# Will This Paper Increase Your *h*-index? Scientific Impact Prediction

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### Scientific Impact

Integral to the success of scientific research is the publication and dissemination of impactful work and findings.

### Scientific Impact

"An emerging area of interest in research on the 'science of science' is the prediction of future impact." How?

> J. A. Evans. Science 342, 2013

What?

D. E. Acuna, S. Allesina, K. P. Kording. Future Impact: Predicting Scientific Success. Nature 489, 2012

D. Wang, C. Song, A.-L. Barabasi. Quantifying long-term scientific impact. Science 342, 2013.

B. Uzzi, S. Mukherjee, M. Stringre, B. Jones. Atypical Combinations and Scientific Impact. Science 342, 2013.

H.-W. Shen and A.-L. Barabási. Collective credit allocation in science. PNAS 111, 2014.

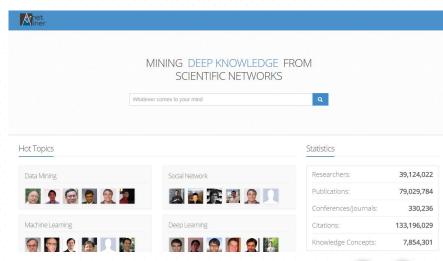
## 1

#### **Academic Data**





- > 1,712,433 authors
- > 2,092,356 papers
- > 4,258,615 collaborations
- > 8,024,869 citations
- http://arnetminer.org/AMinerNetwork





### Scientific Impact: #citations

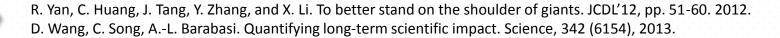
#### The number of citations of each publication

Title 1–20	Cited by	Year
SMOTE: synthetic minority over-sampling technique NV Chawla, KW Bowyer, LO Hall, WP Kegelmeyer Journal of Artificial Intelligence Research (JAIR) 16, 321-357	2471 *	2002
Editorial: special issue on learning from imbalanced data sets NV Chawla, N Japkowicz, A Kotcz ACM Sigkdd Explorations Newsletter 6 (1), 1-6	882	2004
SMOTEBoost: Improving prediction of the minority class in boosting NV Chawla, A Lazarevic, LO Hall, KW Bowyer Knowledge Discovery in Databases: PKDD 2003, 107-119	450	2003
New perspectives and methods in link prediction RN Lichtenwalter, JT Lussier, NV Chawla Proceedings of the 16th ACM SIGKDD international conference on Knowledge	229	2010
SVMs modeling for highly imbalanced classification Y Tang, YQ Zhang, NV Chawla, S Krasser Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on 39	218	2009

### #citations prediction

#### **Predicting** the number of citations of publications

Title 1–20	Cited by	Year
SMOTE: synthetic minority over-sampling technique NV Chawla, KW Bowyer, LO Hall, WP Kegelmeyer Journal of Artificial Intelligence Research (JAIR) 16, 321-357	2471 *	2002
Editorial: special issue on learning from imbalanced data sets NV Chawla, N Japkowicz, A Kotcz ACM Sigkdd Explorations Newsletter 6 (1), 1	882	2004
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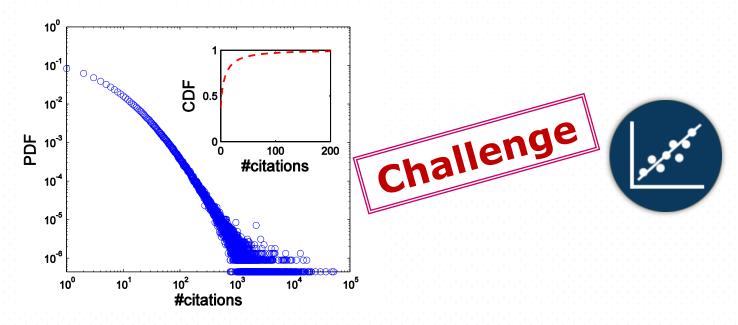






#### #citations prediction

- publications with few citations are extremely common
- publications with many citations are relatively rare



6.91% (155k out of 2 million) of the papers obtain more than 50 citations from 1950 to 2012.

