

Modeling Topic-level Academic Influence in Scientific Literatures

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Shanghai Jiao Tong University

Feb 13, 2016



Outline

- ① Motivation
- ② J-Index Framework
- ③ Reference Topic Model (RefTM)
 - Generative Model
 - Parameter Estimation
- ④ Experiments
 - Datasets
 - Evaluation Aspects
 - Evaluation Results
- ⑤ Conclusions & Future works

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Motivation

When a beginner starts to explore a new field ...

Motivation

Google

Scholar About 2,160,000 results (0.05 sec)

Articles

Machine learning, neural and statistical classification
 D Michie, [DJ Spiegelhalter](#), CC Taylor - 1994 - Citeseer
 Abstract The aim of this book is to provide an up-to-date review of different approaches to classification, compare their performance on a wide range of challenging data-sets, and draw conclusions on their applicability to realistic industrial problems.
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Case law

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Any time

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 Since 2015
 Since 2012
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[BOOK] Statistical learning theory
[VN Vapnik](#), V Vapnik - 1998 - ai.ato.ms
 ... The theory provides a sound **statistical** basis for assessing model adequacy under these circumstances, which are precisely the circumstances encountered in **MACHINE LEARNING**, PATTERN RECOGNITION, and exploratory data analysis. ...
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Sort by relevance
 Sort by date

include patents
 include citations

Create alert

[PDF] Statistical machine learning makes automatic control practical for internet datacenters
[P Bodik](#), R Griffith, [C Sutton](#), A Fox, [M Jordan](#) ... - Proceedings of the ..., 2009 - [usenix.org](#)
 Abstract Horizontally-scalable Internet services on clusters of commodity computers appear to be a great fit for automatic control: there is a target output (service-level agreement), observed output (actual latency), and gain controller (adjusting the number of servers). Yet ...
 Cited by 137 Related articles All 15 versions Cite Save More

Distributed optimization and statistical learning via the alternating direction method of multipliers
[S Boyd](#), [N Parikh](#), [E Chu](#), [B Peleato](#) ... - ... @ in **Machine Learning**, 2011 - [dl.acm.org](#)
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Figure 1 : Result of Google Scholar

Motivation

The screenshot shows a Google Scholar search for "Statistical Machine Learning". The search bar at the top contains the text "Statistical Machine Learning" and a search icon. Below the search bar, the results are displayed in a list format. A red box highlights the text "About 2,160,000 results (0.05 sec)" with an arrow pointing to the question "How to rank these papers?". The search results are organized into sections: "Articles", "Case law", "My library", "Any time", "Sort by relevance", "Sort by date", "include patents", "include citations", and "Create alert". The first article is "Machine learning, neural and statistical classification" by D Michie, DJ Spiegelhalter, and CC Taylor. The second is "[BOOK] Statistical learning theory" by V N Vapnik. The third is "[PDF] Statistical machine learning makes automatic control practical for internet datacenters" by P Bodik, R Griffith, C Sutton, A Fox, and M Jordan. The fourth is "Distributed optimization and statistical learning via the alternating direction method of multipliers" by S Boyd, N Parikh, E Chu, B Peleato, and J Wright.

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Figure 2 : Defects of Google Scholar

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Suppose we intend to follow this direction Which related work should we read?

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Stand on the shoulders of giants

– Isaac Newton

Motivation

Find those giants !!!

