Modeling Topic-level Academic Influence in Scientific Literatures

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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

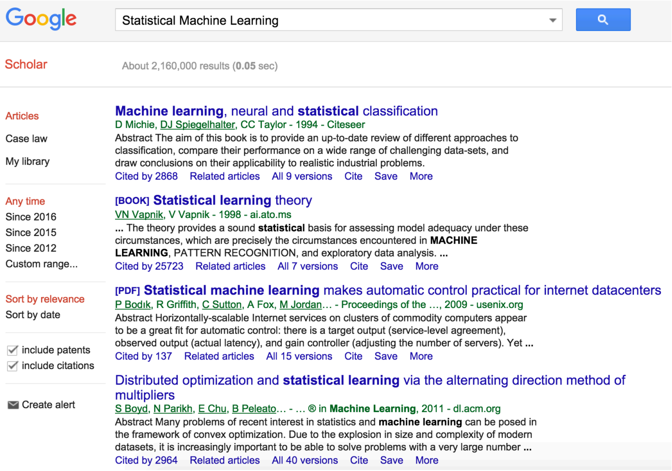

Figure 1 : Result of Google Scholar

Motivation

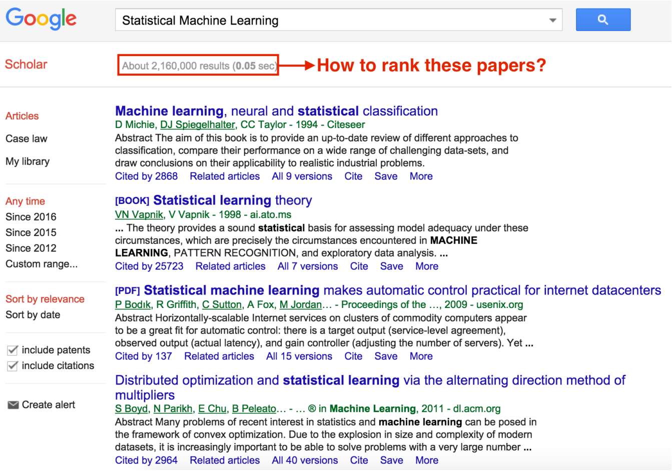

Figure 2 : Defects of Google Scholar

Motivation

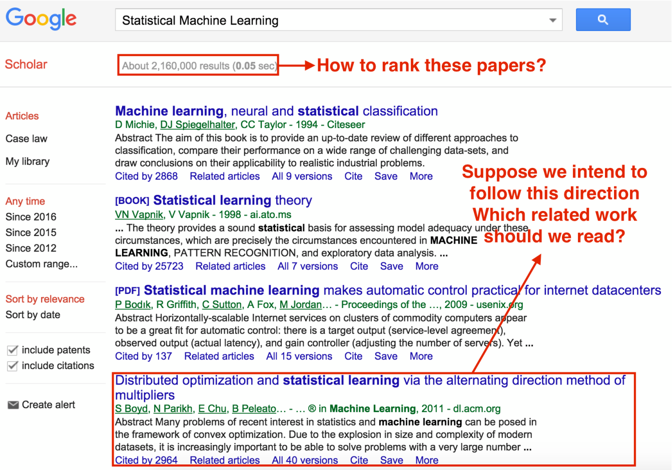

Figure 3 : Defects of Google Scholar

Motivation

Stand on the shoulders of giants

– Isaac Newton

Motivation

Find those giants !!!

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Related works

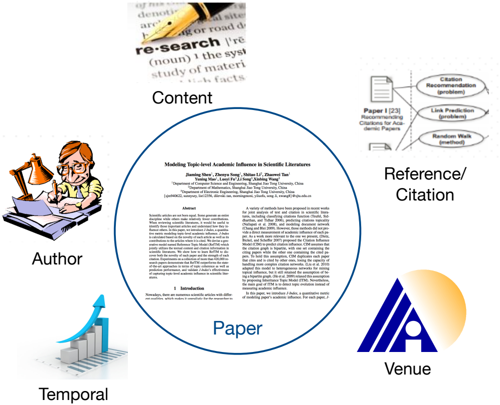

Figure 4 : Factors of one paper

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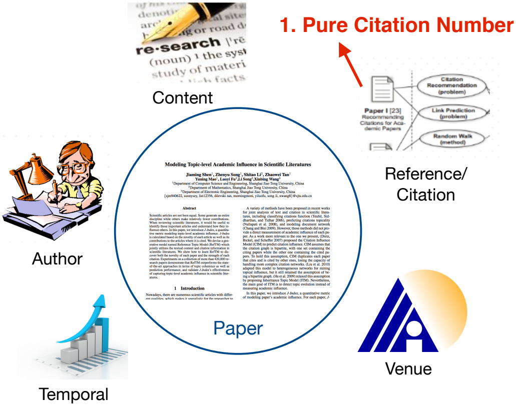