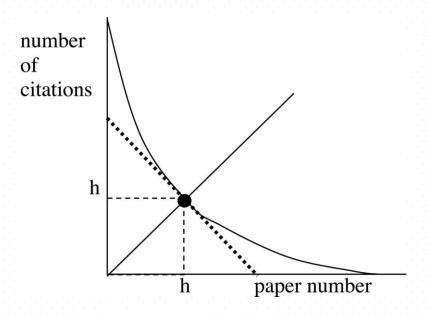


J. E. Hirsch. An index to quantify an individuals' scientific research output. PNAS 102(45). 2005.



### Scientific Impact: h-index

#### *h*-index



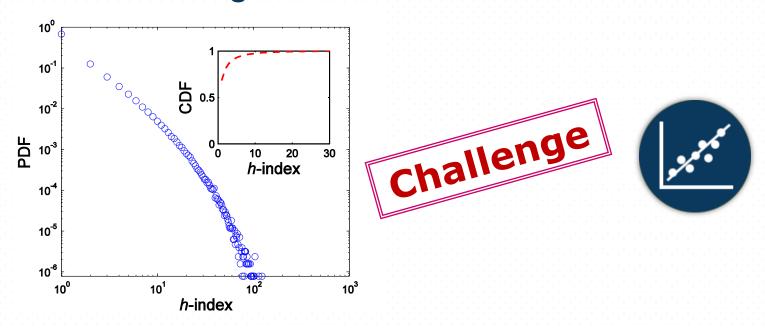
#### The *h*-index of each author

Experts	H-index	Rank
Thomas Huang H-index: 128, #Papers: 766, #Citations: 65956 Professor, Beckman Institute at the University of Illinois	128	1
Anil K. Jain H-index: 128, #Papers: 440, #Citations: 90064 Distinguished Professor, Michigan State University	128	2
Philip S. Yu H-index: 127, #Papers: 812, #Citations: 68713 Professor and Wexler Chair in Information Technology, Department of Computer Science, University of Illinouis Chicago	127	3
Jiawei Han H-index: 116, #Papers: 652, #Citations: 90056 Professor, Department of Computer Science, University of Illinois at Urbana-Champaign	116	4
H. Garcia H-index: 115, #Papers: 429, #Citations: 55531 Professor, Departments of Computer Science and Electrical Engineering, Stanford University	115	5



### *h*-index prediction

#### Predicting the *h*-index of each author?



0.0125% (159 out of 1.7 million) of the researchers have an h-index over 60





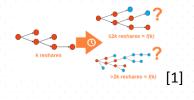
### Scientific Impact

- > Predicting the #citations of each
- > Predicting the h-index



Predicting whether a cascade will double in size<sup>[1]</sup>





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### Scientific Impact Prediction Problem

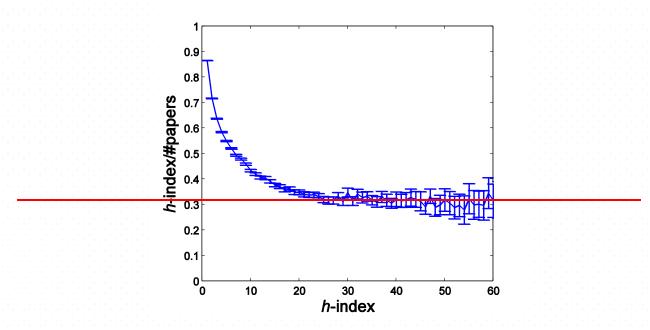
Given one paper and its author information, will it increase its primary author's h-index within a given time-frame  $\Delta t$ ?

the author of the given paper with the highest *h*-index.





#### *h*-index vs. *h*-index/#papers



The ratio between one's h-index ( $\geq$ 20) and her/his number of papers stabilizes at 0.3.