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Related works

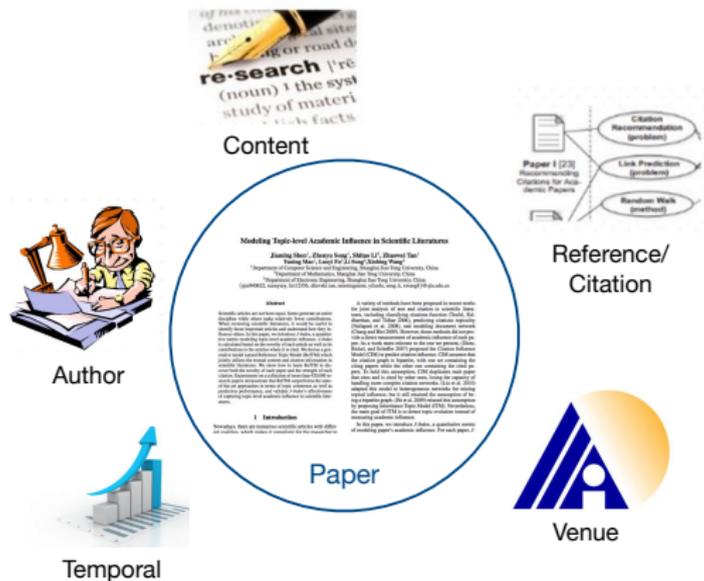


Figure 4 : Factors of one paper

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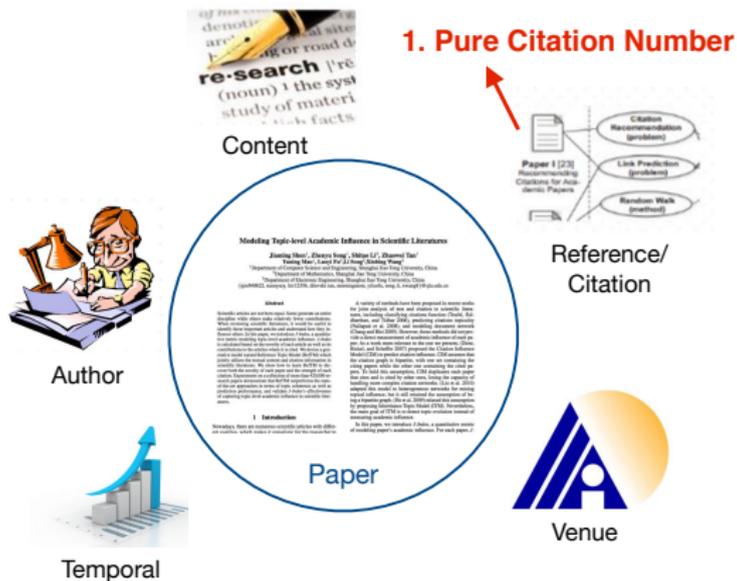


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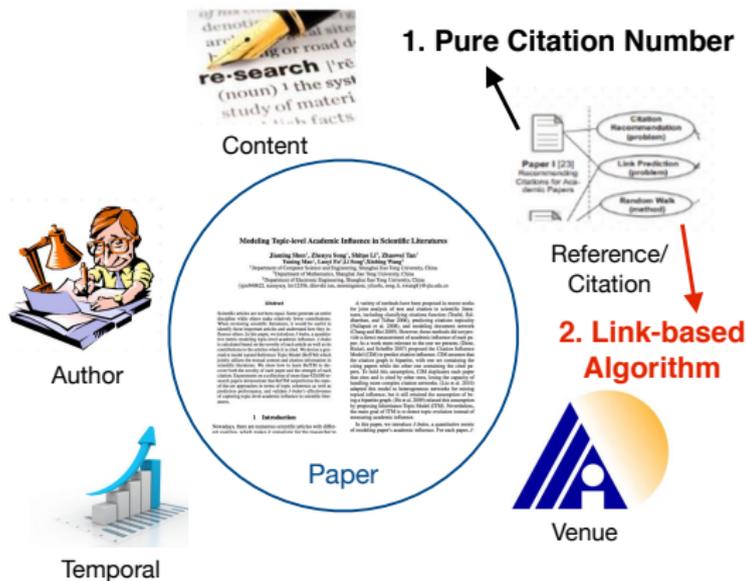


Figure 6 : Factors of one paper

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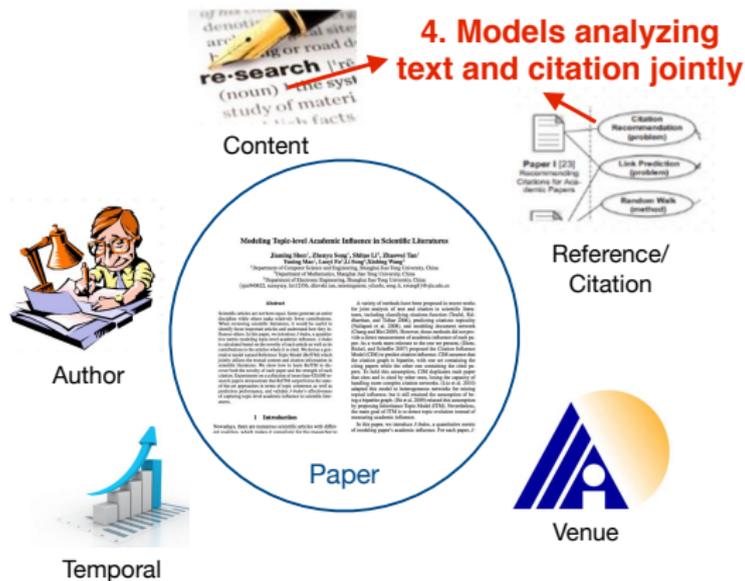


