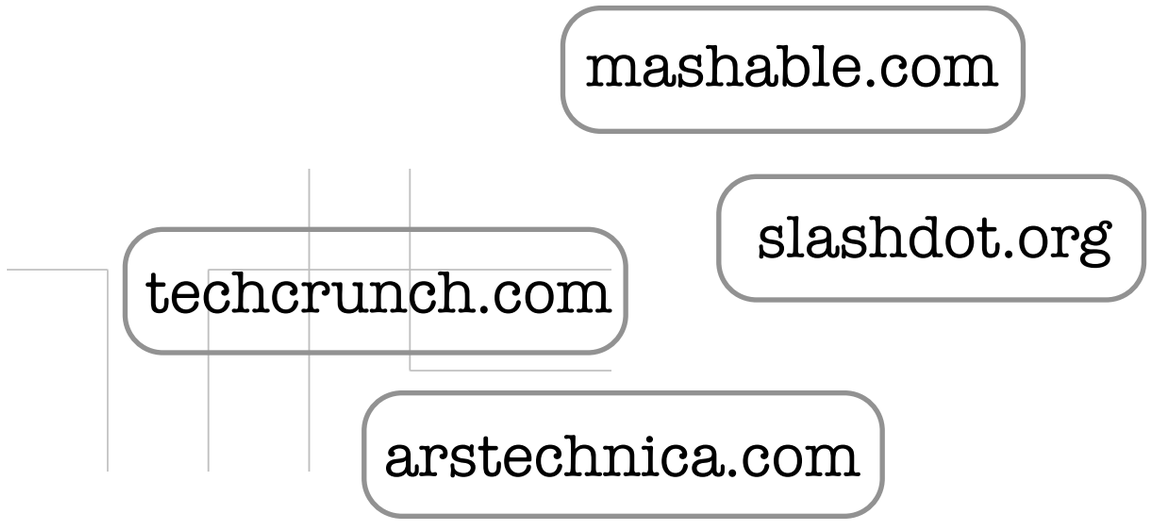

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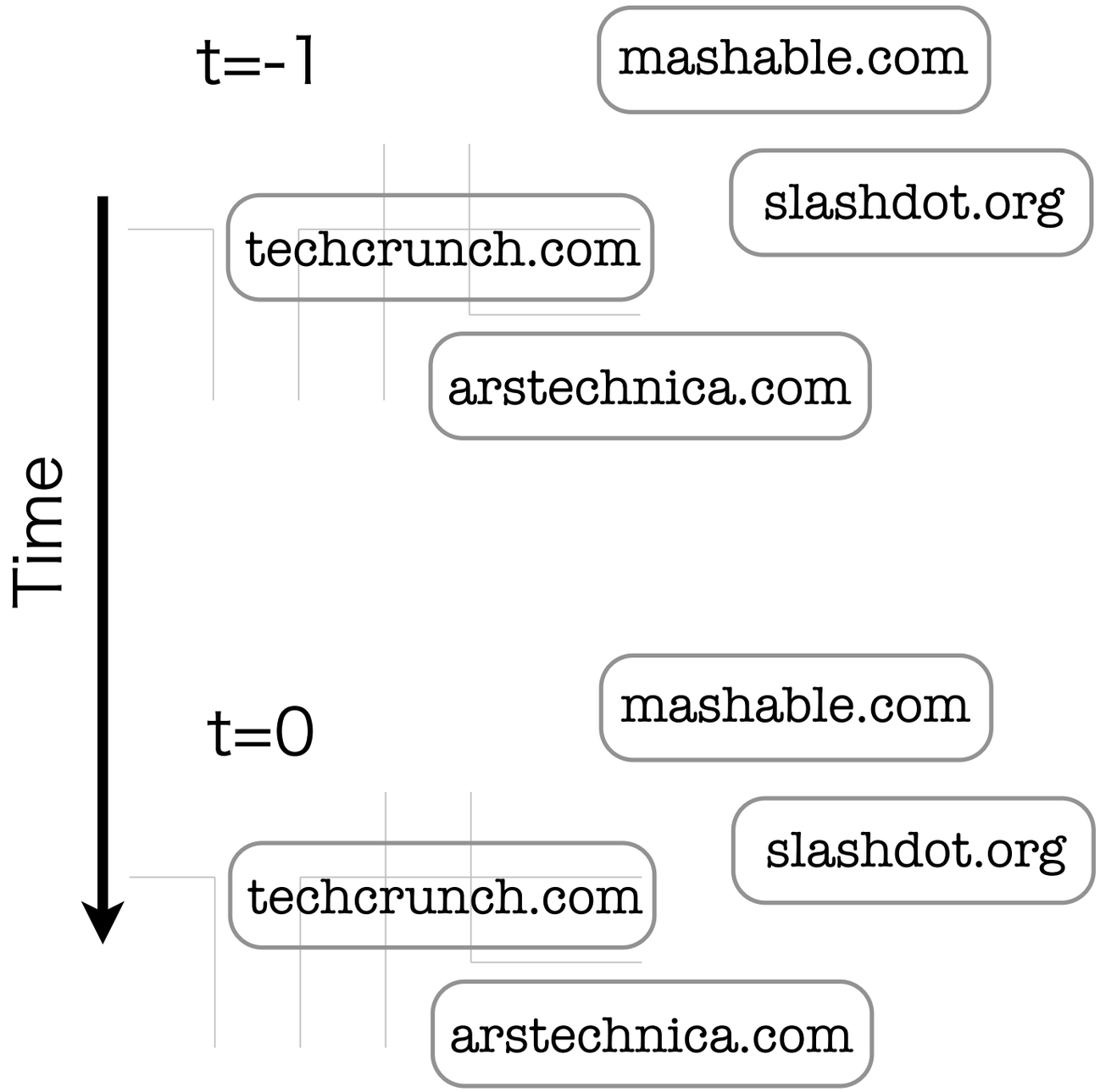

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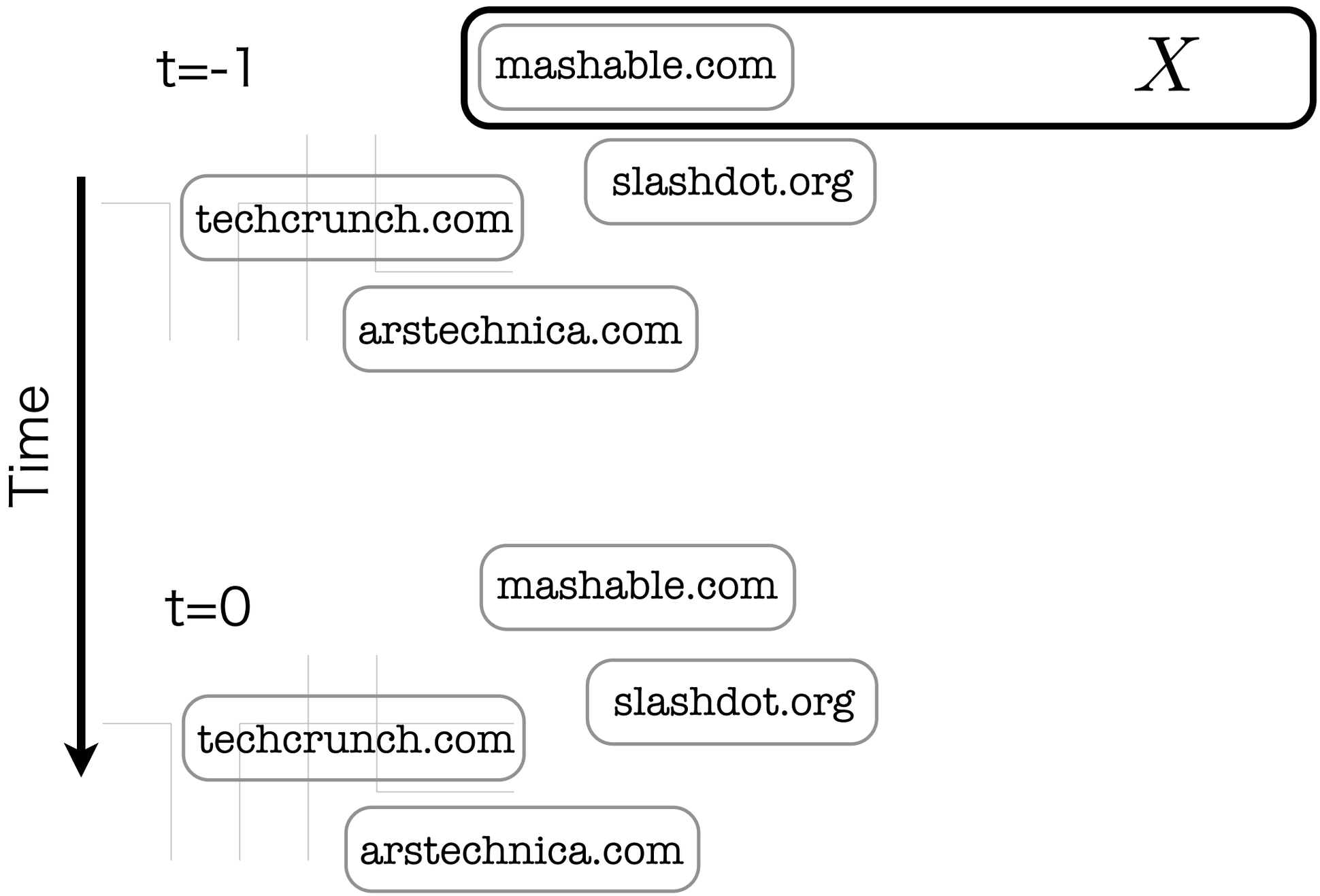

