

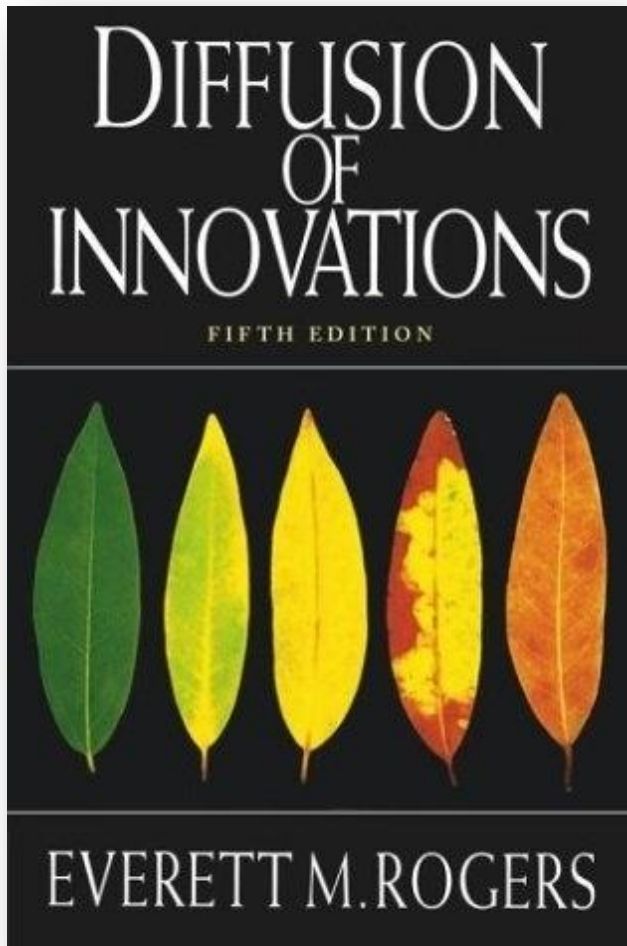
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Challenges and Perspectives

June 1999



-- Loren Lutzenhiser



“It is unthinkable to study diffusion [of innovations] without some knowledge of the **social structure** in which potential adopters are located as it is to study blood circulation without adequate knowledge of the veins and arteries.”

-- Elihu Katz

A NEW PRODUCT GROWTH FOR MODEL CONSUMER DURABLES^{*}

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A growth model for the timing of initial purchase of new products is developed and tested empirically against data for eleven consumer durables. The basic assumption of the model is that the timing of a consumer's initial purchase is related to the number of previous buyers. A behavioral rationale for the model is offered in terms of innovative and imitative behavior. The model yields good predictions of the sales peak and the timing of the peak when applied to historical data. A long-range forecast is developed for the sales of color television sets.

The concern of this paper is the development of a theory of timing of initial purchase of new consumer products. The empirical aspects of the work presented here deal exclusively with consumer durables. The theory, however, is intended to apply to the growth of initial purchases of a broad range of distinctive "new" generic classes of products. Thus, we draw a distinction between new classes of products as opposed to new brands or new models of older products. While further research concerning growth rate behavior is currently in process for a wider group of products, attention focuses here exclusively upon infrequently purchased products.

Haines [6], Fourt and Woodlock [5], and others have suggested growth models for new brands or new products which suggests exponential growth to some asymptote. The growth model postulated here, however, is best reflected by growth patterns similar to that shown in Figure 1. Sales grow to a peak and then level off at some magnitude lower than the peak. The stabilizing effect is accounted for by the relative growth of the replacement purchasing component of sales and the decline of the initial purchase component. We shall be concerned here only with the timing of initial purchase.

Long-range forecasting of new product sales is a guessing game, at best. Some things, however, may be easier to guess than others. The theoretical framework presented here provides a rationale for long-range forecasting. The theory stems mathematically from the contagion models which have found such widespread application in epidemiology [2]. Behaviorally, the assumptions are similar in certain respects to the theoretical concepts emerging in the literature on new product adoption and diffusion, [7, 8, 9, 13] as well as to some learning models [3, 12]. The model differs from models based on the log-normal distribution [1, 4, 10] and other growth models [11] in that the behavioral assumptions are explicit.