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J-Index Framework

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 - ① A paper's academic influence increases as it gains more citations.
 - ② A paper with stronger citations intends to be more influential.
 - ③ A paper cited by more innovative papers is more influential.
- We define the *J-Index* as follows:

$$\text{J-Index-Score}(u) = \sum_{c \in C(u)} \lambda(c) \times \delta(c, u)$$

- $C(u)$: the set of paper u 's citations, obtained from input dataset.
- $\lambda(c)$: the innovativeness of paper c .
- $\delta(c, u)$: the citation strength between paper c and paper u .
- Both $\lambda(c)$ and $\delta(c, u)$ are obtained from subsequent model.

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- **Topic Innovation: come from one's own idea.**

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- Topic Innovation: come from one’s own idea.
- Topic Inheritance: come from one of cited papers.
- Citation Strength: determine which reference is selected

Generative Model

1. For each topic index $k \in \{1, \dots, K\}$
 - (a) Draw a word distribution $\varphi_k \sim \text{Dir}(\beta)$
2. For each document index $m \in \{1, \dots, M\}$
 - (a) Draw a topic distribution $\theta_m \sim \text{Dir}(\alpha)$
 - (b) Draw a reference distribution $\delta_m \sim \text{Dir}(\eta | L_m)$
 - (c) Draw an inheritance index $\lambda_m \sim \text{Beta}(\alpha_{\lambda_n}, \alpha_{\lambda_c})$
 - (d) For each word $n \in \{1, \dots, N_m\}$ in document m :
 - (i) Flip a coin $s_{m,n} \sim \text{Bern}(\lambda_m)$
 - (ii) if $s_{m,n} = 0$:
 - Draw a topic $z_{m,n} \sim \text{Multi}(\theta_m)$
 - Draw a word $w_{m,n} \sim \text{Multi}(\varphi_{z_{m,n}})$
 - (iii) else ($s_{m,n} = 1$):
 - Draw a reference $c_{m,n} \sim \text{Multi}(\delta_m)$
 - Draw a topic $z_{m,n} \sim \text{Multi}(\theta_{c_{m,n}})$
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Figure 10 : Generative Model of RefTM

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- Inference: Observation \rightarrow Parameters
- In RefTM, observations: words & citations; parameters (we mainly concerned): λ and δ

RefTM Inference: Gibbs Sampling

$$p(s_i = 0 | \mathbf{s}_{-i}, \mathbf{w}, \mathbf{z}, \cdot) \propto \frac{(n_m^{s_i(0)} - 1) + n_m^{s_i(1)} + \alpha}{n_m^{(\cdot)(0)} + n_m^{(\cdot)(1)} + K\alpha - 1} \cdot \frac{N_m^{(0)} - 1 + \alpha\lambda_n}{N_m^{(1)} + (N_m^{(0)} - 1) + \alpha\lambda_n + \alpha\lambda_c}$$

$$p(s_i = 1 | \mathbf{s}_{-i}, \mathbf{w}, \mathbf{z}, \mathbf{c}_i, \cdot) \propto \frac{n_{c_i}^{s_i(0)} + (n_{c_i}^{s_i(1)} - 1) + \alpha}{n_{c_i}^{(\cdot)(0)} + n_{c_i}^{(\cdot)(1)} + K\alpha - 1} \cdot \frac{N_m^{(1)} - 1 + \alpha\lambda_c}{(N_m^{(1)} - 1) + N_m^{(0)} + \alpha\lambda_n + \alpha\lambda_c}$$

$$p(c_i | \mathbf{c}_{-i}, \mathbf{w}, \mathbf{z}, s_i = 1, \cdot) \propto \frac{n_{c_i}^{s_i(0)} + (n_{c_i}^{s_i(1)} - 1) + \alpha}{n_{c_i}^{(\cdot)(0)} + n_{c_i}^{(\cdot)(1)} + K\alpha - 1} \cdot \frac{R_m^{c_i} - 1 + \eta}{R_m^{(\cdot)} + L_m \eta - 1}$$

$$p(z_i | \mathbf{z}_{-i}, \mathbf{w}, s_i = 0, \cdot) \propto \frac{n_{z_i}^{w_i} + \beta - 1}{n_{z_i}^{(\cdot)} + V\beta - 1} \cdot \frac{(n_m^{z_i(0)} - 1) + n_m^{z_i(1)} + \alpha}{n_m^{(\cdot)(0)} + n_m^{(\cdot)(1)} + K\alpha - 1}$$

$$p(z_i | \mathbf{z}_{-i}, \mathbf{w}, s_i = 1, c_i, \cdot) \propto \frac{n_{z_i}^{w_i} + \beta - 1}{n_{z_i}^{(\cdot)} + V\beta - 1} \cdot \frac{n_{c_i}^{z_i(0)} + (n_{c_i}^{z_i(1)} - 1) + \alpha}{n_{c_i}^{(\cdot)(0)} + n_{c_i}^{(\cdot)(1)} + K\alpha - 1}$$