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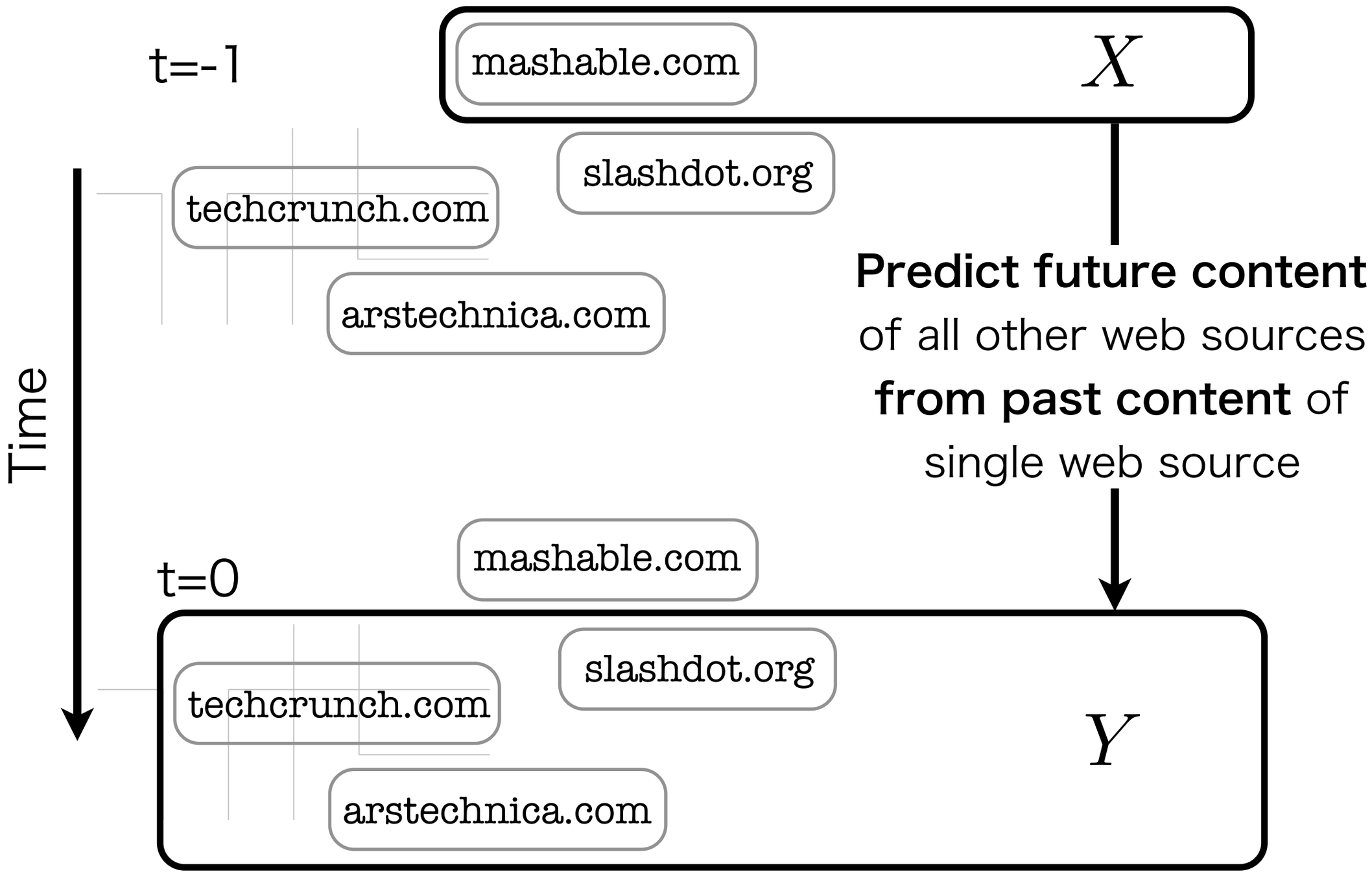
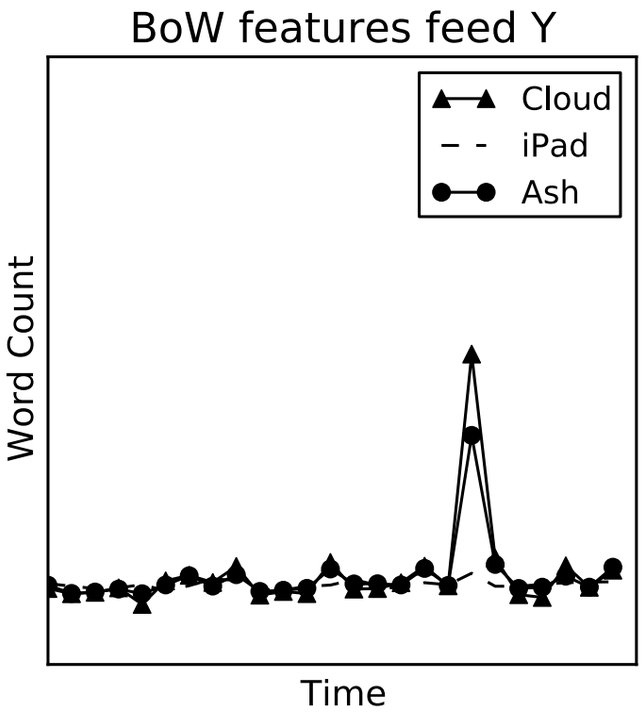
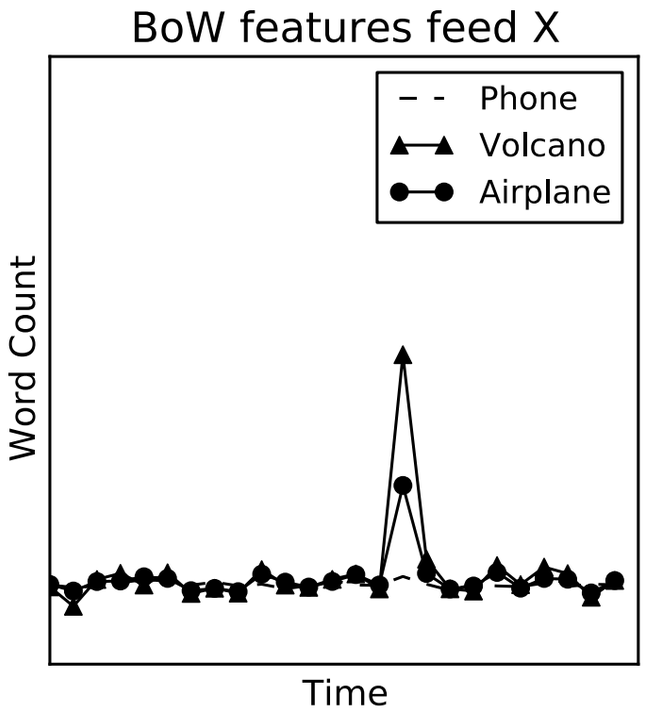


Detecting ‘Trendsetting’ News Websites

A Toy Data Example:
News on eruption of Eyjafjallajoekull

Detecting ‘Trendsetting’ News Websites





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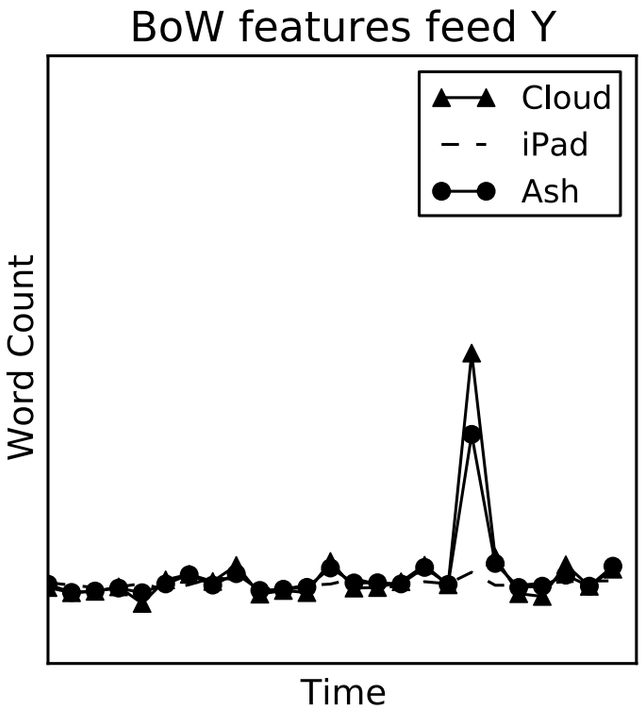
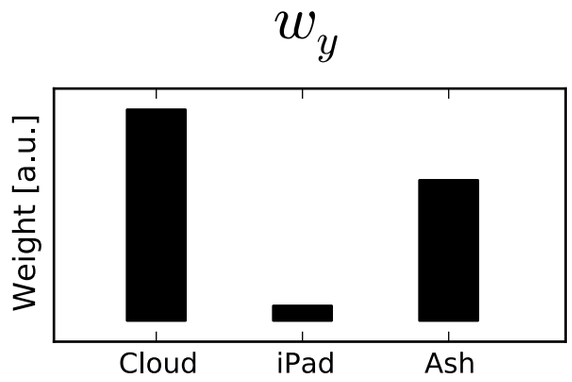
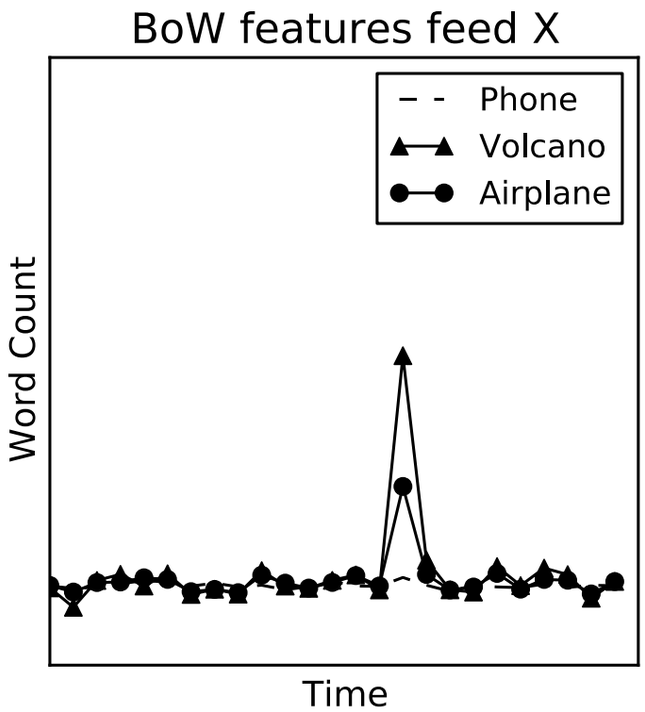
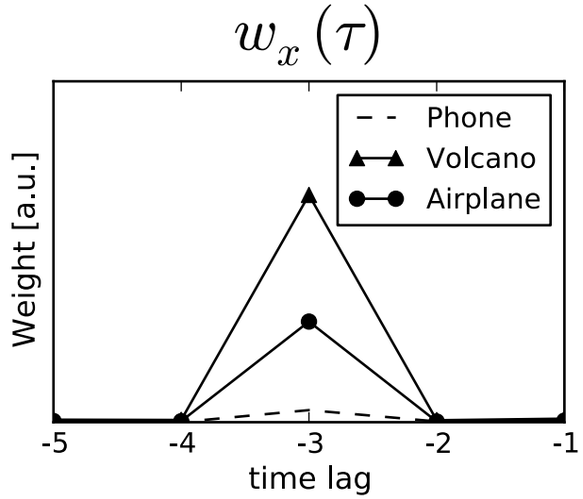




