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Measuring the Value of Word-of-Mouth and Its Impact in Consumer Communities

Paul Dwyer

As online product communities proliferate, managers want to measure the value generated by consumer word-of-mouth. This study develops a metric and uses it to demonstrate the importance of expert power and high-value content in a virtual consumer network.

Paul Dwyer is a doctoral student at Texas A&M University

Report Summary

Word-of-mouth is a network phenomenon: by exchanging units of discourse on the Internet, consumers create informational and social networks. Current measures of such consumer-generated media focus on quantity (number of word-of-mouth occurrences) but not the influence this word-of-mouth exerts. In this study, Dwyer proposes a metric for word-of-mouth importance and investigates the impact that highly valued discourse has on involvement in a network context. He also offers a model of the relationship between involvement and the growth and decay of product-oriented online communities.

To begin, he validates the applicability of Google's PageRank metric for determining the importance of websites to assessing the importance of community members and knowledge content. This measure ("adapted PageRank" or APR) is shown to be a better measure of value (i.e., knowledge and social capital) than the prevalent centrality-based metric that is based on the number of immediate ties.

Dwyer then demonstrates the superiority of the APR metric regarding preferential attachment, that is, whether people join a network by choosing people similar to them (homophily) or people who know more than they do (expert power). He demonstrates that expert power is the primary attraction between members. Content of high value to the community attracts attention with little reference to who originated the content.

He also quantifies and investigates the interplay between preferential attachment and decay in the social network and changes in community knowledge capital over time. Expert power, in whatever form is respected by the community, is the prime influence on how the knowledge network causes the social network to evolve. High-value content in the knowledge network explains 10% of social network growth.

Using the APR metric, companies can automate the process of filtering community message traffic to identify the information that attracted the most customer attention and the members who typically provided that information. Since high-quality content plays a significant role in increasing product involvement, companies that have products with large and active online communities should consider hosting a blog so they can play an active and visible role in injecting such content into their user community. ■

Introduction

"There go the people. I must follow them, for I am their leader."
—Alexandre Ledru-Rollin

Jim Nail (2005) of Forrester Research recently reported that VNU, a large market and media research company, purchased a stake in BuzzMetrics, a word-of-mouth measurement startup. He interpreted this move as a signal that the measurement of consumer-generated media was becoming as important as traditional market research methods. BuzzMetrics recently expanded its practice by offering a research service that monitors the millions of TV viewers who converse over the Internet in virtual communities such as chat rooms, message boards, and blogs (*weblogs*). Academic research, such as Wang and Fesenmaier (2003) and Richins, Bloch, and McQuarrie (1992), supports the BuzzMetrics approach of inferring "consumer engagement" by measuring word-of-mouth.

Similarly, the Advertising Research Foundation, the American Association of Advertising Agencies, and the Association of National Advertisers have announced a joint venture to define a "consumer engagement" metric to complement traditional exposure metrics (such as Nielsen ratings).

Word-of-mouth is a network phenomenon: people create ties to other people with the exchange of units of discourse that link to create an informational network and a social network. Despite its prevalence on the Internet, however, there are few quantitative measures of the impact or importance of such computer-generated media on involvement. This paper proposes a metric for word-of-mouth importance and investigates the impact that highly valued discourse has on involvement in a network context.

Theoretical Background

General network typology

Newman (2003) lists four types of networks: social, informational, technological, and biological. He defines a *social network* as a set of people or groups with some pattern of contact or interaction among them. (See Appendix for a glossary of italicized terms.) Social networks have been heavily studied by sociologists and marketing scholars. Most of these studies are like the Reingen et al. (1984) exploration of brand-use commonality in a sorority: the sample size is small, the data are qualitative, and the network is analyzed as a static snapshot of its state at one particular time. More extensive studies include Ebel, Mielsch, and Bornholdt's (2002) study of e-mail communications among 5,000 students at Keil University and Holme, Edling, and Liljeros's (2004) examination of an online dating community. Holme, Edling, and Liljeros (2004) performed one of the few analyses documenting the changes in a social network structure over time.

Informational networks model how separate pieces of related information fit together. The most often cited example of such a network is the citation network of scientific papers as examined by Price (1965), in which the nodes of the network are journal articles and the ties between nodes indicate that one paper cited another.

Burnett (2000) pointed out that virtual communities are both social and informational networks. Units of discourse create an informational network while people create a social network; further, the content of community messages can be classified as informational, social, or both.

Brand and virtual communities as social networks

Boorstin (1974) described invisible communities of consumption evolving after the Industrial Revolution. He observed that community, once exclusively based on geographic, political, or religious similarity, evolved toward a structure based on commonalities in product use. Schouten and McAlexander (1995) described a more visible subculture of consumption in their immersive study of Harley-Davidson owners.

Even though Reingen et al. (1984) did the first study of commonalities in brand use within a social network, Muniz and O'Guinn (2001) suggested the first model of a consumer or brand community that was also a social network.

Rheingold (1993) introduced the idea of a virtual community in his discourse about WELL, a pioneering computer conferencing system that allowed people from around the world to participate in public conversations and exchange electronic mail. Wellman and Gulia (1999) performed the first social network analysis of a virtual community. Dholakia, Bagozzi, and Pearo (2004) recognized virtual communities as consumer groups of varying sizes that meet and interact online for the purpose of achieving personal and shared goals. A brief perusal of the virtual communities hosted by Yahoo reveals that many of these communities thrive exclusively on the discussion of specific products or product types and are thus both brand and general consumption communities.

Involvement

I adopt Zaichkowsky's (1985) definition of involvement as "a person's perceived relevance of the object based on inherent needs, values and interests." She created the highly used Personal Involvement Inventory, a 20-item scale to measure an individual's involvement with a product, advertisement, or purchase decision. She found that a measure of high involvement on her scale correlated with an interest in reading more about the product, a process of detailed product comparison before purchase, and the eventual purchase of a product.

This research adopts a broader focus than Zaichkowsky (1985), which was primarily on the purchase decision. I would suggest that the resources of an online community can be used by prospective buyers not only to facilitate information gathering, but also to connect with a community of users to enhance their enjoyment after purchasing and using a product. The central premise of this study is that community participation is directly correlated to involvement; this is consistent with Zaichkowsky's (1985) findings in that high prepurchase community participation is the online representation of the information search process she described.