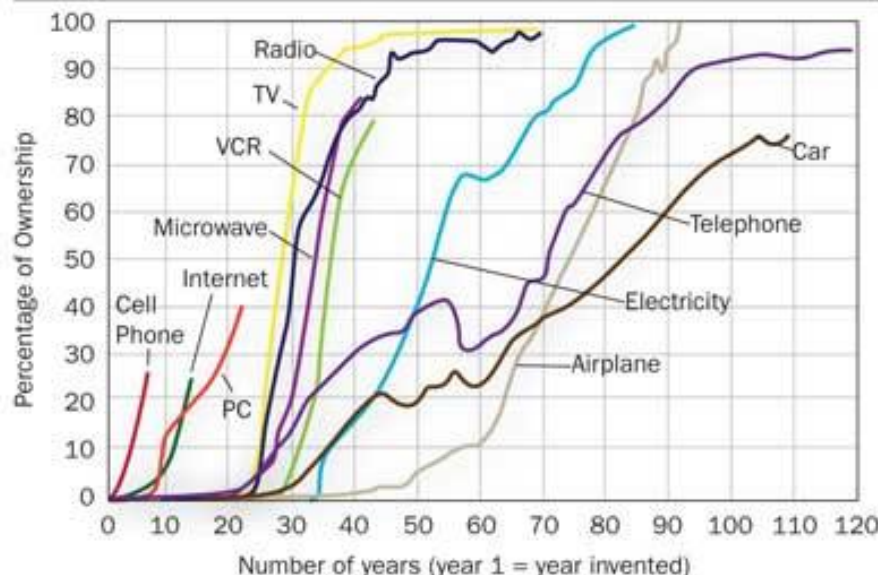
The Theory of Adoption and Diffusion

The theory of the adoption and diffusion of new ideas or new products by a social system has been discussed at length by Rogers [13]. This discussion is largely literary. It is, therefore, not always easy to separate the premises of the theory from the conclusions. In the discussion which follows an attempt will be made to outline the major ideas of the theory as they apply to the *timing* of adoption.

* Received March 1967 and revised August 1967.

¹ Some of the basic ideas in this paper were originally suggested to the author by Peter Frevert, now of the University of Kansas. Thomas H. Bruhn, Gordon Constable, and Murray Silverman provided programming and computational assistance.