Canonical Trend

Analysis



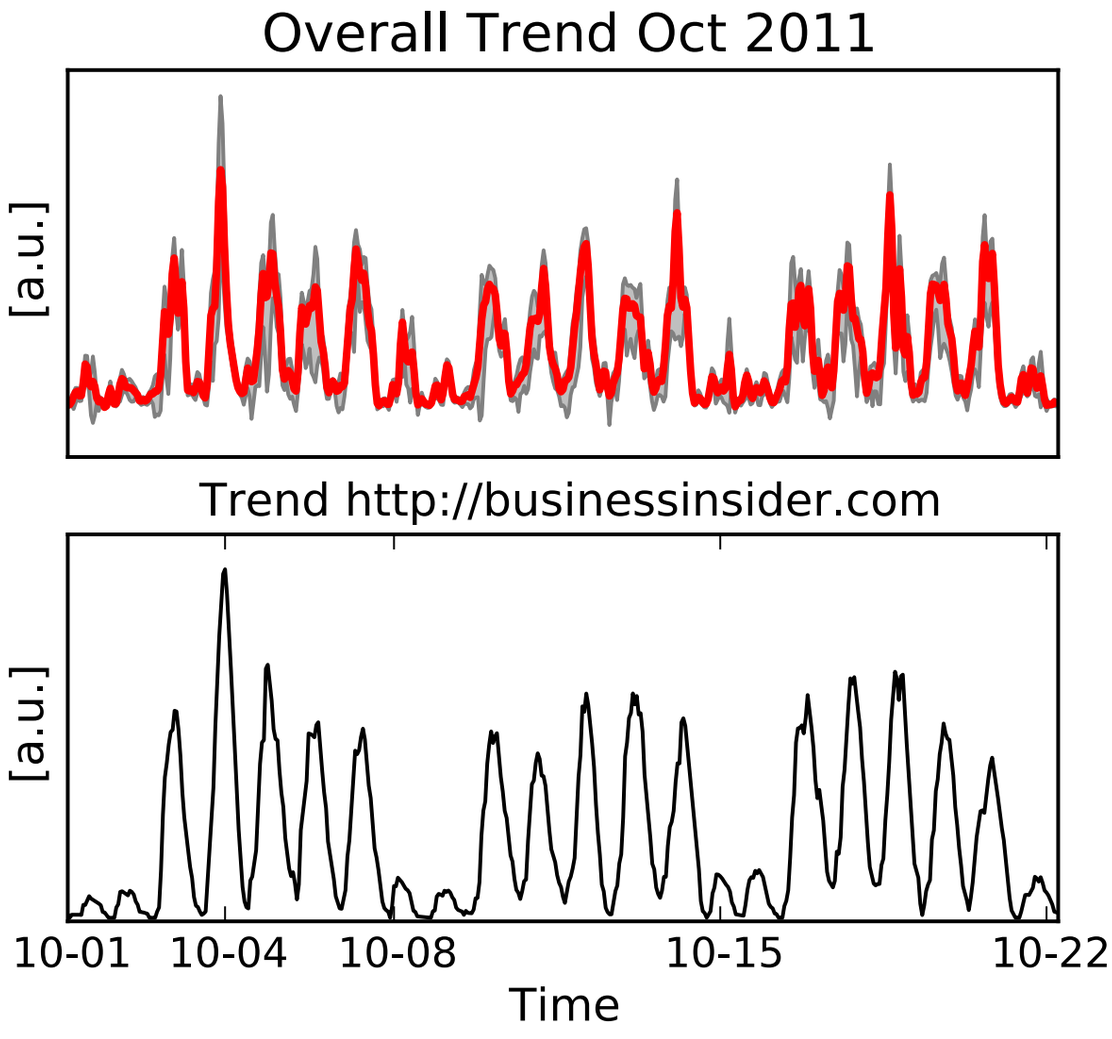


Detecting ‘Trendsetting’ News Websites

Real Data Example:

BoW Features from 96 Technology News Feeds in October 2011

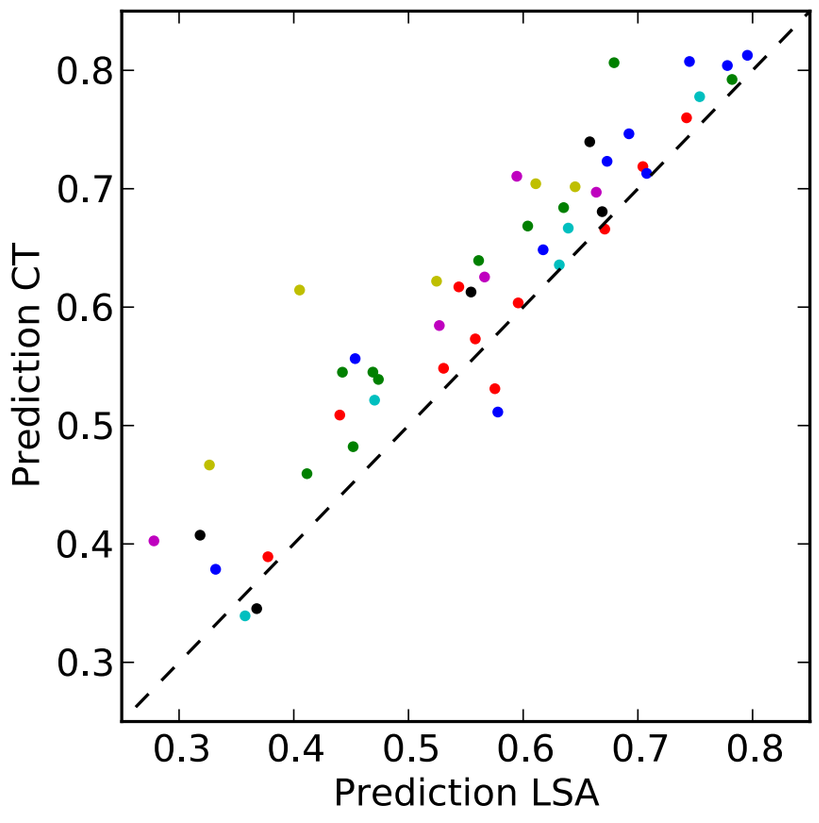
$y_f(t)$



$\hat{y}_f(t)$

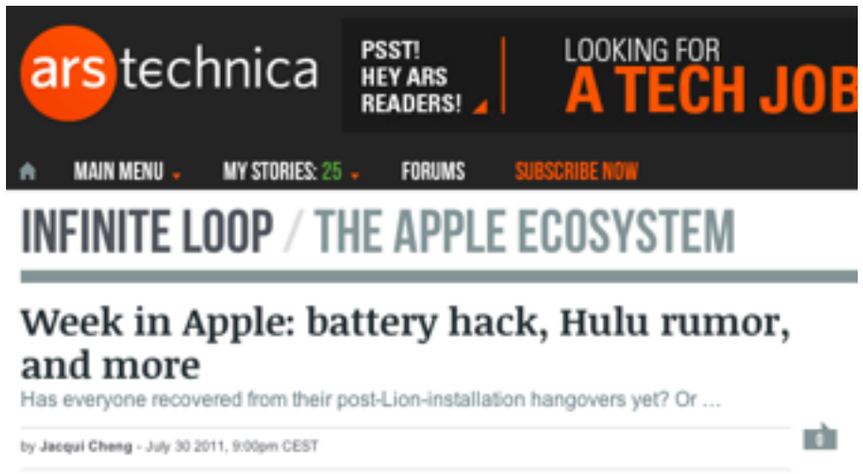
Comparison Canonical Trend Analysis and LSA

Canonical trend analysis **between** X_f and Y_f
vs. LSA on X_f and Y_f **separately**