Involvement and word-of-mouth

Holmes and Lett (1977) found that product usage and purchase intention, both signs of product involvement, resulted in word-of-mouth behavior. They also found that the highly involved excitement of a purchase dissipates over time. Their findings have been generally supported, albeit with some modification, by the work of later researchers such as Richins, Bloch, and McQuarrie (1992).

Houston and Rothschild (1978) were the first to make a distinction between enduring involvement and the situational involvement that surrounds a purchase. They stated that external stimuli (e.g., a new dishwasher was sought because the old one was beyond repair) cause situational involvement and internal factors (such as a high linkage between product use and personal happiness) cause enduring involvement. Wang and Fesenmaier (2003) found that enduring involvement was the major reason for online community participation. They also found the secondary motives of seeking benefits for oneself (e.g., information) and offering help to others to be important precursors of community word-of-mouth.

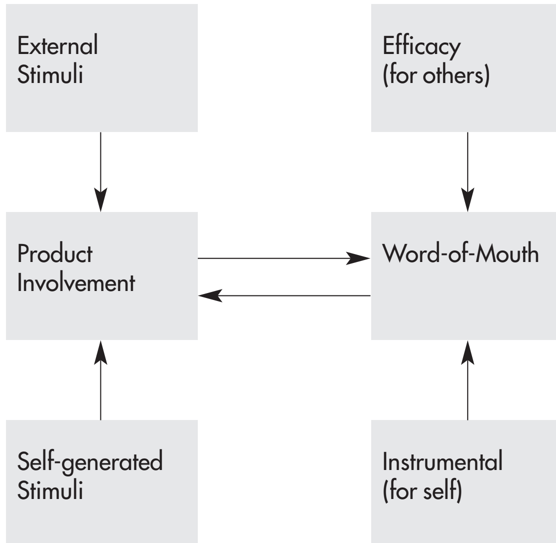
Figure 1 illustrates the interaction between product involvement and word-of-mouth.

Network dynamics

Holme, Edling, and Liljeros (2004) demonstrated that network dynamics can be observed by doing a time-series analysis of the metrics used to measure static networks. The models that explain how networks change are of two types: growth and destruction.

Growth. The principal explanation for how networks grow is *preferential attachment*. Price (1965) and Barabasi and Albert (1999) presented

Figure 1
Interaction of Involvement and Word-of-Mouth



variations on a preferential attachment model. In this network model, nodes that already have a lot of ties are the most likely attachment points for new network members. It is a "rich get richer" model of network growth. Lazarsfeld and Merton (1954) defined a secondary dynamic: *homophily*, in which similar nodes will be attracted and create ties. The two dynamics have been combined to suggest that highly connected nodes are attracted to other highly connected nodes.

Word-of-mouth acts through the mechanism of preferential attachment to grow the online social and informational network. That is, when someone posts a message to the community they must either start a new topic/thread or reply to an existing message. If they choose to reply to an existing message, they will apply some selection criterion based on the subject or the author of the existing message. That act of selection is preferential attachment.

Destruction. A network can be weakened by the deletion of nodes until communication through the network becomes impossible. Albert, Jeong, and Barabasi (2000) found that removing important nodes had a devastating effect on communication flow. Holme et al. (2002) expanded this area of study by looking at how the removal of key ties can also be devastating. Newman (2003) discussed how this research assesses the resilience of the Internet to the failure of the computers that are its nodes. Carley, Lee, and Krackhardt (2001) applied destruction research to terrorist networks. They speculated that the leaders of the decentralized terrorist networks would not be found by looking for the people with the most ties; rather, they would be the individuals with "high cognitive load," who emerge as leaders because they delegate tasks and are seen as having special knowledge or *expert power*.

Unlike terrorist and technological networks, consumer networks are not subject to attack. They do, however, exhibit decay due to the dissipation of involvement. This phenomenon was noticed by Holme (2003) in his study of dating networks. He noticed that ties decay exponentially as time goes on because of decreasing contact.

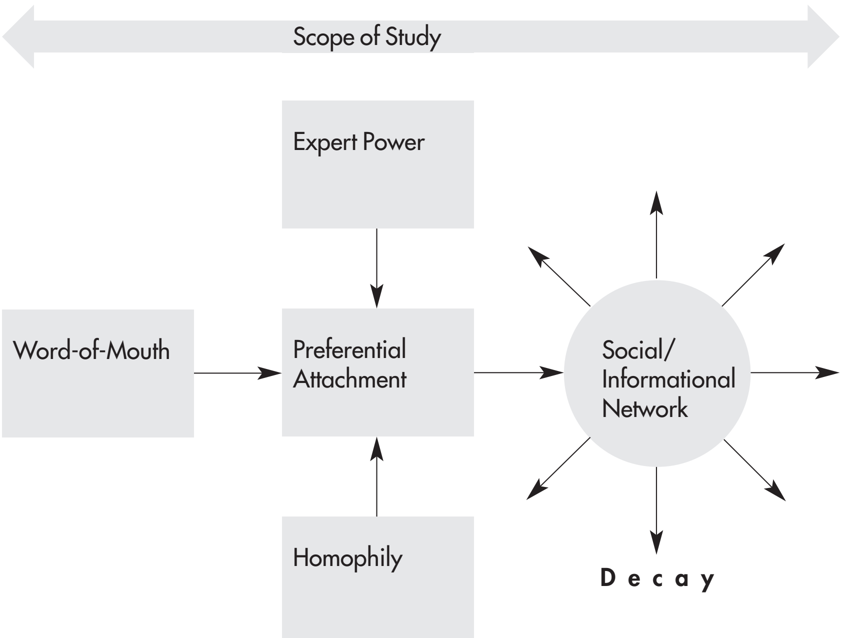
Figure 2 illustrates this view of network dynamics.

Centrality, prestige, and PageRank™

Wasserman and Faust (1994) define two measures of network node importance: *centrality* and *prestige*. Centrality is defined as the number of nodes a given node is directly connected to. Prestige is a variant of centrality but distinguishes the direction of the links that connect nodes; it can be defined as the proportion of incoming ties to outgoing ties. That is, in a virtual community network, a member gains prestige by posting messages that inspire others to post replies, while at the same time being very selective in replying to others. (Also see *outdegree* in Appendix glossary.)

Burnett (2000) recommends that content analysis be used to determine the importance of the text messages posted to online communities.