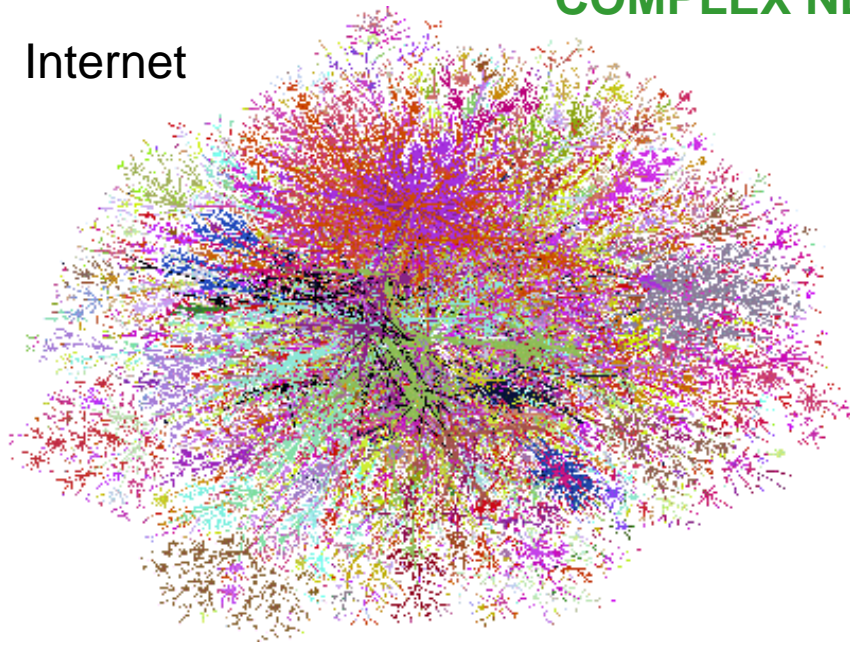
Technology Adoption



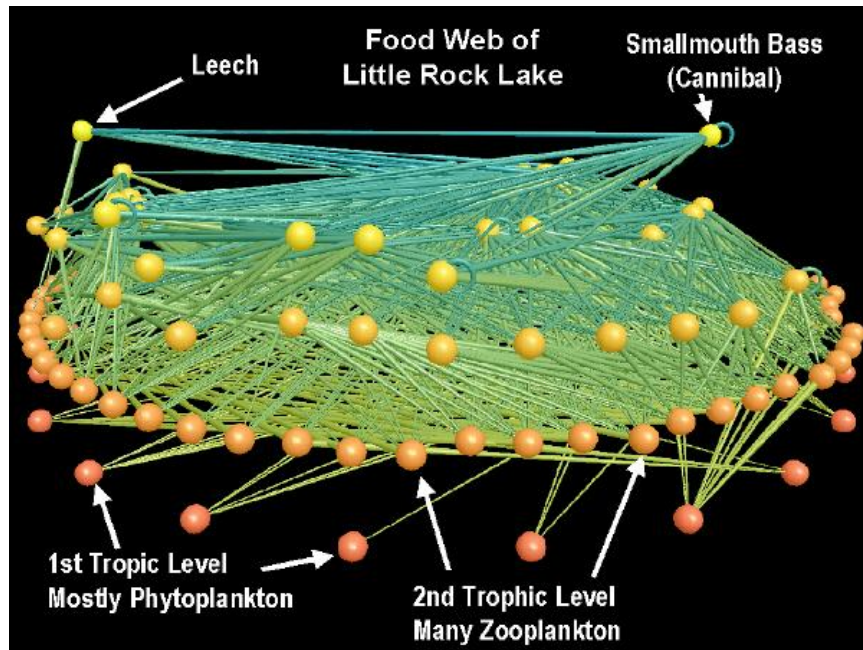
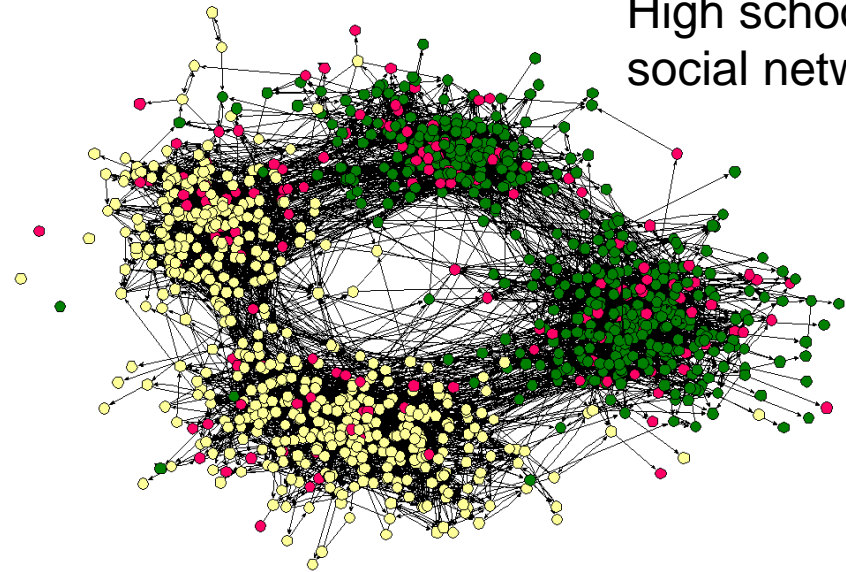
Source: Forbes Magazine