Canonical Topics predict overall topics
better than Latent Semantic Indexing

Canonical Trend Analysis For Social Networks



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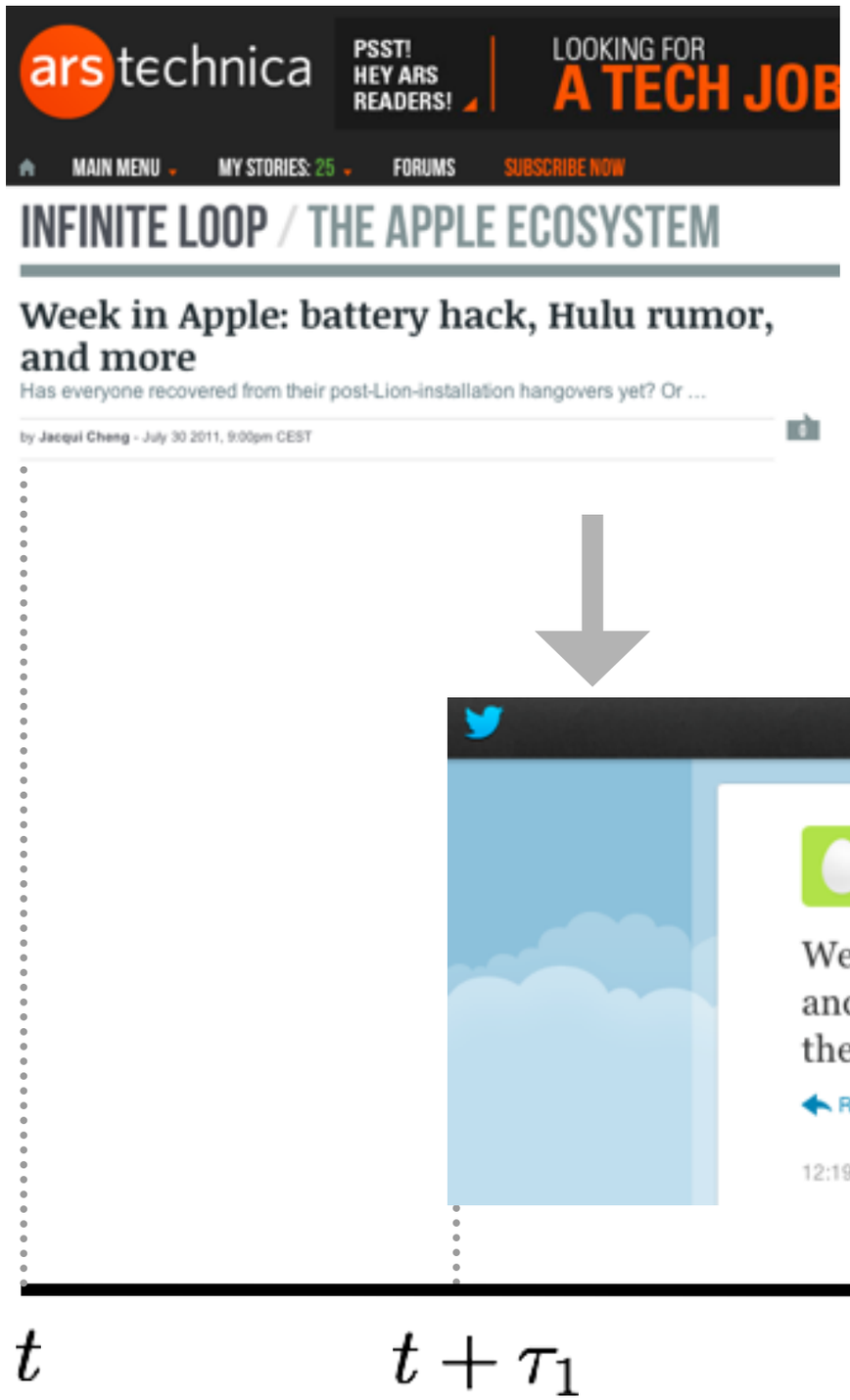
... which is **retweeted**

Canonical Trend Analysis For Social Networks



Some **news web site X** publishes some content ...

... which is **retweeted**

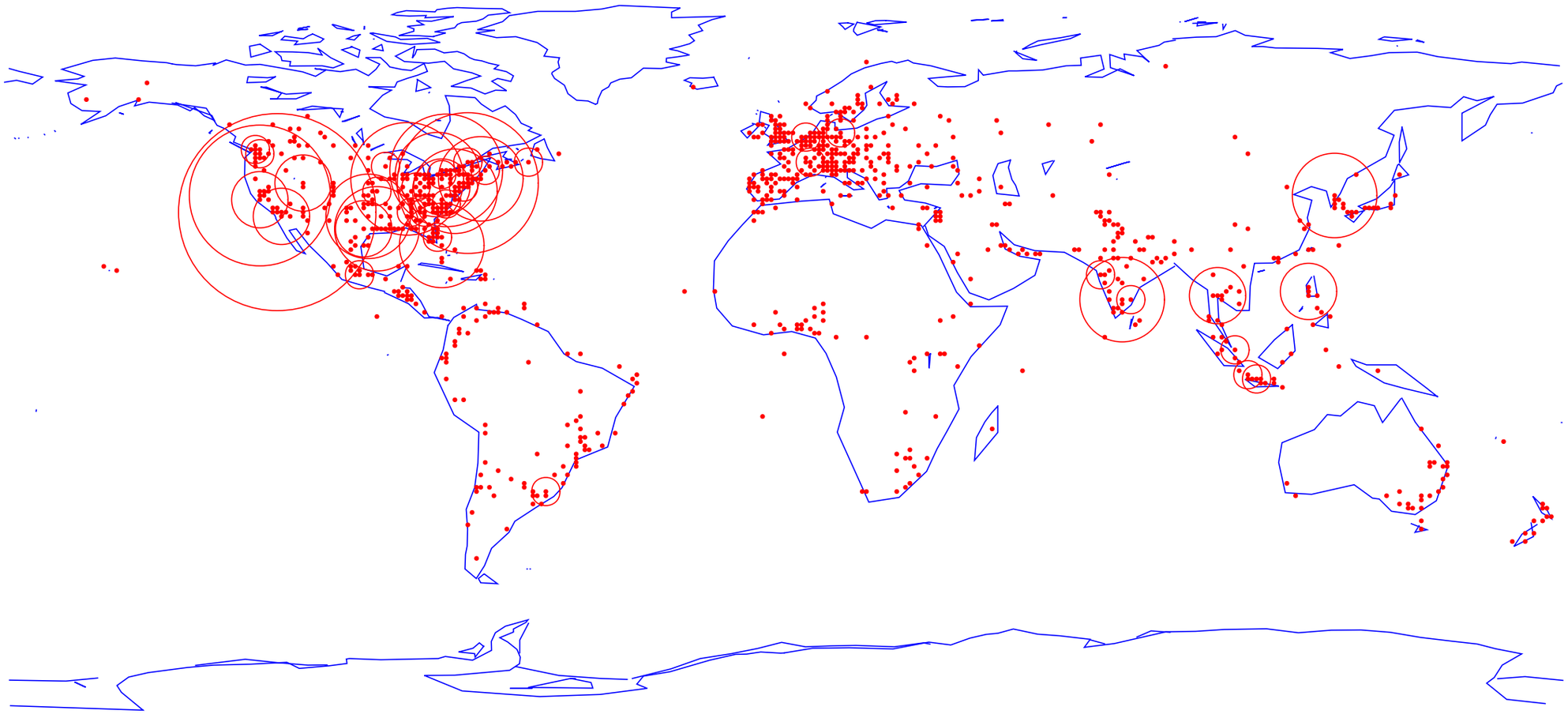
Canonical Trend Analysis For Social Networks

Some **news web site X** publishes some content ...

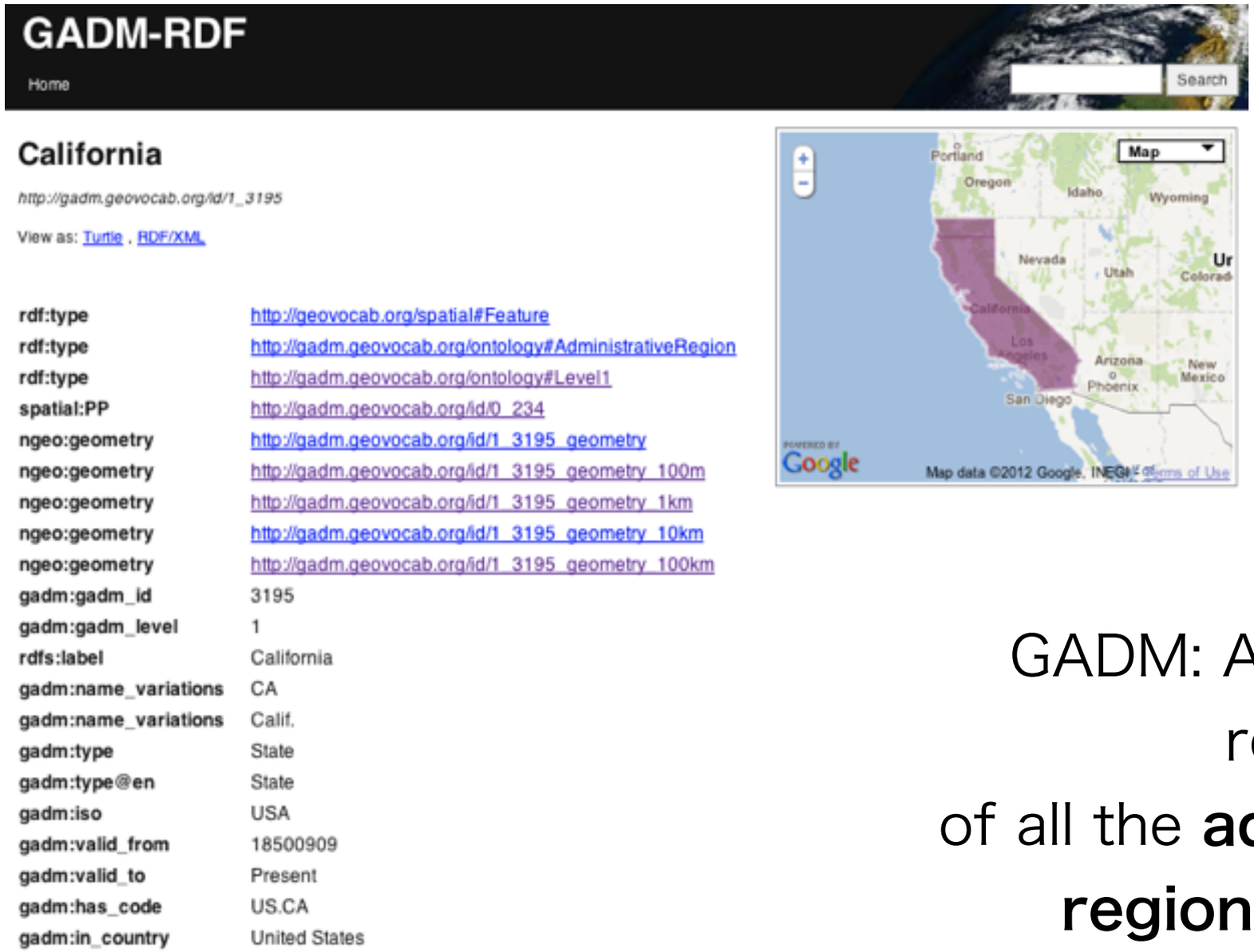
... which is **retweeted**

... at different locations Y

Spatio-temporal Impact of Retweeted News Articles



Downsampling of Geographic Information



GADM: An RDF spatial representation of all the **administrative regions** in the world

Comparisons: Mean, PCA and Canonical Trends

Comparisons: Mean, PCA and Canonical Trends

Canonical Trends

Mean

PCA

Comparisons: Mean, PCA and Canonical Trends

Canonical Trends

$$\underset{w_y(\tau), w_x}{\operatorname{argmax}} \operatorname{Corr}(\hat{x}_f(t), \hat{y}_f(t))$$