Figure 2
Network Dynamics



(However, he admits that it is extremely difficult to specify the criterion for importance in content analysis.) The Internet search engine Google™ adopted a "populist" criterion for importance: the web pages that had the most incoming ties were the most important. Google's PageRank™ algorithm also factors in the concept of prestige, where page importance is decreased in proportion to the number of outgoing ties, and inheritance effects, where the importance of incoming links increases the importance of the page being assessed (see *proportioning factor* in Appendix glossary).

According to Bianchini, Gori, and Scarselli (2005), the PageRank™ (x_p) of page p is computed by taking into account the set of pages ($pa[p]$) pointing to p:

$$x_p = d\sum_{q \in pa[p]} \frac{x_q}{h_q} + (1-d) \qquad (1)$$

where $d \in (0,1)$ is a *proportioning factor* and h_q is the *outdegree* of q, that is, the number of links com-ing out from page q. The proportioning factor determines the amount of importance added to p by the pages linking to it. Page p has an inherent importance of $1–d$.

Knowledge capital, social capital, and adapted PageRank™

This algorithm can be applied to the informational and social networks of virtual communities. As an informational network, an online community's assets are the messages posted to it. These messages, and the way they relate to each other, have value which increases as more content is added. This value is called *knowledge capital*. Using an adapted PageRank™ (APR), the knowledge capital of an individual message is measured as the value of information nodes derived from or inspired by it. The sum of the individual message APRs yields a measure of the whole community's knowledge capital.

As a social network, an online community's assets are the message writers who post to it. What constitutes value in a social network is very specific to its context, and has been proposed to be the expertise or knowledge of the message writer. Using APR, the *social capital* of an individual is measured as their inherent worth (i.e., their unique knowledge and skills) plus the knowledge they can access from others. Thus, an individual's social capital APR is a function of the number of messages authored, both new threads of discussion ("seeds") and contributions to existing threads ("replies"). The sum of the individual APRs yields a measure of the whole community's social capital.

The adapted PageRank™ metric described in this paper is a way of expressing the value a community has assigned to all or part of its informational and social networks. Figure 3 compares centrality-based measures of importance to the APR metric of knowledge and social capital. Using centrality, informational node A would be ranked twice as important as node B, even though node B is the basis for a much larger information network.

Figure 3
Centrality versus APR

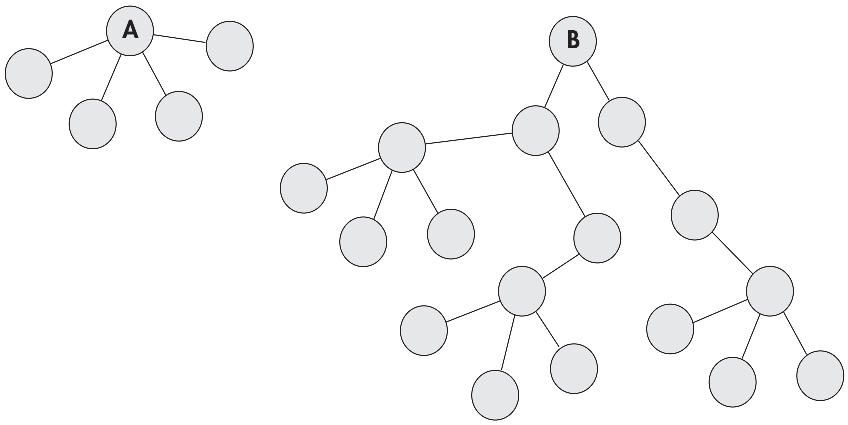


Table 1
Data Sources

Group	Type	Members	Messages
1ALL_ROSWELL	TV-*Roswell*	2,227	27,960
2004-Prius	Brand–Automobile	2,517	42,419
7th_heaven	TV–*7th Heaven*	912	6,311
burningman-bcwa	Brand–Annual Event	789	18,291
cb-750	Brand–Motorcycle	4,541	93,134
jumptheshark	TV–Generic	1,124	53,514
SimWatch	Brand–Computer Game	4,303	40,944
sportsterowners	Brand–Motorcycle	1,630	36,900
TheWestWing	TV–*The West Wing*	1,160	12,887
x-files	TV–*X Files*	1,655	28,844
Total		**20,858**	**361,204**

Study

Purpose

The first phase of this study validates the superiority of the APR algorithm in demonstrating preferential attachment, compared to the prevalent centrality-based method. In so doing, this study tests the hypothesis that the APR metric is not merely a reflection of authored message volume and longevity of community participation but is also a measure of the community's appreciation of that participation. The second phase of this study uses the APR as a measure of knowledge capital to determine the role of highly valued content in the informational network in opposing decay in the social network.

Data

The entire archives of 10 product-oriented Yahoo™ groups (Table 1) were used to construct the social and informational networks studied. The data are therefore observational rather than experimental. Figure 4 includes a sample screen shot from the Yahoo™ archives that indicates the author of each message, the date posted, and the thread hierarchy of messages and their replies (e.g., message 18370 is a reply to message 17870). This allows a knowledge network for each group to be constructed, in addition to a social network between authors. These groups were deliberately selected to get large, highly active groups with wide diversity in their underlying subject matter and large volumes of messages.

If you observe each community as it evolves, you can see the exact time when each member "joins" or announces his or her presence by posting the first message. You can also see when ties are created between message authors by replying to each other's messages. By calculating the average time between messages, you can estimate when a member has left the community and thereby estimate the influence of decay. Messages that result in the most replies are considered to be the most valuable, using the adapted PageRank™ algorithm.

Methodology

Directed acyclic graphs. The analyses used in this study make reference to Glymour et al.'s (1987) methodology for *directed acyclic graphs* (DAGs). This methodology uses the correlation between variables and any knowledge of temporal relationships to construct a diagram of nodes, representing variables, and arcs, representing causal dependency among the variables. These diagrams are compared with known theory as a litmus test for their validity. Once such a diagram has been accepted as theoreti-

Figure 4
Sample Yahoo Forum Screen Shot (1ALL_ROSWELL)

17870	Save Roswell	Robyn	Feb 28, 2001
18370	Save Roswell	Alexandra Aleman	Mar 7, 2001
25416	Save Roswell	Suzi	Jan 30, 2002
17878	Save Roswell**We Need a Season Three**Sign Peti	desha	Feb 28, 2001
17888	Tess haters - Tess Lovers / Something I noticed i	bartonc@...	Feb 28, 2001
17969	Re: Tess haters - Tess Lovers / Something I notic	bello@...	Feb 28, 2001
17889	help save roswell!!!!	~*~LouLou~*~	Feb 28, 2001

cally correct, then the same techniques used to calculate parameter values and fit in *structural equation models* (SEMs) can be used because DAGs are structural equation models.