COMPLEX NETWORK SCIENCE

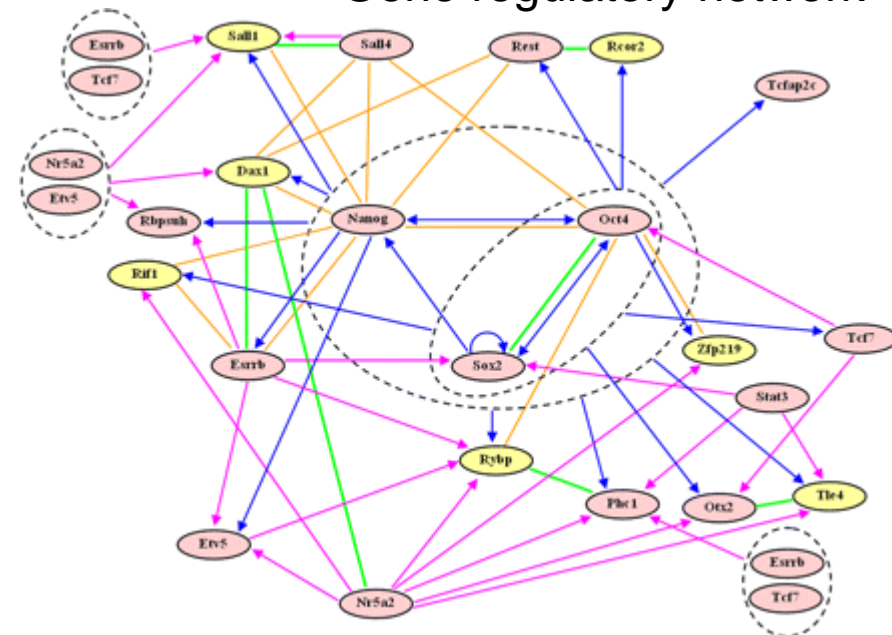
Internet



High school social network



Gene regulatory network



Computational Social Science

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We live life in the network. We check our e-mail regularly, make mobile phone calls from almost any location, swipe transit cards to use public transportation, and make purchases with credit cards. Our movements in public places may be captured by video cameras, and our medical records stored as digital files. We may post blog entries accessible to anyone, or maintain friendships through online social networks. Each of these transactions leaves digital traces that can be compiled into comprehensive pictures of both individual and group behavior, with the potential to transform our understanding of our lives, organizations, and societies.

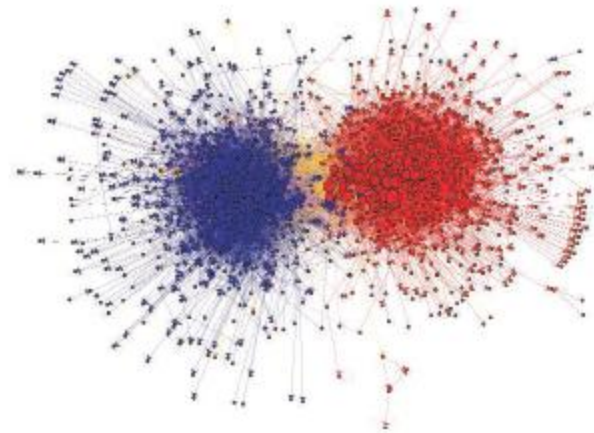
The capacity to collect and analyze massive amounts of data has transformed such fields as biology and physics. But the emergence of a data-driven "computational social science" has been much slower. Leading journals in economics, sociology, and political science show little evidence of this field. But computational social science is occurring—in Internet companies such as Google and Yahoo, and in govern-

ment agencies such as the U.S. National Security Agency. Computational social science could become the exclusive domain of private companies and government agencies. Alternatively, there might emerge a privileged set of academic researchers presiding over private data from which they produce papers that cannot be

A field is emerging that leverages the capacity to collect and analyze data at a scale that may reveal patterns of individual and group behavior.

critiqued or replicated. Neither scenario will serve the long-term public interest of accumulating, verifying, and disseminating knowledge.