Figure 5 : Factors of one paper

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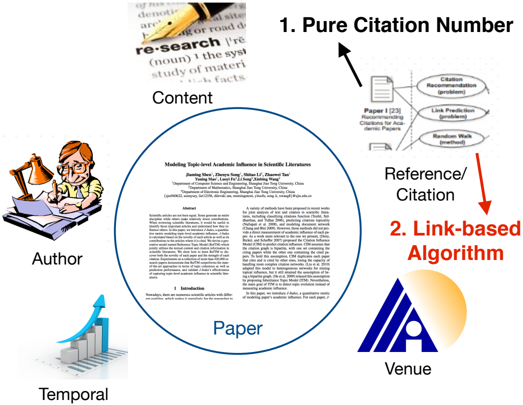

Figure 6 : Factors of one paper

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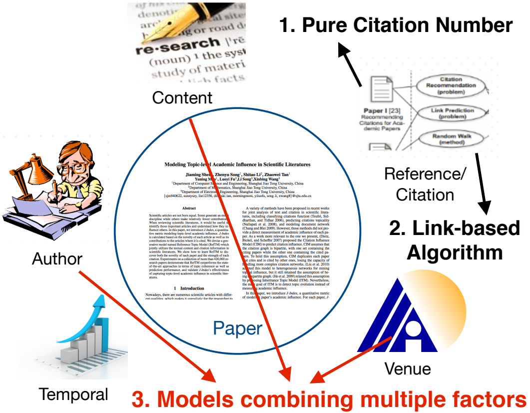

Figure 7 : Factors of one paper

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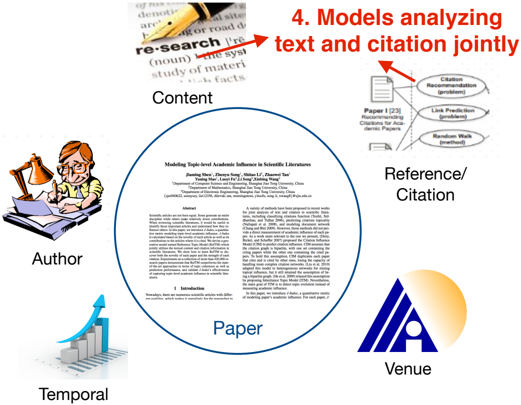

Figure 8 : Factors of one paper

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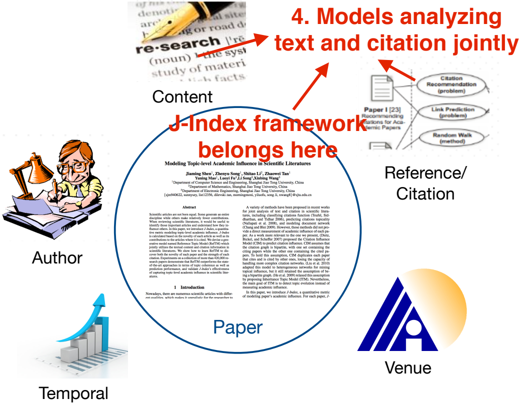

Figure 9 : Factors of one paper

J-Index Framework

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  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.
- Topic Inheritance: come from one of cited papers.
- Citation Strength: determine which reference is selected

Generative Model

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

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- In RefTM, observations: words & citations; parameters (we mainly concerned): λ and δ

RefTM Inference: Gibbs Sampling

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

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

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

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

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Algorithm 1 Gibbs Sampling Algorithm for RefTM