In both the DAG and SEM methodologies, the modeler examines past research to gain some insight into how the variables being studied interrelate. The DAG methodology uses artificial intelligence techniques to examine the data gathered and to propose relationships between variables. In addition to a correlation matrix, these artificial intelligence algorithms also accept metadata describing prior knowledge, such as what relationships must exist based on theory and how these variables relate temporally (i.e., one variable changed before another it affects).

There is no universally accepted methodology for the artificial intelligence algorithms that underlie DAGs. This study uses one of the best-supported methodologies, proposed by Glymour et al. (1987). Their methodology begins by assuming no relationship between the variables in the model and then uses F-tests, a correlation matrix, and prior knowledge metadata to find the relationships supported by the data.

The DAG methodology is similar to *exploratory factor analysis* in that it can provide insight where prior theory is lacking or ambiguous. A full explanation of the DAG methodology is beyond the scope of this paper. Glymour et al. (1987) is a good introduction for the interested reader. This methodology is growing in use and is extremely powerful in its ability to provide insight.

Statistical and causal models. This study adopts the terminology used by Hunt (2002) to describe statistical and causal models. It uses both *deductive-statistical* (D-S) and *inductive-statistical* (I-S) explanations. The theoretical background used for this study, summarized above and in figures 1 and 2, invariably used I-S explanations. This background was used to determine which explanations for the observed phenomena were both relevant and probable and is therefore a D-S foundation for this study. The findings of this research project are I-S explanations of the observed phenomena, as statistical probabilities are used to confer a certain likelihood of correctness rather than certainty. The evidence presented for the findings offered by this study are generally a comparison of population means by standard testing methods and measures of covariation under conditions where one effect occurred before another (temporal precedence) and when effects occur at the same time (contemporaneous). I have endeavored to point out which method applies when one is used.

The causal models in this project are what Hunt (2002) would call explanatory sketches, that is, they are of the form "X can produce Y" rather than "X invariably produces Y" or "X is necessary for Y." Hunt (2002) gives four criteria for causality: temporal precedence, covariation, no plausible alternative explanations, and theoret-

Table 2
New Message Attachment to Top 5%

Forum	Percentage of Messages Attaching to the Top 5%			
	APR		Centrality	
	KN	SN	KN	SN
1ALL_ROSWELL	79.7	27.9	43.0	13.1
2004-Prius	55.0	12.9	30.8	25.3
7th-Heaven	71.3	13.7	23.1	19.6
burningman-bcwa	59.7	26.6	18.5	43.4
cb-750	68.7	21.9	17.9	32.3
jumptheshark	70.3	35.5	22.6	51.0
SimWatch	68.4	22.3	29.2	26.8
sportsterowners	71.0	17.1	25.1	48.3
TheWestWing	65.7	12.1	21.4	30.3
x-files	69.9	14.2	24.1	28.3
Mean	68.0	20.4	25.6	31.8

KN = Knowledge/information network; SN = Social network.

Table 3 (a) and (b)
Differences in Methods across Networks Using the Wilcoxon Signed Ranks Test

(a)	KN vs. SN	(b)	APR vs. Centrality
APR	$Z = -2.803$, $\rho = .005$	**KN**	$Z = -2.803$, $\rho = .005$
Centrality	$Z = -1.070$, $\rho = .285$	**SN**	$Z = -2.191$, $\rho = .028$

ical support. The work described in this paper cannot claim there are no alternative explanations for the phenomena observed.

Phase one—Validation of the APR

The first phase of this study was designed to validate the superiority of the APR algorithm in demonstrating preferential attachment, compared to the prevalent centrality-based method. I calculated the APR and centrality of each message to express how each method shows the value of the message in the knowledge network, and then ranked these in descending order. I then took the messages in the top 5% of each ranking and calculated the percentage of messages attached to each. Tables 2, 3a, and 3b summarize the results. The *Wilcoxon Signed Ranks Test* was used to do pairwise comparisons of means showing where there are significant differences in the use of the two methodologies across the two networks (tables 3a and 3b).[1]

Table 3a shows that centrality is unable to detect a difference between attaching messages to the top 5% of the social network and attaching messages to the top 5% of the knowledge network. Table 3b shows there is a significant difference between the ways the two methods measure attachment in the social and knowledge networks. The APR metric shows that message posters are drawn to reply to information of highest value to the group, regardless of who the author is, while centrality is unable to make any such distinction.

When message APRs are converted to z-scores to remove the influence of network size, every message that attains a top 5% APR fits a curve of the form presented in Figure 5 with an $R^2 > .8$. Observe how these messages attract comment early and quickly build their APR score.

As already described, an individual's social capital APR is a function of the number of messages authored, both new threads of discussion ("seeds") and contributions to existing threads ("replies"). It would be logical to suggest that social capital APR is also be a function of duration of participation. However, if social capital APR is a true representation of the quality of a member's contributions, then it is necessary to show that this metric is not purely a function of the volume of messages posted and the length of community membership.

Thus, I divided the contribution and longevity data for every community member at the time of their maximum APR into two sets: prior and post. When these two data sets are processed using the Glymour et al. (1987) methodology, two directed acyclic graphs (DAGs), shown in figures 6 and 7, are significant at $\rho = .05$. The weights assigned to the arrows are the result of processing simultaneous linear equations with SAS PROC CALIS with adjusted goodness-