Algorithm 1 Gibbs Sampling Algorithm for RefTM

Input: $K, w, \alpha, \beta, \eta, \lambda_c, \lambda_n$

Output: Parameter sets $\{\theta, \varphi, \delta, \lambda\}$

Read in data and zero out all count caches

Randomly initialize z_i, c_i, s_i

for $iter = 1$ to N_{iter} **do**

for all documents $m \in [1, M]$ **do**

for all words $n \in [1, N_m]$ in document m **do**

if $s_{m,n} = 0$ **then**

 Update the counts $n_m^{(k)(0)}, n_m^{(0)}$

else

 Update the counts $n_c^{(k)(1)}, n_c^{(1)}, R_m^c, R_m$

 Draw a new \bar{s} from Eqs.(2-3)

if $\bar{s} = 0$ **then**

 Update the counts $n_k^{w_{m,n}}, n_k$

 Draw a new topic \bar{k} from Eq.(5)

 Update the counts $n_m^{(k)(0)}, n_m^{(0)}, n_k^{w_{m,n}}, n_k$

else

 Draw a new reference \bar{c} from Eq.(4)

 Update the counts $R_m^c, R_m, n_k^{w_{m,n}}, n_k$

 Draw a new topic \bar{k} from Eq.(6)

 Update the counts $n_c^{(k)(1)}, n_c, n_k^{w_{m,n}}, n_k$

 Read out parameters set $\theta, \varphi, \lambda, \delta$ by Eqs.(7-10)

Figure 12 : Gibbs sampling equations & Algorithm for RefTM

Visualization of RefTM's output

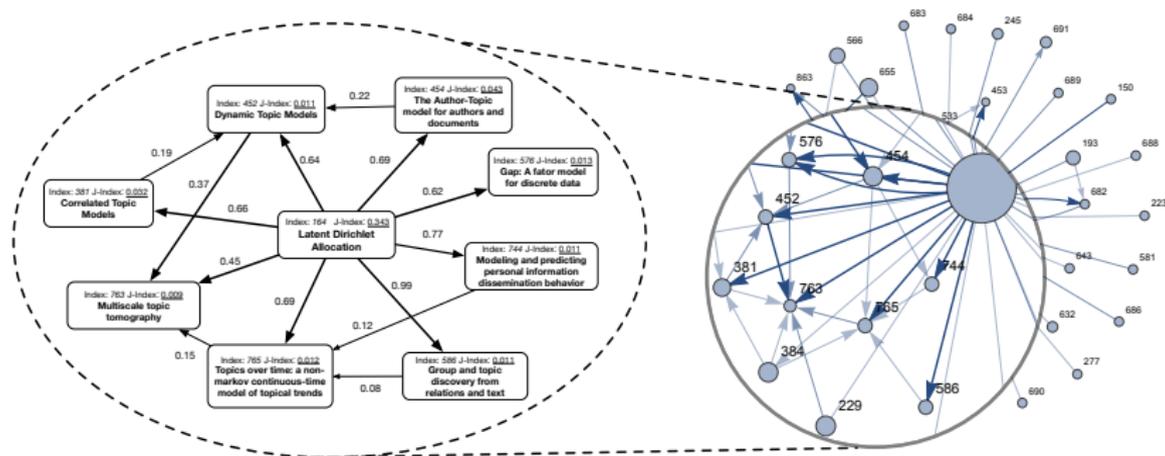


Figure 13 : Right hand side is an illustrative citation graph in which the thickness of edge represents the citation strength and the vertex size indicates one papers academic influence. Left hand side presents each paper's *J-Index*.

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Datasets

- Dataset 1: a large unsupervised collection of 426728 articles with over 209 million citations.
- Dataset 2: a small supervised collection of 799 papers obtained from (Liu et al. 2010).
- The average paper length of two corpora are 83 and 98 words.