### Scientific Impact Prediction Problem

#### Can Cascades be Predicted?

Justin Cheng Stanford University jcccf@cs.stanford.edu Lada A. Adamic Facebook ladamic@fb.com P. Alex Dow Facebook adow@fb.com

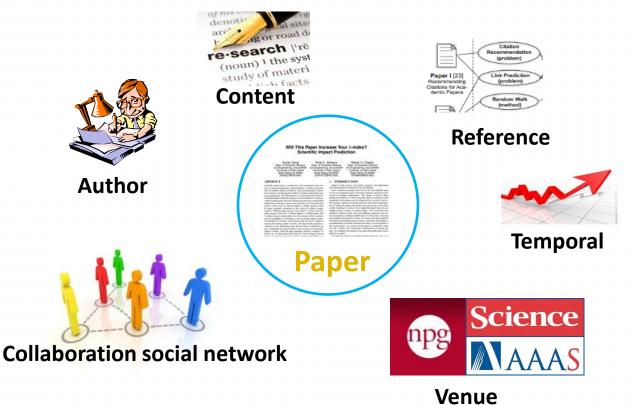
primary author\*

h-index: 81

Jon Kleinberg Cornell University kleinber@cs.cornell.edu Jure Leskovec Stanford University jure@cs.stanford.edu

Given this paper at t=2014 and its primary author, the task is to predict whether it will get at least 81 citations within  $\Delta t=5$  years.

## Factors driving scientific impact



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#### Factors --- author



#### Can Cascades be Predicted?

first author

Justin Cheng Stanford University icccf@cs.stanford.edu Lada A. Adamic Facebook Iadamic@fb.com P. Alex Dow Facebook adow@fb.com

primary author

*h*-index: 81

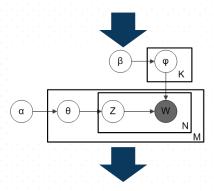
Jon Kleinberg Cornell University kleinber@cs.cornell.edu Jure Leskovec Stanford University jure@cs.stanford.edu all authors average author

#### Factors --- content



#### Will This Paper Increase Your h-index? Scientific Impact Prediction

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RACT	1. INTRO	DUCTION



scientific impact: 0.5 science of science: 0.4 social network:

#### topic popularity deep learning is hot!

topic novelty divergence of topics between this paper and its reference

> topic diversity divergence of topics of this paper

topic authority authors' authority on the topics of this paper





#### Factors --- venue



Venue 2 factors

Top publications - Data Mining & Analysis Learn more

Publication	h5-index
ACM SIGKDD International Conference on Knowledge discovery and data mining	69
IEEE Transactions on Knowledge and Data Engineering	57
3. ACM International Conference on Web Search and Data Mining	54
ACM Conference on Recommender Systems	36
5. IEEE International Conference on Data Mining (ICDM)	36
SIAM International Conference on Data Mining	35

average citations of papers in this venue

h-index contribution ratio of papers in this venue

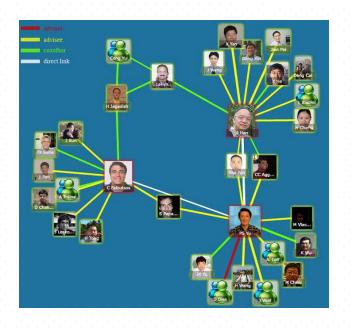




#### Factors --- social



Collaboration social network
4 factors



degree
Pagerank
coauthors' h-indices





#### Factors --- reference



#### Reference 2 factors

#### 7. REFERENCES

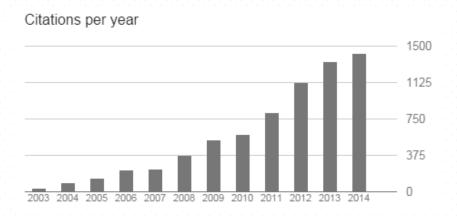
- [1] M. Ahmed, S. Spagna, F. Huici, and S. Niccolini. A peek into the future: Predicting the evolution of popularity in user generated content. In WSDM '13, pages 607–616. ACM, 2013.
- [2] S. Bethard and D. Jurafsky. Who should I cite: Learning literature search models from citation behavior. In CIKM '10, pages 609–618. ACM, 2010.
- [3] D. M. Blei, A. Y. Ng, and M. I. Jordan. Latent Dirichlet allocation. JMLR, 3:993–1022, 2003.
- [4] C. Castillo, D. Donato, and A. Gionis. Estimating the number of citations using author reputation. In *SPIRE '07*, pages 107–117. Springer, 2007.
- [5] J. Cheng, L. Adamic, P. A. Dow, J. M. Kleinberg, and J. Leskovec. Can cascades be predicted? In WWW '14, pages 925–936, 2014.
- [6] E. Garfield. Citation indexes for science: A new dimension in documentation through association of ideas. *Science*, 122(3159):108–111, 1955.

citations of references h-index of references

### **Factors** --- temporal



**Temporal** 4 factors



authors' h-index increasing rate





### •

#### **Factor Definition**

Table 1: Factor Definition. We employ six categories of factors, comprised of author, topic, reference, social, venue, and temporal attributes. max-h-index denotes the h-index of the primary author (i.e., the author with the maximum h-index) of a given paper.