Figure 5
Typical Pattern of Message Knowledge Capital Accrual

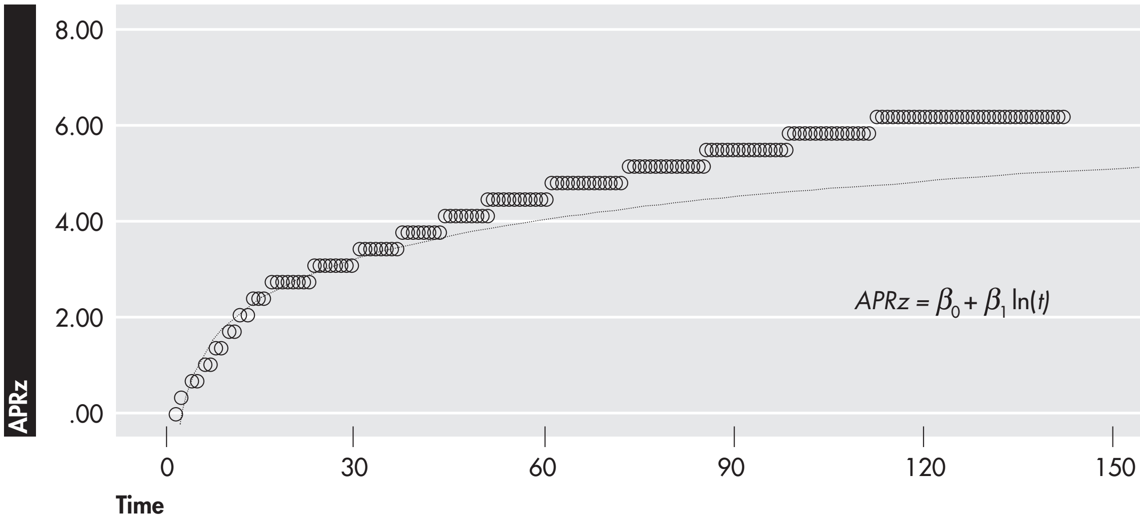
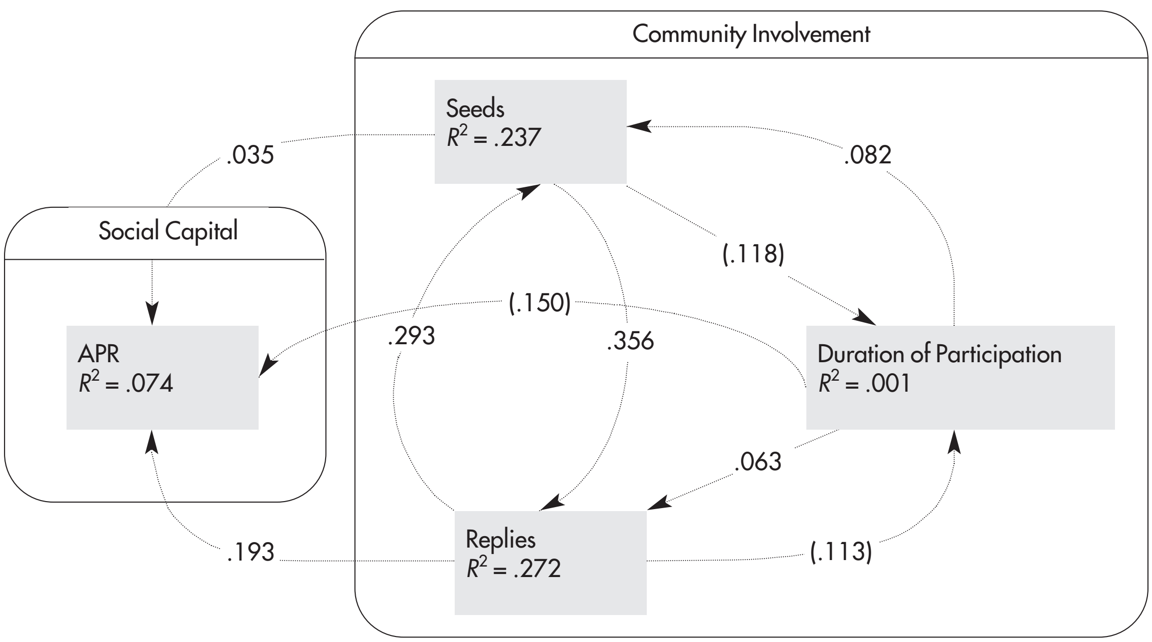


Figure 6
Effect of Message Volume and Duration on Social Capital

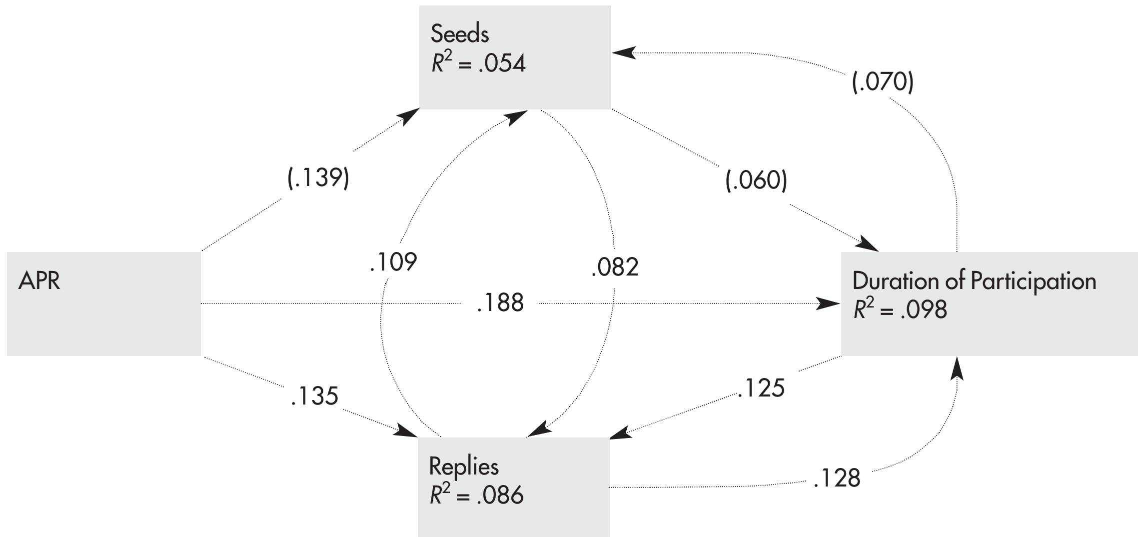


Note: Ovals denote latent variables and boxes denote measured variables. Arrows labeled with standardized coefficients represent correlations. Parentheses denote negative values.

of-fit (AGFI) equal to 1.00. Even though these findings are statistically significant, the explanatory power is weak. As a result, I conclude that the APR metric is not merely measuring the volume and longevity of activity, but is measuring the quality of contributions.