Mean

PCA

Comparisons: Mean, PCA and Canonical Trends

Canonical Trends

$$\underset{w_y(\tau), w_x}{\operatorname{argmax}} \operatorname{Corr}(\hat{x}_f(t), \hat{y}_f(t))$$

Mean

$$w_x^\top = \mathbf{1}_x/N, w_y(\tau) = \mathbf{1}_y/N$$

PCA

Comparisons: Mean, PCA and Canonical Trends

Canonical Trends

$$\underset{w_y(\tau), w_x}{\operatorname{argmax}} \operatorname{Corr}(\hat{x}_f(t), \hat{y}_f(t))$$

Mean

$$w_x^\top = \mathbf{1}_x/N, w_y(\tau) = \mathbf{1}_y/N$$

PCA

$$\underset{w_y(\tau)}{\operatorname{argmax}}(w_y(\tau)^\top \tilde{Y}_f \tilde{Y}_f^\top w_y(\tau)),$$

$$\underset{w_x}{\operatorname{argmax}}(w_x^\top X X^\top w_x),$$

$$\text{s.t. } w_y(\tau)^\top w_y(\tau) = w_x^\top w_x = 1$$

Comparisons: Mean, PCA and Canonical Trends

	Hypothesis
Canonical Trends	News Content helps predicting retweet frequency
Mean	Mean Wordcount predicts mean tweet frequency best
PCA	Wordcount variance predicts tweet variance