	Factor	Description
	A-first-max	The first author's h-index divided by the max-h-index.
	A-ave-max	The average h-index of all authors divided by the max-h-index.
	A-sum-max	The sum of h-indices divided by the max-h-index.
Author	A-first-ratio	The ratio between max-h-index and the number of papers attributed to the first author.
	A-max-ratio	The ratio between max-h-index and the number of papers attributed to the primary author.
	A-num-authors	The number of authors of the given paper.
	A-num-first	The number of papers by the first author.
	C-popularity	The average number of citations over different topics (see Eq. 1).
	C-popularity-ratio	The average number of citations over different topics divided by the max-h-index.
	C-novelty	The topic novelty of this paper (see Eq. 2).
Content	C-diversity	The topic diversity of this paper (see Eq. 3).
	C-authority-first	The consistence between the first author's authority and this paper (see Eq. 4).
	C-authority-max	The consistence between the primary author's authority and this paper.
	C-authority-ave	The average consistence between each author's authority and this paper.
Venue	V-ratio-max	The ratio between the number of papers ≥max-h-index citations divided by the max-h-index.
venue	V-citation	The average number of citations of all references divided by the max-h-index.
	S-degree	The number of co-authors of the paper's authors.
Social	S-pagerank	The PageRank values of the paper's authors in the weighted collaboration network.
Social	S-h-co-author	The average h-index of co-authors of the paper's authors divided by the max-h-index.
	S-h-weight	The weighted average h-index of co-authors of the paper's authors divided by the max-h-index
Dafaranaa	R-ratio-max	The ratio between the number of references ≥max-h-index and the total number of references.
Reference	R-citation	The average number of citations divided by the maximum h-index.
Temporal	T-ave-h	The average $\Delta h$ -indices of the authors between now and three years ago.
	T-max-h	The maximum $\Delta h$ -index between now and three years ago.
	T-h-first	The $\Delta h$ -index of the first author between now and three years ago.
	T-h-max	The $\Delta h$ -index of the max- $h$ -index author between now and three years ago.

26 factors



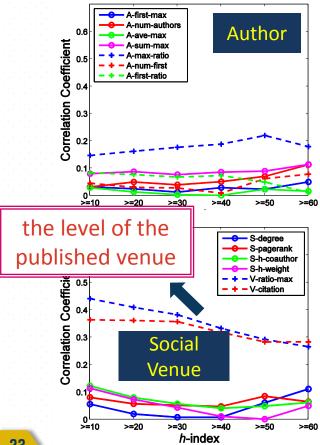
6 groups

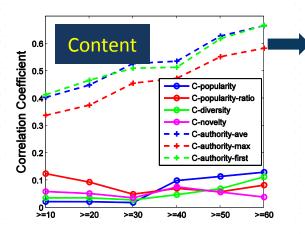


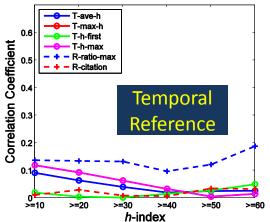


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#### **Factors Correlation**







authors' authority on the topics of this paper

$$t = 2007$$
$$\Delta t = 5$$

X-axis: primary author's *h*-index

Y-axis: correlation coefficient





#### **Factors Correlation**

A scientific **researcher's authority** on a topic is the most decisive factor in facilitating an increase in his or her *h*-index.

#### **Factors Correlation**

The level of the venue in which a given paper is published is another crucial factor in determining the probability that it will contribute to its authors' *h*-indices.

#### **Factors Correlation**

Publishing on an academically "hot" but unfamiliar topic is difficult to further one's scientific impact, at least as measured by an increase in one's h-index.



Is Scientific Impact Predictable?