Figure 7

Effect of High Social Capital on Subsequent Community Involvement



Note: Boxes denote measured variables. Arrows labeled with standardized coefficients represent correlations. Parentheses denote negative values.

Table 4

Homophily in Preferential Attachment

Forum	Originating Author's Average APR *z*-Score	Replying Author's Average APR *z*-Score
1ALL_ROSWELL	.24	1.07
2004-Prius	.64	1.00
7th-Heaven	.10	.72
burningman-bcwa	.33	.56
cb-750	.39	.98
jumptheshark	.30	.66
SimWatch	.39	1.07
sportsterowners	.38	.54
TheWestWing	.18	.78
x-files	.13	.88
Mean	.31	.83
Z	−2.193	
ρ	.028	

Phase one—Homophily and preferential attachment

The second part of phase one was designed to discover the extent of homophily, or the creation of ties between people of similar social capital, in the mechanism of preferential attachment. I reenacted the evolution of each forum beginning with its first message. As each subsequent message was added, I calculated the APR of every member of the community and converted it to a *z*-score. I then accumulated an average of the incoming and originating message authors' APRs. The final averages are given in Table 4. The Wilcoxon test shows the two sets of averages are significantly different. Message originators come from the full spectrum of community membership, but the people who reply to these messages usually have greater social capital and, by implication, greater expert power.

However, Table 5 shows that homophily is present as the density of ties between the top 5% of social capital holders is significantly greater than that of the community as a whole. I can conclude therefore that, while homophily is present in most networks, it is not an important driver of preferential attachment.

Phase two—The effect of knowledge capital on the social network

In the final part of this study, I quantified and

Table 5
Presence of Homophily

Forum	Density of Top 5% in Social Network	Overall Network Density
1ALL_ROSWELL	11.9	2.4
2004-Prius	11.1	3.9
7th-Heaven	5.2	7.9
burningman-bcwa	35.6	12.7
cb-750	28.3	5.6
jumptheshark	24.8	18.1
SimWatch	25.4	4.3
sportsterowners	13.8	7.1
TheWestWing	8.2	8.8
x-files	2.7	6.1
Mean	16.7	7.7
Z	−2.193	
ρ	.028	

Table 6
Attachment and Decay Measured

Forum	Average Percentage		
	Ongoing	Joiners	Leavers
1ALL_ROSWELL	59.2*	16.7*	23.2*
2004-Prius	49.6*	19.9*	28.1*
7th-Heaven	59.2*	17.8*	20.0*
burningman-bcwa	81.1*	14.9*	10.0
cb-750	67.1*	16.8*	16.1
jumptheshark	68.8*	15.9*	12.7*
SimWatch	69.3*	15.4*	19.6
sportsterowners	73.3*	15.1*	15.6
TheWestWing	69.4*	16.9*	20.0*
x-files	57.4	16.9*	19.7*
Mean	65.4	16.6	18.5
σ	9.1	1.5	5.2

*Satisfies the Dickey and Fuller (1981) test of *stationarity* with $t < -2.89$ (95% sig.)

investigated the interplay between preferential attachment and decay in the social network and changes in community knowledge capital over time. Table 6 summarizes some measurements of attachment and decay.

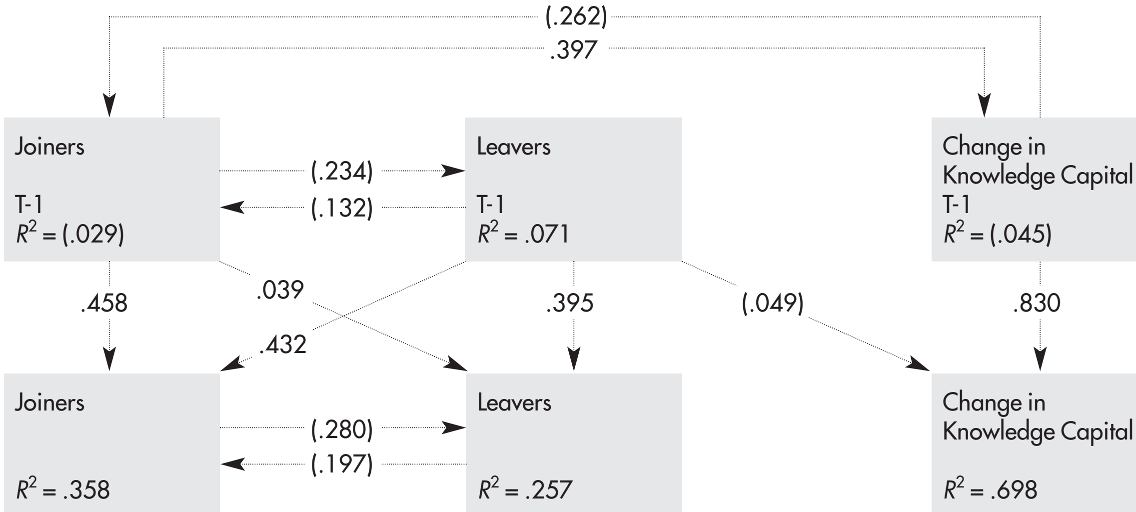
The "ongoing" column contains the proportion of community membership that carries over from month to month. The "joiners" column is the proportion of new members. The "leavers" column is the proportion of members making their last contribution of content. Most of these series are stationary about a mean; however, the means vary considerably. When the source data for Table 6 are corrected for heteroskedasticity, the result is the Glymour et al. (1987) DAG model of Figure 8 (ρ = .05, AGFI = .97). The model shows a high degree of autoregressive interaction between the variables of interest. When autoregression is removed from the model, it simplifies to the *contemporaneous* model of Figure 9 (ρ = .05, AGFI = 1.00).

In Figure 9, we see that changes in knowledge capital and leavers are endogenous drivers of joiners. The negative coefficient on the arrow reflects that leavers are subtracted from the social network, while joiners and the knowledge network change only in a positive direction. Since there is no way that leavers could actually be influencing joiners, I interpret these causal relationships to mean that there is an unobserved effect that causes members to join, the absence of which causes members to leave (Figure 10). My survey of relevant theory leads me to suggest that this unobserved effect is product involvement.