Comparisons: Mean, PCA and Canonical Trends

Canonical Trends

Mean

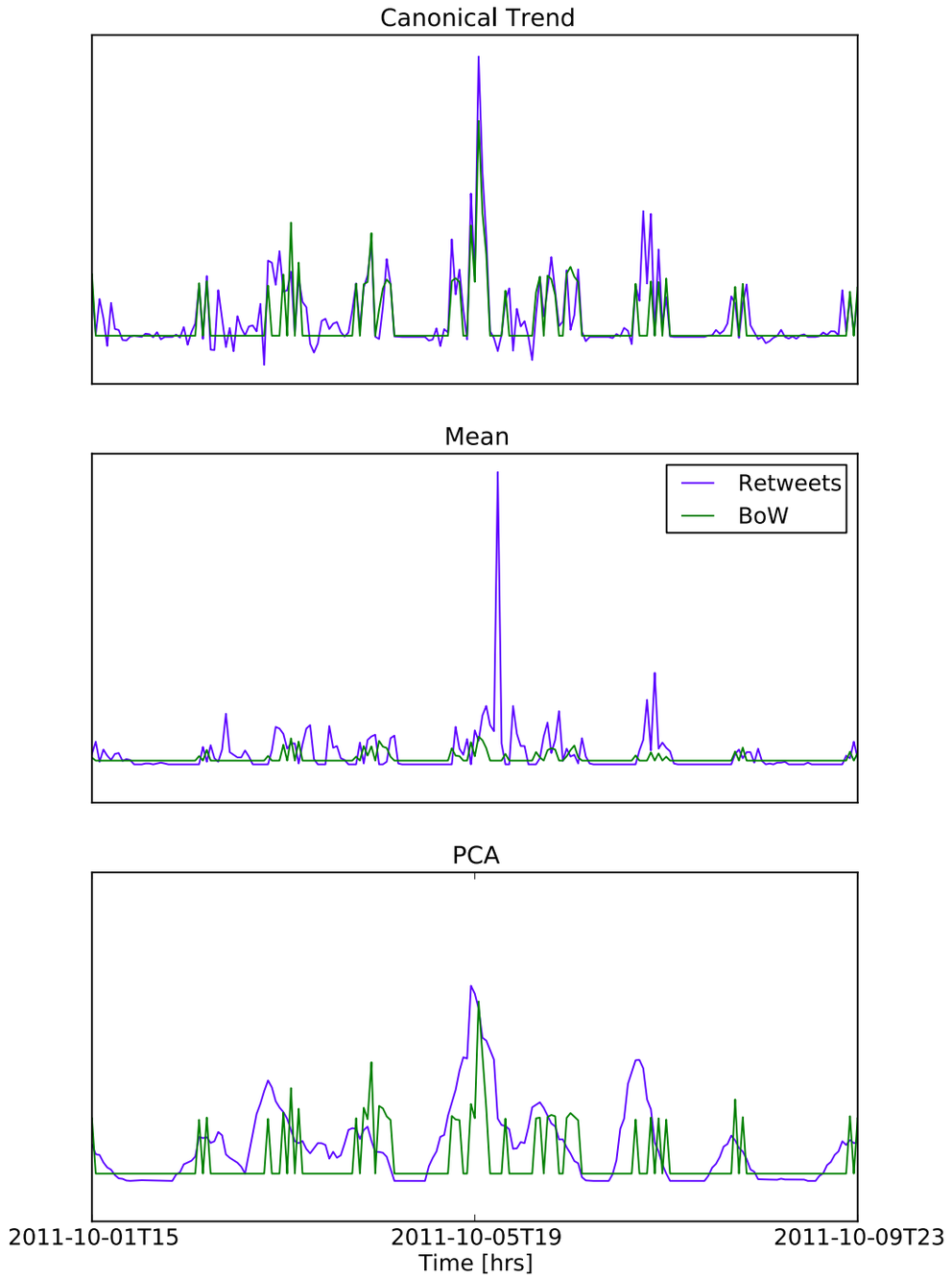
PCA

Comparisons: Mean, PCA and Canonical Trends

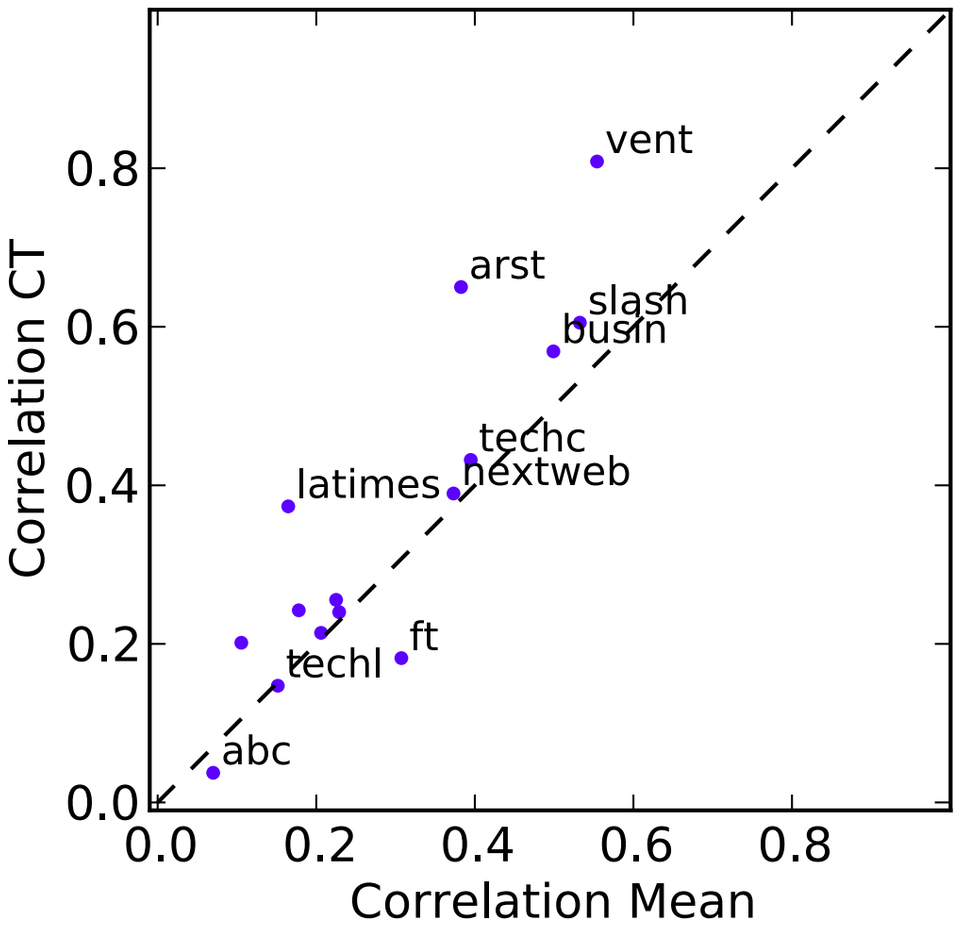
Canonical Trends

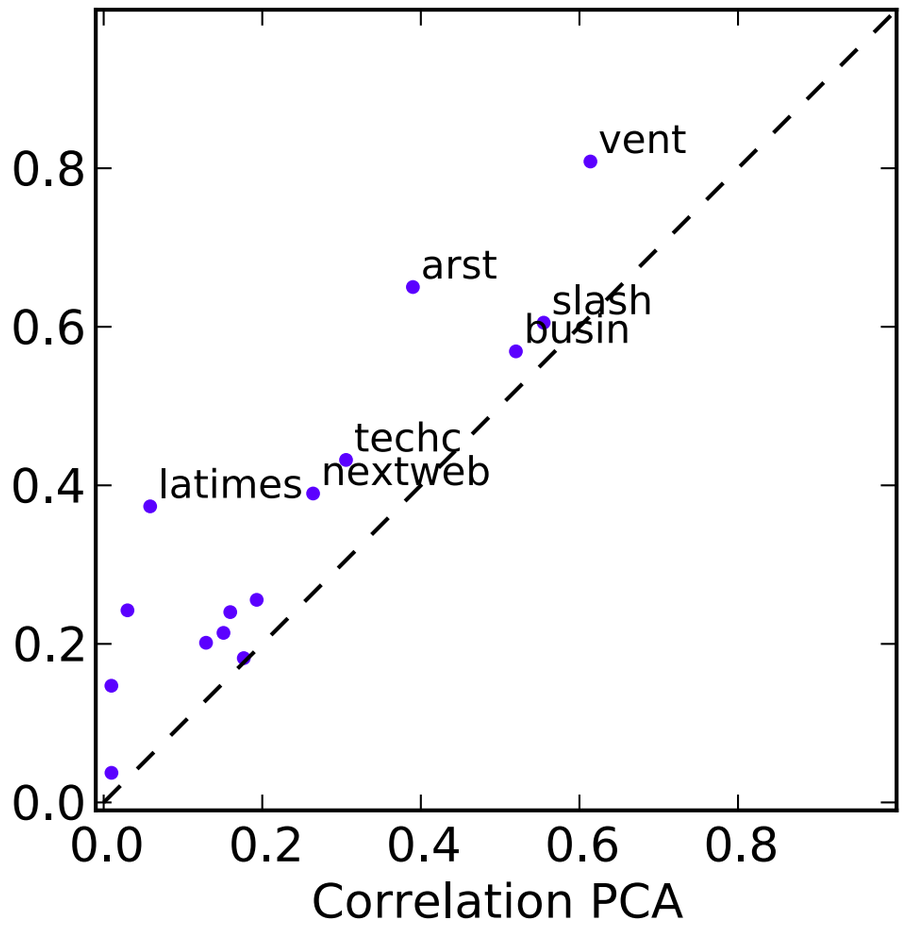
Mean

PCA



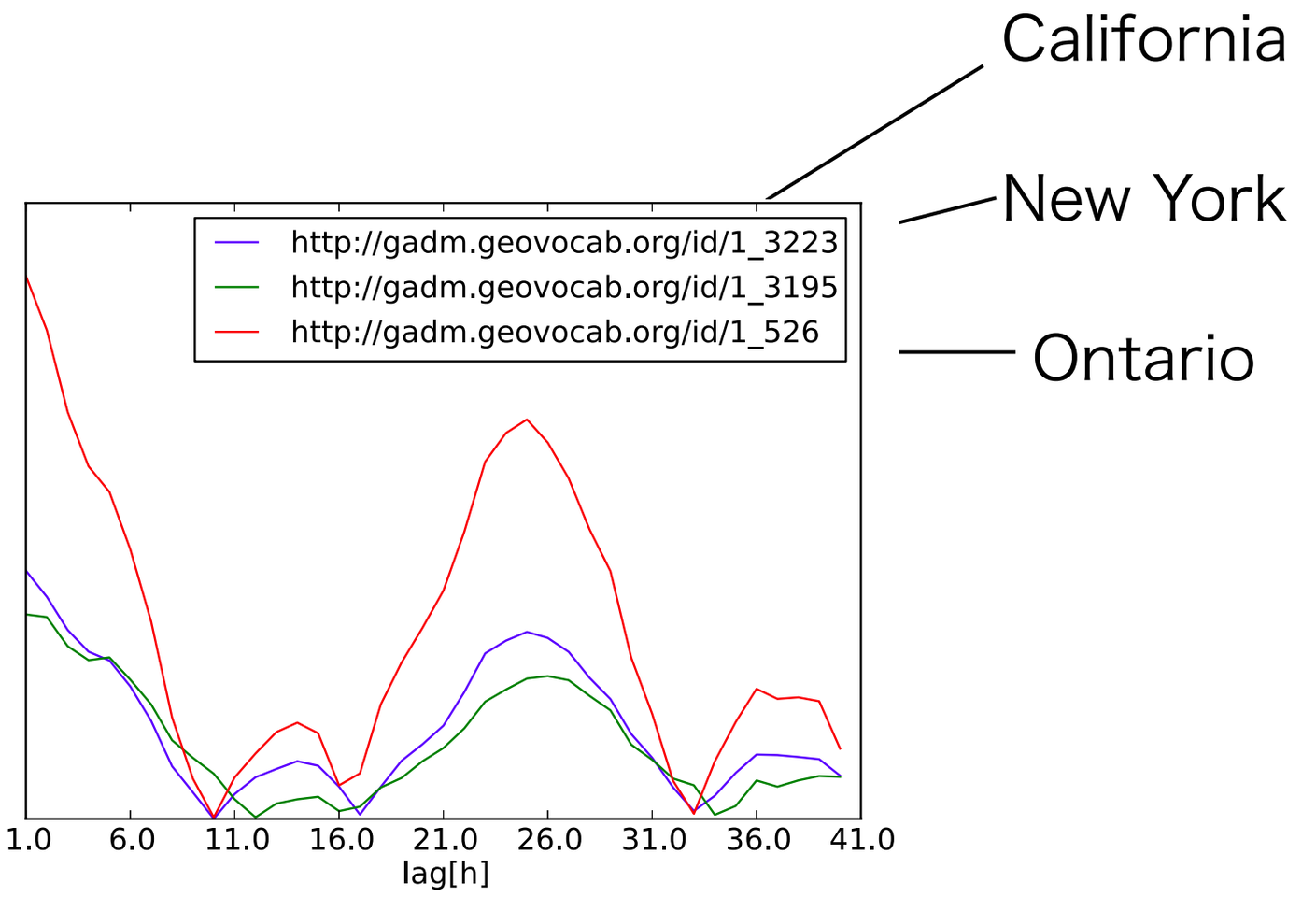
Comparisons: Mean, PCA and Canonical Trends





Canonical Trends

Canonical Convolution



Excerpts from LA Times
Spatiotemporal Response

Canonical Convolution

$$\tau = 1\text{hrs}$$

Canonical Convolution

$$\tau = 12\text{hrs}$$

Spatiotemporal Analysis of Retweets of News

We used canonical correlation analysis to compute

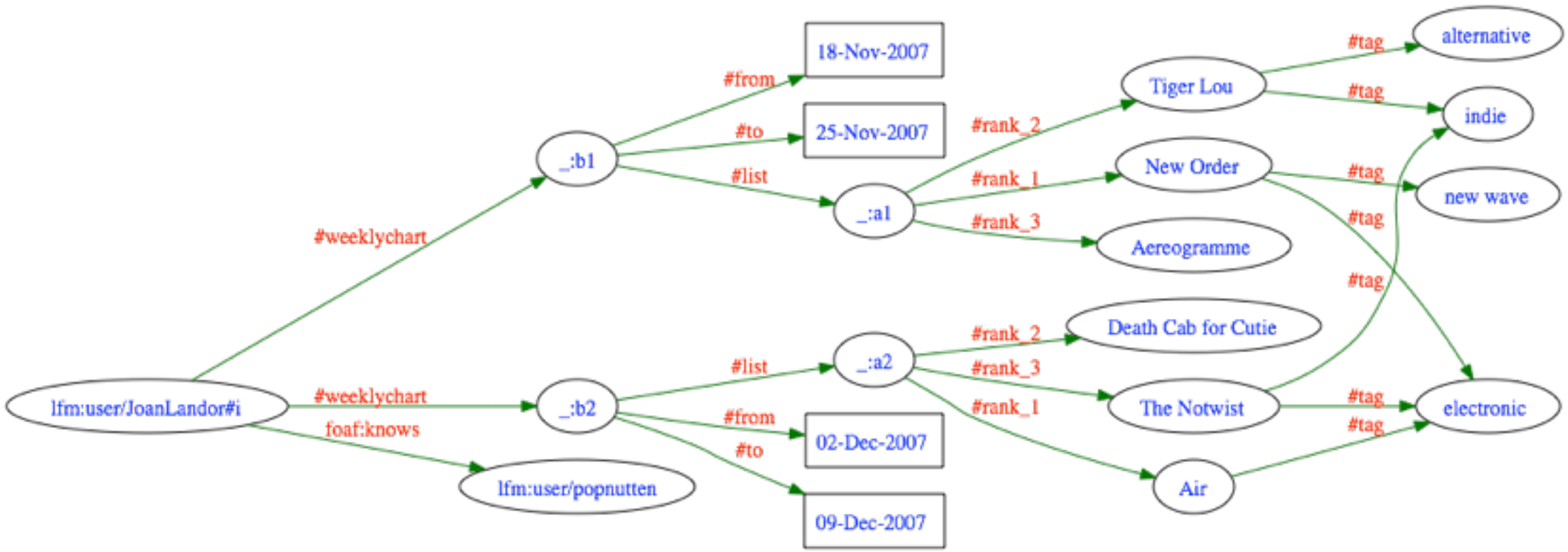
- Bag-of-Word subspace (topic)
- spatiotemporal twitter response patterns