### **Prediction: predictability**

t = 2007  $\Delta t = 5$  21,519 papers

On average, 30.5% of papers successfully contributed to their primary author's *h*-indices in 2012.

Task: predict whether the number of citations for each paper published in 2007 is larger than or equal to the primary author's *h*-index in 2012

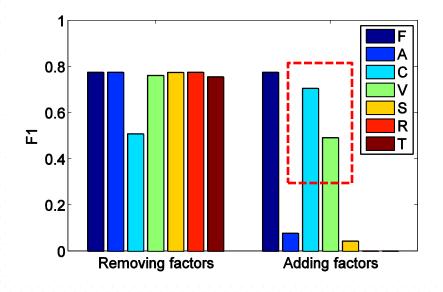
R: Random guess Features: 26 factors

LRC: Logistic regression Half training, half test

Method	Pre.	Rec.	$F_1$	AUC	Accu.	Pre@3	MAP
R	0.305	0.500	0.375	0.500	0.500	0.674	0.522
LRC	0.854	0.711	0.776	0.938	0.875	0.925	0.965



#### Prediction: factor contribution



F: Full factors

A: Author

C: Content

V: Venue

S: Social

R: Reference

T: Temporal

$$t = 2007$$
  
 $\Delta t = 5$   
Logistic regression

#### Can Cascades be Predicted?

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Published at 2014

$$\Delta t = 5 \text{ years}$$

$$\Delta t = 10 \text{ years}$$

Is a paper more predictable given a long or short timeframe  $\Delta t$ ?

#### Published at 2014

#### Inferring User Demographics and Social Strategies in Mobile Social Networks

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#### Can Cascades be Predicted?

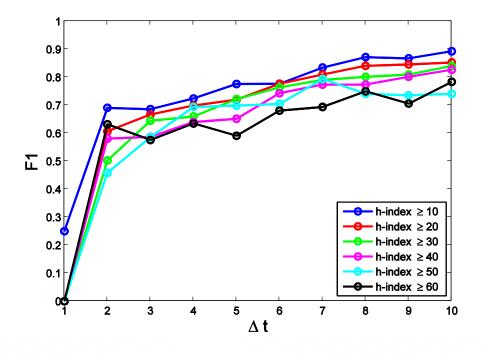
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Jon Kleinberg Cornell University kleinber@cs.cornell.edu Jure Leskovec Stanford University iure@cs.stanford.edu

Primary author's *h*-index: 33

Primary author's h-index: 81

Is a primary author with a high or a low *h*-index more predictable?



 $t + \Delta t = 2012$ Logistic regression

- 1. more difficult for papers with a high h-index primary author
- 2. more difficult when given a shorter timeframe  $\Delta t$ .



#### Future work

1. Only work on computer science domain

TODO: physics, mathematics, biology ...

2. Authors' h-indices evolve within  $\Delta t$ 

**TODO:** co-evolution of authors' h-indices and #citations





When a measure becomes a target, it ceases to be a good measure

---Charles Goodhart



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Army Research Laboratory
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National Science Foundation (NSF)

#### Thanks

Standing on the shoulders of giants
--- Isaac Newton

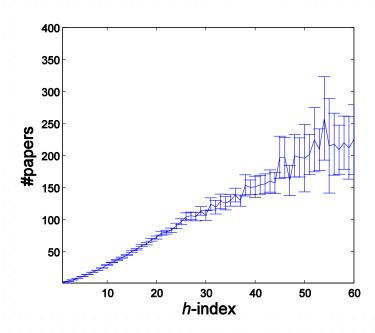
Q&A





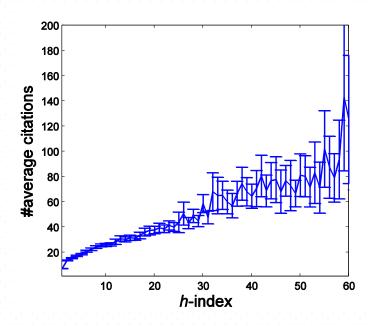


#### h-index vs. #papers





#### h-index vs. #average-citations

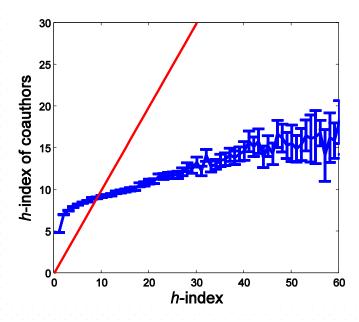


The average number of citations for each author is larger than her/his h-index.