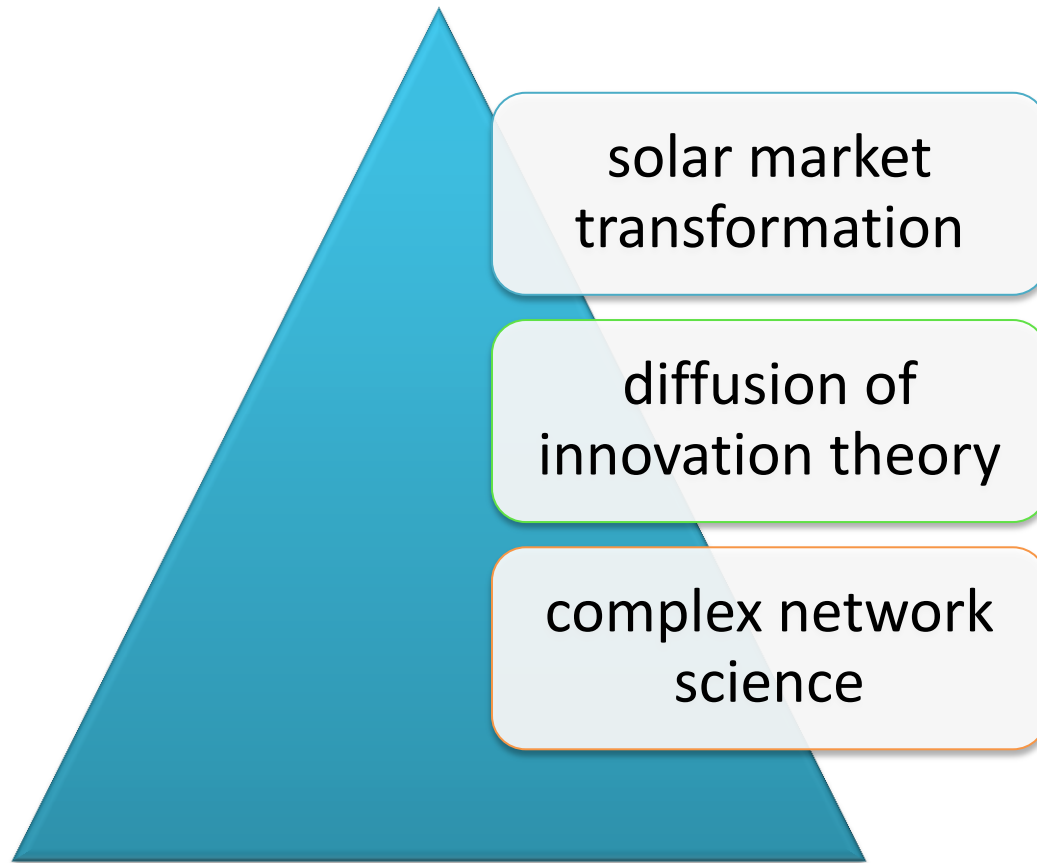
What value might a computational social science—based in an open academic environment—offer society, by enhancing understanding of individuals and collectives? What are the



Data from the blogosphere. Shown is a link structure within a community of political blogs (from 2004), where red nodes indicate conservative blogs, and blue liberal. Orange links go from liberal to conservative, and purple ones from conservative to liberal. The size of each blog reflects the number of other blogs that link to it. [Reproduced from (8) with permission from the Association for Computing Machinery]

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“computational social science is emerging that leverages the capacity to collect and analyze data with an unprecedented breadth and depth and scale”



Population-size datasets and powerful computational tools are enabling new discoveries about how ideas and innovations spread.

It's time for a paradigm shift in market transformation strategy.