Performing a common factor analysis on leavers and joiners finds the indicated result explaining 49% of the variance in leavers and joiners, albeit with a miserable Kaiser-Meyer-Olkin (KMO) statistic of .5. An increase in high-value content seems to explain about 10% (58.6 − 49.0 = 9.6) of what causes people on the sidelines to join in on the discussion and become active members (i.e., joiners). Change in knowledge capital is Pearson-correlated to this common factor at .091 (ρ = .02). If this common factor represents an underlying product involvement, it is consistent with this discussion that it should be positively correlated with changes in knowledge capital.

Figure 8

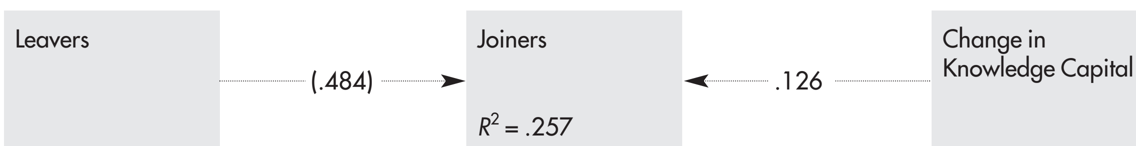
Dynamics of Knowledge Capital, Joiners, and Leavers



Note: Boxes denote measured variables. Arrows labeled with standardized coefficients represent correlations. Parentheses denote negative values.

Figure 9

Effect of Changes in Knowledge Capital and Leavers on Joining



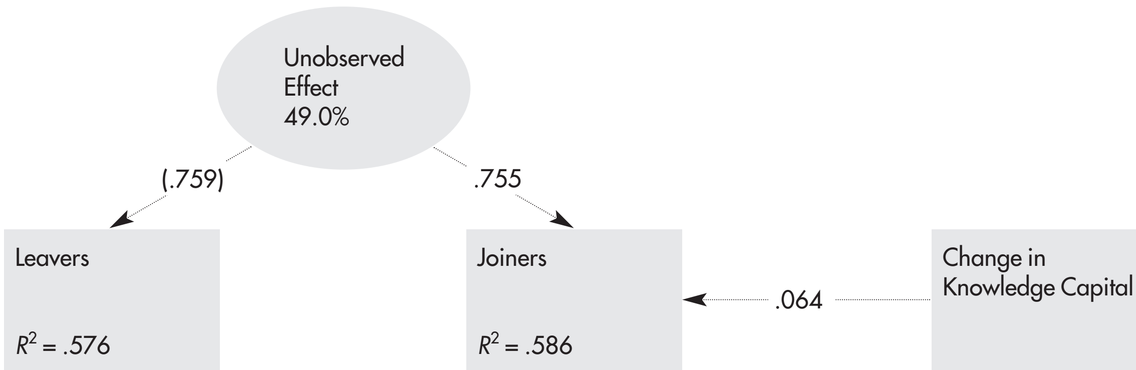
Note: Boxes denote measured variables. Arrows labeled with standardized coefficients represent correlations. Parentheses denote negative values.

Summary and Conclusions

The PageRank™-based algorithm for measuring importance (i.e., knowledge and social capital) in the informational and social networks is superior to the prevalent centrality-based metric. Content of high value to the community attracts attention with little reference to who originated the content. Thus expert power, in whatever form is respected by the community, is the prime influence on how the knowledge network causes the social network to evolve. High-value content in the knowledge network explains 10% of social network growth. Changes in people's enjoyment of the products they use should account for a large part of the network changes this model has not explained. Validating this supposition would be a logical avenue for further research.

As stated in the introduction, many companies have started monitoring online communities of their customers as a source of feedback. They seem to be aware that community members are often the most fanatical of their customers and act as product evangelists. With the APR metric, companies can automate the process of filtering community message traffic to identify

Figure 10
Unobserved Common Effect



Note: Boxes denote measured variables. Arrows labeled with standardized coefficients represent correlations. Parentheses denote negative values.

the information that attracted the most customer attention and the members who typically provided that information.

Since high-quality content plays a significant role in increasing product involvement, companies that have products with large and active online communities should consider hosting a blog so they can play an active and visible role in injecting such content into their user community. Such efforts should be in the spirit of Alexandre Ledru-Rollin's lead-by-following philosophy, that is, the company must restrain itself from trying to control its consumer communities and let emergent forces among the consumers be the guiding influence. The effort a company applies to this mode of marketing communications should be rewarded by increased sales, as the enthusiasm of consumer-evangelists is maintained and producers gain greater ability to create products their customers desire. ■

Appendix Glossary

Autoregression: When the current value of a variable is partially based on its previous value, or indeed the previous values of other variables, that variable is said to show *autoregression*. Sometimes it is useful to know to what extent a variable's current value is based on previous values; however, if you are trying primarily to determine the extent to which a current value is based on the present values of other variables, then you will want to remove the autoregressive portion so that it will not be a source of confusion.

Centrality: In a network or a set of connected entities, *centrality* is a common way of denoting which entity or entities are most important. Centrality, expressed simply, is the number of direct ties connected to an entity by other entities in the same network. The more ties an entity has, the more "central" it is said to be. Centrality is often more specifically called *degree centrality*. Sometimes centrality is expressed as a percentage: if you know 30% of the people in a room—all members of a club (i.e., in a network)—your centrality is 30%.

Contemporaneous: In the above definition of autoregression, I distinguish between past and present influences on a variable's current value. The present influences are said to be *contemporaneous*.

Decay: People come and go from social networks and communities, making the community subject to the opposing forces of growth and *decay*. People are motivated to stay in communities by satisfying social and tangible rewards (e.g., information). When these rewards lessen, people leave. If this perception of lessened rewards becomes widespread, then the community will eventually disappear.

Directed acyclic graph (DAG): A DAG is a diagram showing how a group of variables affect each other's values. It is termed *acyclic* because it never depicts a variable as having its value determined by itself, either directly or through one or more other variables. A DAG is a type of *structural equation model* (defined below).

Endogenous: A situation in which a variable's value is fully determined or explained by the value of other variables that it is known to be in a relationship with. For example, in the basic equation for a straight line:

$$y = mx + b\,. \tag{2}$$

The variable y is *endogenous* in that its value is fully determined by the values of variables m, x, and b.

Exogenous: Exogenous is the opposite of endogenous. In Equation 2, variables m, x, and b are termed exogenous because their value is determined by something other than any relationship defined by Equation 2.