such that news content and retweets are maximally correlated

Results can be interpreted w.r.t

- Impact of web source on social network
- Spatio-temporal evolution of impact

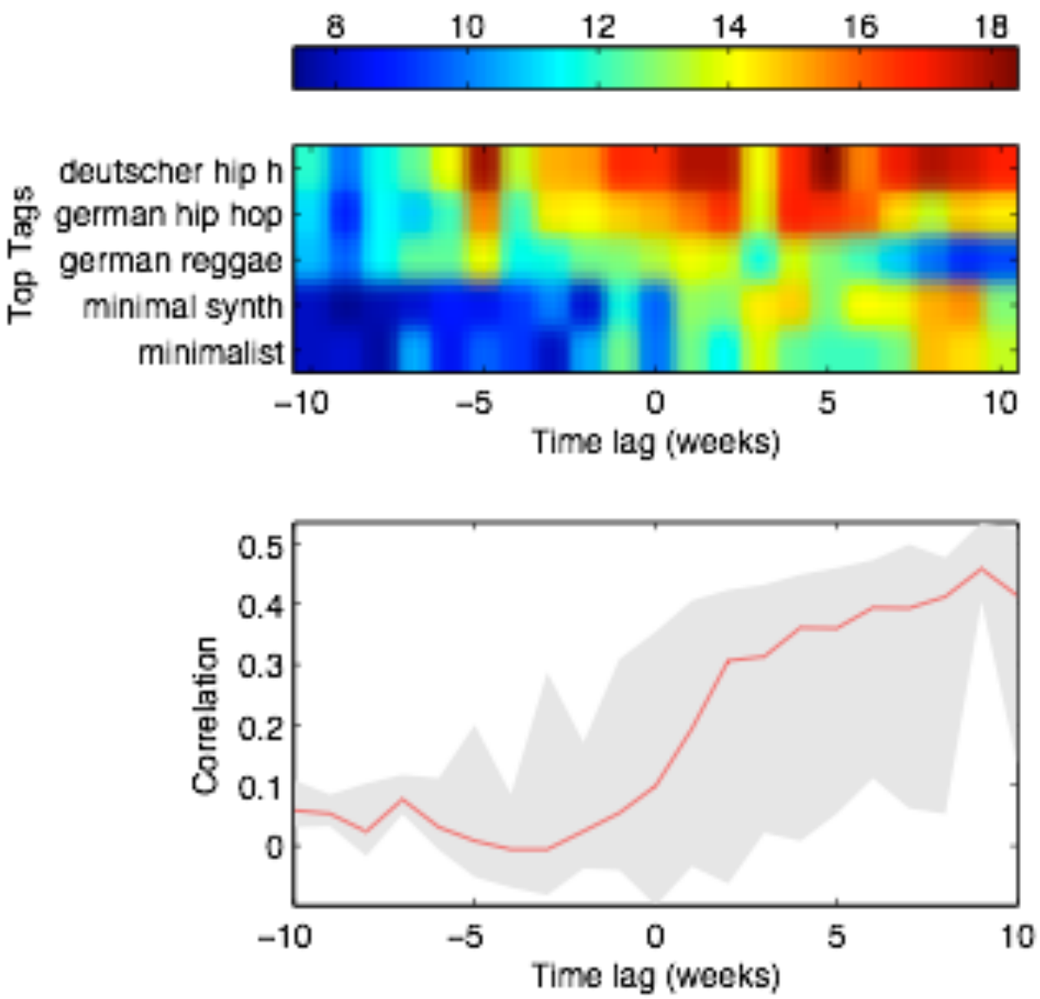
Music Trends on Last.fm



A last.fm user subgraph

Users and Trends on Last.fm

Behind the Trend



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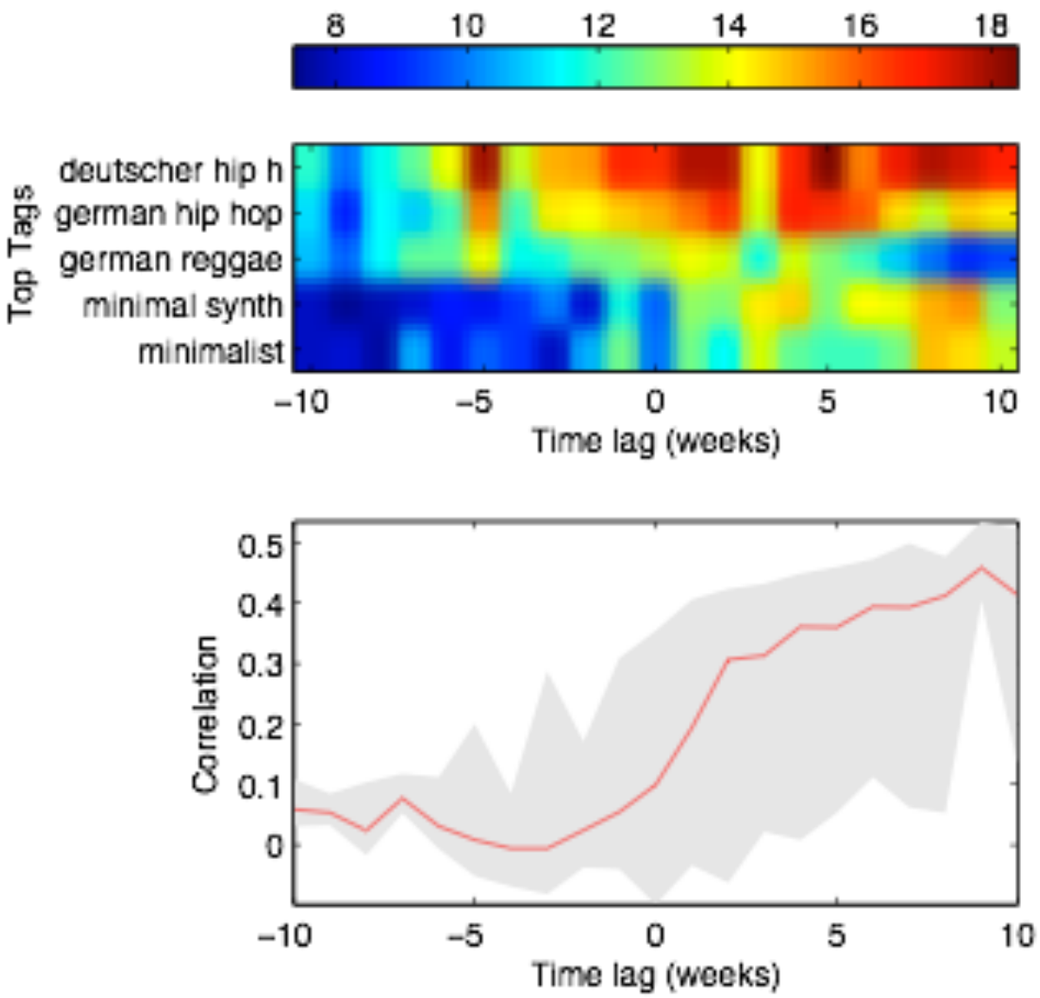
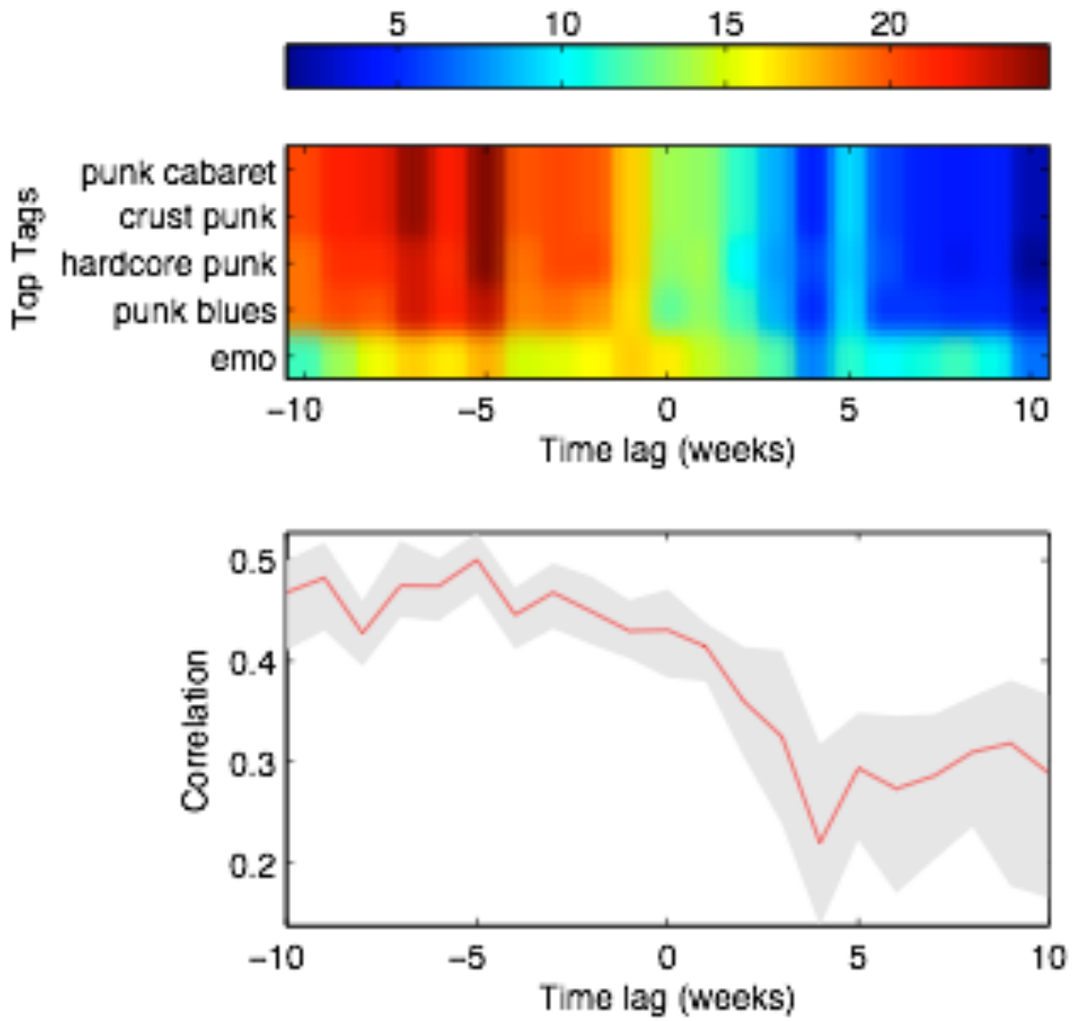


Ahead of Trend



Online Canonical Trend Analysis

For large data sets, kernels become too big (NxN)

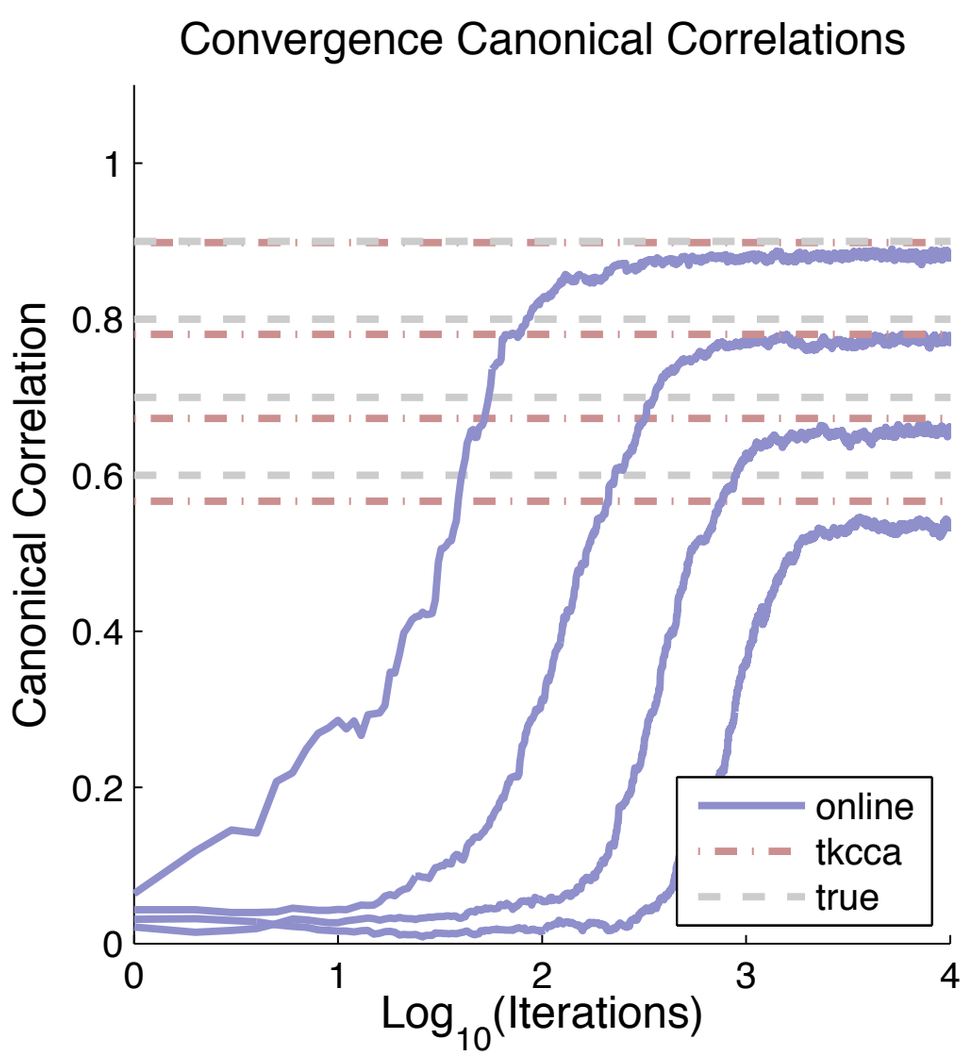
- Subsample
- Change temporal resolution
- Use Stochastic gradient descent (SGD)