Evaluation Aspects

- Topic Coherence

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- Case Study: Rank INFOCOM

Topic Coherence

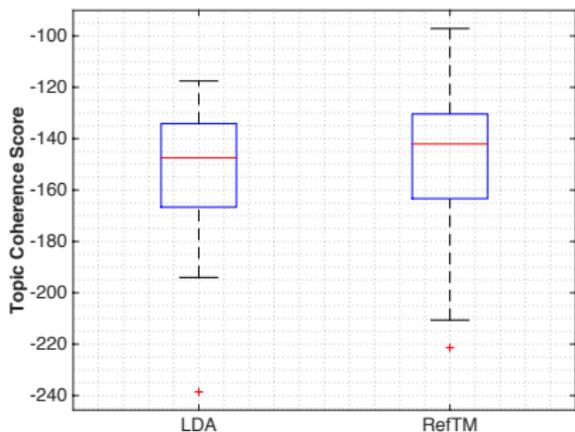
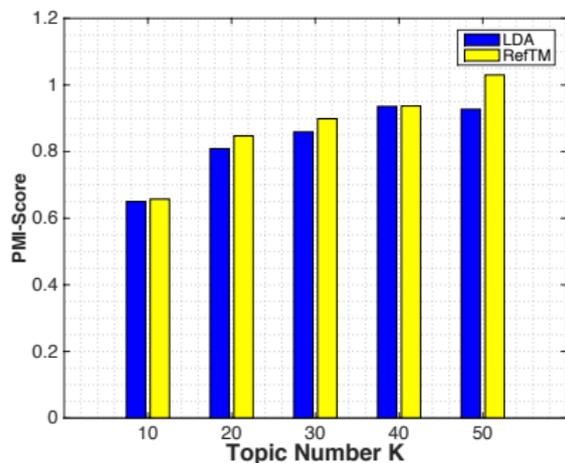


Figure 14 : Topic Coherence Evaluation

- PMI-Score: RefTM outperforms LDA by 12% when $K = 50$.
- *Topic Coherence-Score*: RefTM outperforms LDA slightly.

Citation Strength Prediction

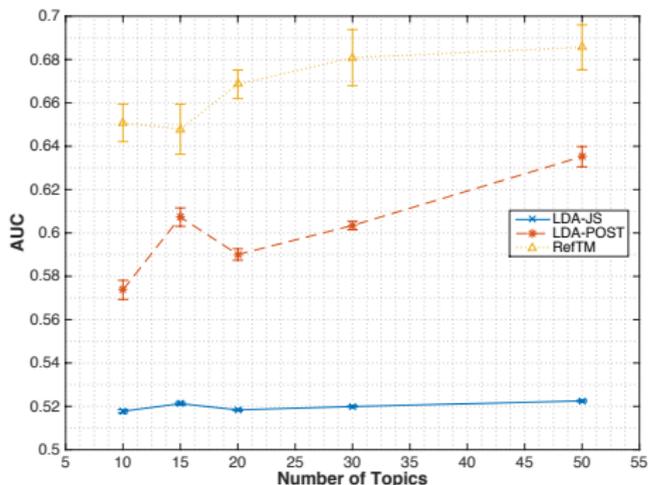


Figure 15 : Citation Strength Prediction measured by averaged AUC

- Reduce the normalization constraint of δ in RefTM.
- RefTM clearly outperforms two baseline methods.

Case Study: Rank INFOCOM

Table 2: Top 5 Articles in INFOCOM 2003 ranked by *J-Index* & citations

Title	<i>J-Index</i>	citation counts
Top 5 Articles in INFOCOM 2003 ranked by <i>J-Index</i>		
Ad hoc positioning system (APS) using AOA	6.75	115
Performance anomaly of 802.11b	5.17	127
Packet leashes: a defense against wormhole attacks in wireless networks	4.13	74
Unreliable sensor grids: coverage, connectivity and diameter	4.00	82
Sensor deployment and target localization based on virtual forces	3.61	60
Top 5 Articles in INFOCOM 2003 ranked by citation number		
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Ad hoc positioning system (APS) using AOA	6.75	115
Optimal routing, link scheduling and power control in multihop wireless networks	2.26	109
Sprite: a simple, cheat-proof, credit-based system for mobile ad-hoc networks	2.43	88
Unreliable sensor grids: coverage, connectivity and diameter	4.00	82

Figure 16 : Citation Strength Prediction measured by averaged AUC

- Rankings by *J-Index* and citations number are correlated.
- *J-Index* favors those paper that propose novel “ideas”.

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 - ② Consider multiple factors, especially the temporal information.

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Thank you!

Q & A