Heteroskedasticity: Suppose that you are trying to determine how the weight of a calf increases over time as it grows. Let's say that you weigh the calf using the same scale every day for 100 days and then weigh it again for another 100 days using a different scale. It might seem reasonable that you could take all 200 values, plot a trend line, and thereby get a good estimate of how calves gain weight. However, because the two scales might vary in their accuracy, you have a potential for the introduction of error in your weight estimation due to heteroskedasticity. In this paper, data are gathered from a variety of different communities, all possessing unique levels of variance. When these data are merged to derive findings true of communities in general, *heteroskedasticity* must be removed. In this situation, all values are converted to z-scores (see definition below), removing the variance unique to a community.

Homophily: Suppose you, a prospective club member, enter a room filled with members of that club. One general theory that tries to explain what strategy you will employ to become integrated with the club (or network) is *homophily*, that is, you will look for people similar to you. In an online community, we become aware that a new member has joined when he or she posts a message. If the new member chooses to announce his or her presence by deliberately attaching a message to that of another member, then he or she has practiced homophily. The similarity of homophily can be expressed in almost unlimited ways.

Informational network: When separate pieces of information are linked together and to other pieces of information because they have been judged to be thematically or semantically related, that collection of interrelated information can be called an *informational network*. In this paper, I use this term interchangeably with knowledge network (see definition below). An online community's only tangible asset is the information contained in the messages members post to it. Members generally add their messages so they logically relate to those already there. As a result, these communities are informational networks.

Knowledge capital: As in an informational network, an online community's only tangible asset is the messages posted to it. These messages, and the way they relate to each other, have value and increase in value as more content is added. This value is called *knowledge capital*. The adapted PageRank™ metric described in this paper is a way of expressing the value a community has assigned to all or part of its information network.

Knowledge network: As said in the definition of informational network, this paper uses *infor-*

mational and *knowledge network* interchangeably. Other writers in the marketing discipline define the term differently.

Metadata: This word literally means "data about data." The directed acyclic graph methodology (defined above) is able to take into account prior knowledge about the relationships between variables in a model. This prior knowledge is *metadata*.

Node: A network is composed of *nodes* connected by ties. Nodes refer to entities that belong to a network. The relationships that connect these entities are *ties*. A family is a common network. One example of a family might consist of a husband, wife, and two children. The four people are nodes, and the marital, parental, sibling, and familial relationships are all ties.

Outdegree: The term *outdegree* uses the word degree in a manner similar to its use in the phrase degree centrality. If you enter a room full of networked strangers and make 10 new friends, then your outdegree in that context is 10. A related term is *indegree*, the number of relationships others have initiated with you. These two terms are integrated in the concept of prestige (defined below).

Preferential attachment: If, when you join a network, you exercise a strategy for selecting specific members of the network for the creation of a relationship (such as friendship), then you have demonstrated *preferential attachment*. Homophily, defined above, is an example of preferential attachment strategy. In this paper, I discuss two preferential attachment strategies: homophily and expert power. *Expert power* refers to a strategy of creating ties with people who possess superior knowledge.

Prestige: *Prestige* is a type of centrality (defined above) where a node has a much larger number of incoming ties (indegree) than outgoing ties (outdegree). The implication is that others have sought you out for preferential attachment, but that you are more self-sufficient and have not sought many ties with others.

Proportioning factor: When Google™ calculates a web page's PageRank™, it uses a portion of the PageRank™ of web pages that it links to. The linking page inherits some of the importance of pages it references. This idea can be transferred to social networks: your importance is partially based on the importance of the people you know. Google™ keeps secret the exact proportion it uses. This paper uses an arbitrary value of 15%.

Purposive selection: There are two ways to select a sample for a scientific study: randomly or purposively. Random sampling is commonly used in laboratory settings when you want to avoid introducing sources of bias or nonrandom variation. However, in a real-world setting, you can accomplish the same goal by deliberately looking for wide diversity in your test subjects. Even though many product-oriented online communities have been started, few are highly active. A random sampling of these communities would probably result in an attempt to derive conclusions from a small amount of data. As a result, I used *purposive selection*, purposely looking for large and active communities interested in a wide variety of product classes. While this might bias the findings toward attributes peculiar to large and active communities, it is my contention that this risk of bias does not impair my ability to meet the goals of this study.

Social capital: The value of your social network added to your own inherent worth (i.e., unique knowledge and skills) is your *social capital*. A whole network can also have social capital—the sum of the individual social capital of all its members. What constitutes value in a social network is very specific to its context. Theorists have proposed that expertise or knowledge is the core determinant of value. You have value because of what you know and the knowledge you can access through your friends.

Social network: When a group of people are linked together by any relationship or set of relationships, from casual acquaintance to immediate family, the group is said to be a *social network*. Members of the same online community may never have physically met; however, if they have communicated ideas to each other, they have met semantically and thereby become connected.

Stationarity: When some value is measured over time, it may exhibit an upward or downward trend; it may also fluctuate about some average value. In the latter situation, the value can be said to be stationary about a mean. There are ways of testing whether a series of values is *stationary*; this study uses the method proposed by Dickey and Fuller (1981).

Structural equation model (SEM): The relationships between a set of variables that affect each other's values can be expressed as a diagram such as that in Figure 8. Measured variables are depicted as boxes connected by arrows that denote directions of influence. The degree of influence is represented by a number on the arrow. SEMs can also depict the influence of latent variables (see Figure 10), that is, variables that have not been directly measured but whose value and influence can be inferred from the other variables in the model.

Wilcoxon Signed Rank Test: The Wilcoxon test is a nonparametric alternative to a paired *t*-test. Where the *t*-test assumes the studied population is normally distributed, nonparametric tests make no assumptions about the nature of the distribution. The result of a Wilcoxon test is expressed as a *z*-score and a two-tailed probability. The *z*-score indicates the distance between the two means with a probability that the means are equal.

***Z*-score**: A *z*-score or standard score is calculated using Equation 3:

$$z = \frac{X - \mu}{\sigma} \tag{3}$$

where X is a member of a set of values having a mean of μ and a standard deviation of σ. *Z*-scores are useful when comparing sets of values that differ in size and variance by placing the values on a common footing.

Note

1. The Wilcoxon test is preferred here over a standard t-test because I cannot assume that the values compared are normally distributed or indeed identically distributed. Note that I am not comparing all four columns of tables 3a and 3b to a single mean, only certain pairwise combinations that are presented together to use space efficiently.

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