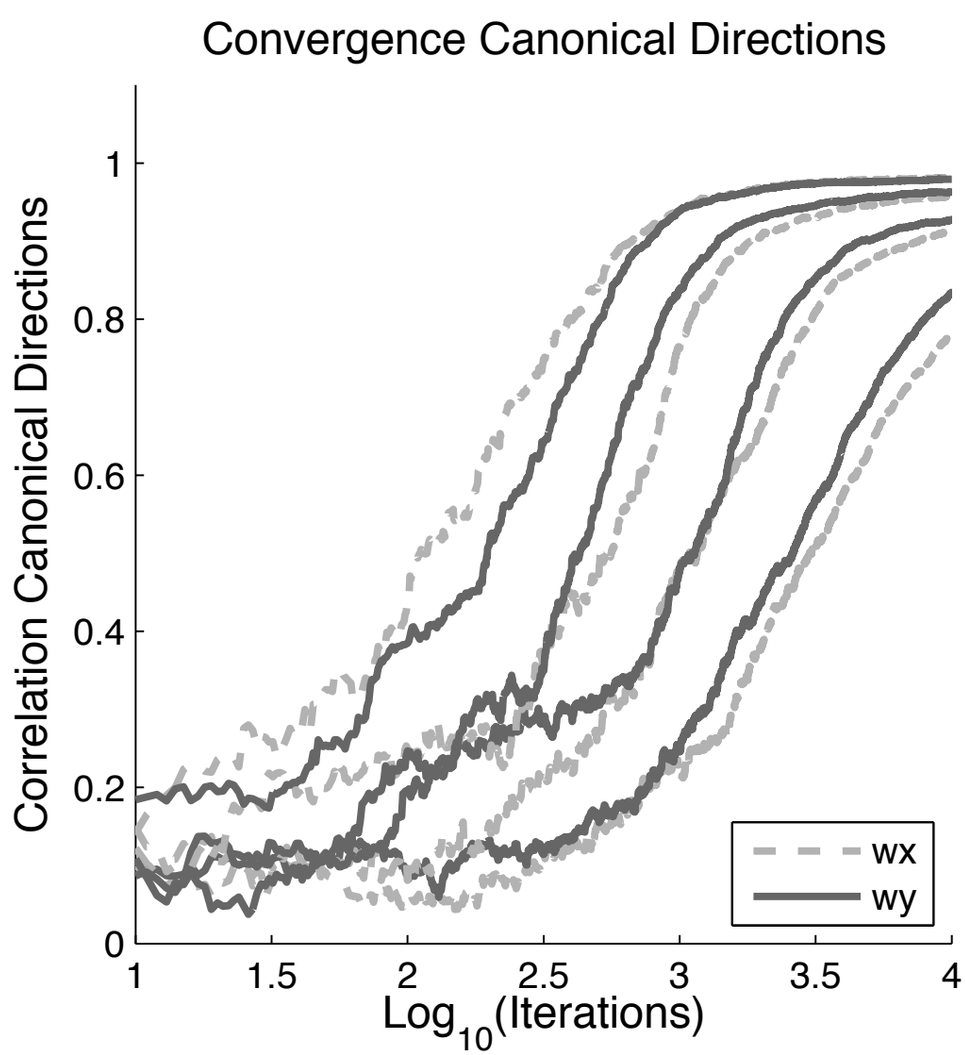
Biessmann et al, Online CCA for Realtime Impact Analysis of Social Media Data, NIPS Workshop, 2012

Algorithm 1: Online Canonical Trend Analysis

Input: Data streams of web sources $\mathcal{X}_f,\ f = 1, \ldots, F$, learning rate η_0
# For each new sample $x_f(t)$
for $t = 1$ **to** T **do**
  # Loop over all news feeds
  for $f = 1$ **to** F **do**
    $y_f(t) = 1/(1-F) \sum_{f' \neq f} x_{f'}(t)$
    # Temporal Embedding (eq. 2)
    $\tilde{x}_f(t) = [x_f(t - N_\tau)^\top, \ldots, x_f(t-1)^\top]^\top$
    # Update $w_{\tilde{X}},\ w_y$ (eq. 7)
    $w_{\tilde{X}} \leftarrow w_{\tilde{X}} + \eta_0/t\ \ \tilde{x}_f(t) y(t)_f^\top w_y$
    $w_y \leftarrow w_y + \eta_0/t\ \ w_{\tilde{X}}^\top \tilde{x}_f(t) y(t)_f^\top$
    # Project canonical directions on unit ball
    $w_{\tilde{X}} \leftarrow w_{\tilde{X}} \|w_{\tilde{X}}\|_2^{-1}$
    $w_y \leftarrow w_y \|w_y\|_2^{-1}$
  end for
  Rank Feeds according to Corr$(w_{\tilde{X}}^\top x_f, w_y^\top y_f)$
end for

Online Canonical Trend Analysis





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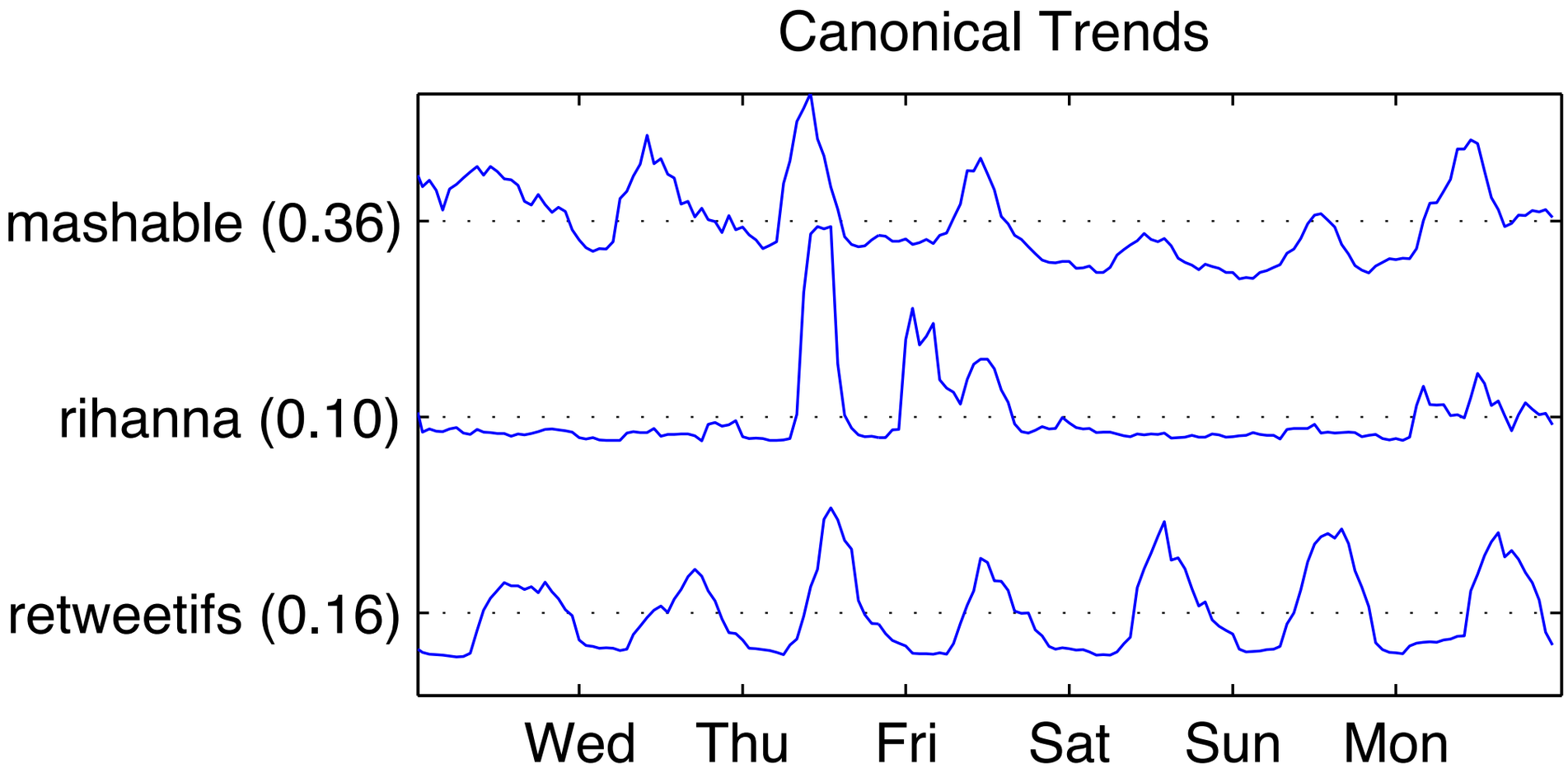

Summary

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Canonical Trend Analysis

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Simple trend detection algorithm

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- Detects web sources that publish trends before others do

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*(for reasonably chosen temporal resolutions)

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Thank you