- Learning by doing? Peer effects → diffusion of innovation over time. Cost data is needed to better understand key drivers of solar diffusion. Need to collect data on peer effects, clustering by address.
- Adoption: supplier vs. consumer adoption. On the supplier side, can we begin to quantify the transition to the “new” market place?
- On the consumer side, in addition to understanding which groups and subgroups, can we begin to better understand the extent to what level technology is diffused?
- Need for network data → more difficult at the company level, more plausible at the consumer level. Data such as linked in data currently underutilized. Specific data sets: Sungevity, Solar City.
- Clusters of suppliers (ex. relationship between contractors and sub-contractors).
- Perception of solar as a “gadget” a “want”, irrespective of the economics/financial ROI.

Making solar as unobtrusive as a TV, “PLUG AND PLAY”.

To what extent can solar adoption be as easy as acquiring a TV: OBSERVABILITY as a catalyst for adoption.

Network→ What is the “right” network?

Visible. Neighborhood level.

Social networks are relevant too, but the real research question here is how do ideas propagate from one individual to another?

How do these different networks and nodes of influence interact with one another to spur adoption?

TVs present an appropriate analogy, compared to fax machines or internet, because of the social element.

What about the notion that online, social networks are representative of “real” social networks. Examine Facebook friends network and then interview to follow up and see if real life friendship networks translate to online social, friendship networks. **Ex) friends facebook > friends real life.** → means to measure strength of ties, attempt to identify whether FB data would be useful.

Behind the meter space is removed from typical channels, complicates decision making in behind the meter space. Network effects play a stronger role in attracting potential adopters → interface with the decision maker. Given that utilities determine rates, (communicated through monthly bill, removed from actual behavior of energy consumption), devaluation effects linked to policy frameworks, particularly with respect to Net Metering in the U.S.A. vs. FITs in Germany. Role of networks in U.S.A potentially larger than Germany, can we conduct a cost-benefit analysis comparing market leaders such as Germany to U.S.A.

Survey, customer attitudes and how that correlates with consumer behavior. → **hierarchy of attitudes**

- Decision = Financial + Social (with different weighting factors)
- Premise that adoption is purely cost driven, and when PV reaches SunShot goals, many market barriers become obsolete.
- Policy questions answered with different kinds of network data → BUT, how do we USE the data?
- What kinds of questions can inform policy?
- (Ex.) low income households needs to be addressed. We must be sure to not ignore the geographic factors and income factors, to identify adoption drivers amongst different socio-economic groups/sectors of society.

- Different actors in the pyramid of adoption (early adopters on the consumer side vs. other adopters such as land lords/lower-middle income populations).
- Opportunities to identify/manipulate potential outcomes based on experiment, not necessarily EXTANT data.
- In hardware sciences, learning curves are central to understanding adoption. **Is there a learning curve for market transformation?**
- Energy efficiency programs separated from solar programs (how can we get at the question of whether it makes sense to have a building integrated approach for efficiency first and solar second)

- Behavior modification → responsible behavior → ability to diffuse via networks? The notion of self commitment to enacting a certain change be it behavioral or otherwise.
- Measure of effectiveness via randomized experiments to gauge social networks ability to affect change.
- Data, technology improvement to get data, agent based modeling. How does one take into account the various factors of adoption (ex. energy independence vs. environmental benefits, based on geography) High dimensional model with various parameters, but need to control for different causal variables to clearly isolate individual effects. Using an iterative process to bring together different individuals, (ex) study of deregulation in Illinois. Brought in computational scientists, operations and maintenance professionals, etc. and created a model of outcomes. **AND MOST IMPORTANTLY → WHAT IS THE PREDICTIVE CAPACITY of such models?** Agent based models show us what data is missing → how to extrapolate behavior → but still need to understand the influence of behavior. **NEED TO UNDERSTAND THE BOTTOM LINE.**
- Study interaction between cost declines → adoption decisions.

Potential Tiered Program

0. Ask a certain question.
1. Data mining from different places that can be used in models.
2. Design models
3. Validate models – do a social experiment