#### *h*-index vs. average *h*-index of coauthors

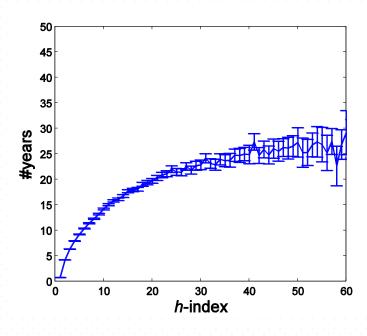


Typically, the author's *h*-index becomes larger than the co-authors' *h*-indices at the expected point of the author's Ph.D. graduation.





#### h-index vs. #career years

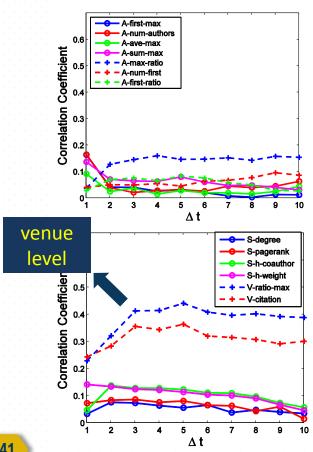


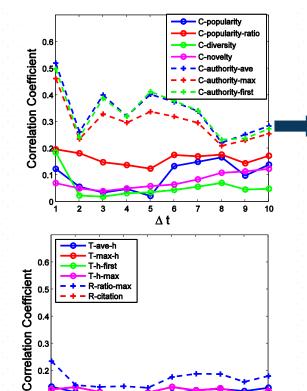
The rate at which the h-index increases itself increases as the length of time spent in academia becomes longer (i.e., the rich get richer).





#### **Factors Correlation 2**





Δt

authors' authority on the topics of this paper

t = 2002

X-axis:

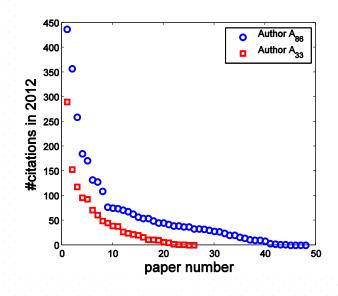
 $\Delta t$ 

Y-axis: correlation coefficient





### Prediction: case study 1



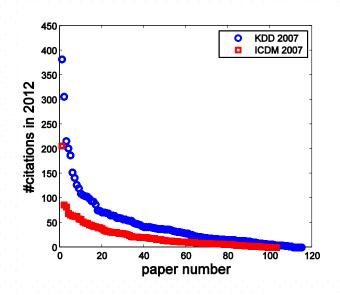
### Two anonymous authors $A_{86}$ and $A_{33}$

Authors	Pre.	Rec.	$F_1$	AUC	Accu.	Pre@k	MAP
$A_{86}$	0.500	0.375	0.429	0.584	0.833	0.375	0.346
$A_{33}$	1.000	0.667	0.800	0.856	0.885	0.667	0.849

$$t = 2007$$
  
 $\Delta t = 5$   
Logistic regression



### Prediction: case study 2



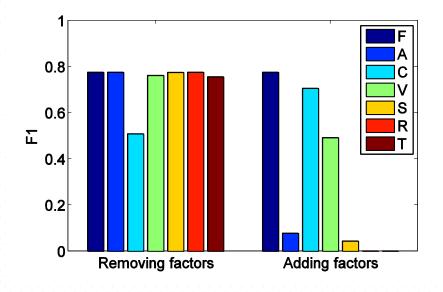
#### Two venues KDD and ICDM

Venues	Pre.	Rec.	$F_1$	AUC	Accu.		
KDD'07	0.800	0.889	0.842	0.884	0.818		
ICDM'07	0.842	0.593	0.696	0.886	0.825		

$$t = 2007$$
  
 $\Delta t = 5$   
Logistic regression



#### Prediction: factor contribution



F: Full

A: Author

C: Content

V: Venue

S: Social

R: Reference

T: Temporal