Input: $K, \boldsymbol{w}, \alpha, \beta, \eta, \lambda_c, \lambda_n$
Output: Parameter sets $\{\boldsymbol{\theta}, \boldsymbol{\varphi}, \boldsymbol{\delta}, \boldsymbol{\lambda}\}$
Read in data and zero out all count caches
Randomly initialize $\boldsymbol{z_i}, \boldsymbol{c_i}, \boldsymbol{s_i}$
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 $\tilde{s}$ from Eqs.(2-3)
      if $\tilde{s} = 0$ **then**
        Update the counts $n_k^{w_{m,n}}, n_k$
        Draw a new topic $\tilde{k}$ from Eq.(5)
        Update the counts $n_m^{(\tilde{k})(0)}, n_m^{(0)}, n_{\tilde{k}}^{w_{m,n}}, n_{\tilde{k}}$
      else
        Draw a new reference $\tilde{c}$ from Eq.(4)
        Update the counts $R_m^{\tilde{c}}, R_m, n_k^{w_{m,n}}, n_k$
        Draw a new topic $\tilde{k}$ from Eq.(6)
        Update the counts $n_{\tilde{c}}^{(\tilde{k})(1)}, n_{\tilde{c}}, n_{\tilde{k}}^{w_{m,n}}, n_{\tilde{k}}$
Read out parameters set $\boldsymbol{\theta}, \boldsymbol{\varphi}, \boldsymbol{\lambda}, \boldsymbol{\delta}$ by Eqs.(7-10)

Figure 12 : Gibbs sampling equations & Algorithm for RefTM

Visualization of RefTM's output

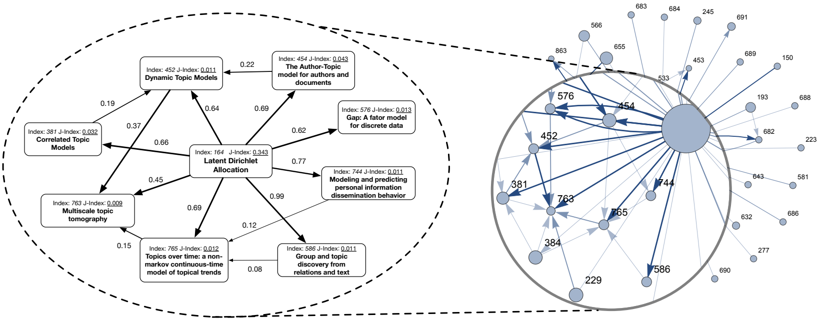

Figure 13 : Right hand side is an illustrative citation graph in which the thickness of edge represents the citation strength and the vertex size indicates one papers academic influence. Left hand side presents each paper's *J-Index*.

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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

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- Case Study: Rank INFOCOM

Topic Coherence

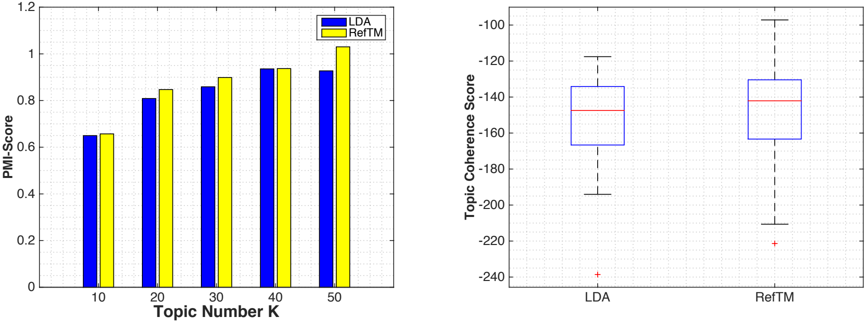

Figure 14 : Topic Coherence Evaluation

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

Citation Strength Prediction

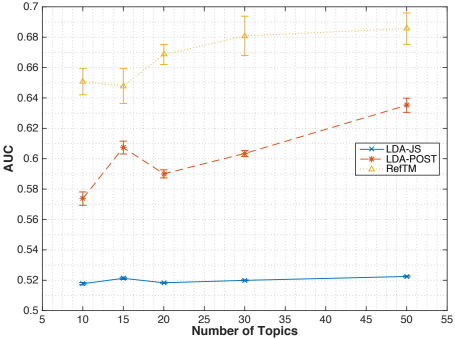

Figure 15 : Citation Strength Prediction measured by averaged AUC

- 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 randked by *J-Index* & citaions

Title	*J-Index*	citation counts
Top 5 Articles in INFOCOM 2003 ranked by *J-Index*		
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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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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- Future works:
  1. RefTM in the incremental citation network.
  2. Consider multiple factors, especially the temporal information.

References

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Thank you!

Q & A