

# The Emerging Scholarly Brain

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**Summary.** It is now a commonplace observation that human society is becoming a coherent super-organism, and that the information infrastructure forms its emerging brain. Perhaps, as the underlying technologies are likely to become billions of times more powerful than those we have today, we could say that we are now building the lizard brain for the future organism.

## 1 Preamble

... the highest level of the ant colony is the totality of its membership rather than a particular set of superordinate individuals who direct the activity of members at lower levels.

Höldobler and Wilson (1990)

## 2 The Super-Organism

For millennia the only means of intra-species cross-generational communication was chemical; information was transferred via genes in a Darwinian process. The structure for some very complex systems have been transferred by these means.

An example would be the reaction to high temperatures. Even single celled organisms avoid excessively hot regions; those which don't get cooked and don't survive. Fast forward a few eons and we have cooperative structures of 50 trillion cells (e.g. humans) which can very rapidly self mobilize to move a finger away from a frying pan.

A second example, indicating just how complex this chemical communication channel can be is that primates (including humans) are innately afraid of snakes (Hebb 1955). To quote Pinker (1997) "People dread snakes without ever having seen one. After a frightening or painful event, people are more prudent around the cause, but they do not fear it; there are no phobias

for electrical outlets, hammers, cars, or air-raid shelters.” Ancient creatures which had an insufficient fear of snakes became lunch rather than becoming our ancestors. The agglomeration of this genetically transmitted information has been called the “collective unconscious” ([Jung 1935](#)).

Creatures can learn: bees, for example can learn which color flowers are the best sources of food, and they can communicate, as bees do with their “waggle dance,” communicating the distance and relative position (to the sun) of a food source. The information needed to perform this dance appears to be entirely genetically transmitted, there is no evidence for a learned component ([von Frisch 1967](#)).

Humans, certainly, are capable of learning communication techniques. The development of language, aided by Darwinian processes ([Pinker 1994](#)) represents a phase transition in the information transfer process across time which is evolution. It became possible for parents to tell their children “eat this mushroom, but not that one!”

This phase transition enabled humans to form large coherent groups where information could be maintained and shared, thus problems could be solved by distributed efforts. Over time, sophisticated bodies of knowledge were built.

The next phase transition in the information transfer process was the development of writing. While oral transmission is powerful, and has provided us with, as an example, the core ideas behind religion, modern civilization is clearly too complex to be achieved without writing.

Writing, along with the two major enabling inventions, paper and printing, has formed the basis for the information transfer system for our globally connected human society. This society, viewed as an entity onto itself, a super-organism, has capabilities far beyond those of single individuals. An example of these capabilities might be the industrial revolution, which was designed and implemented without any central direction.

We are living in another period of phase transition, one that will happen much faster than the previous ones. The time span for phase transitions has been getting shorter by about a factor of 100 each time; implying that the current one will be consummated within a single human lifetime.

The technical underpinnings for the current phase transition are very rapid communication (beginning, perhaps, with the telegraph) and electronic storage. Together our electronic communication and memory network now form a coherent entity, a Super-Brain ([Heylighten and Bollen 1996](#)), for the super-organism which is human society.

Although pure communications networks have existed substantially longer (telegraph, telephone, radio, television), it is the addition of electronic memory which makes the computer network the fundamental technical advance. Within the past few decades computer networks have coalesced to form a single entity (in graph/network studies forming the giant component is usually viewed as a phase transition, [Newman 2003](#)).

With this the human society super-organism has developed the functional equivalent of a brain, but we are clearly just at the beginning of the process.

In the past 60 years the power of the information technologies behind the transition has increased by a factor of (about) a trillion; if this can continue for another 60 years, or indeed (Kurzweil 2001) increase more rapidly, the evolving super-organism might well be incomprehensible to us today.

The exponential growth of technical capabilities is not guaranteed, Moore's law, for example, appears to have reached its physical limits (in the number of transistors on a chip). The nano-bio-cyber convergence currently occurring suggests, however, that the growth will continue, or, following Kurzweil (2001), accelerate.

The nature of the changes are still in the realm of science fiction; Stapledon (1930) foresaw the fate of the "last men," after which (evolutionarily) humans became a new race:

The system of radiation which embraces the whole planet, and includes the million million brains of the race, becomes the physical basis of a racial self...

But chiefly the racial mind transcends the minds of groups and individuals in philosophical insight into the true nature of space and time, mind and its objects, cosmical striving and cosmical perfection....

For all the daily business of life, then, each of us is mentally a distinct individual, though his ordinary means of communication with others is "telepathic." But frequently he wakes up to be a group-mind...

Of this obviously, I can tell you nothing, save that it differs from the lowlier state more radically than the infant mind differs from the mind of the individual adult, and that it consists of insight into many unsuspected and previously inconceivable features of the familiar world of men and things.

### 3 Architecture

It appears that we humans, like the Krell (MGM 1956), will be (or indeed are) increasingly interconnected with an electro-mechanical system of almost unimaginable power. Already we communicate near telepathically with almost anyone on the planet, at almost any time, via cell phone; already our memories are tremendously augmented by internet search engines.

While we cannot know exactly what the future will bring, we can intuit some things concerning the elements of our new environment, based on past trends. The elements we construct will be extraordinarily complex; each with a multitude of design decisions. This is unlike the exact sciences, where there is a single correct description of a physical reality; it is more like architecture, there is no single exactly correct bridge or building design.

Certainly there are architectural elements which persist, such as a key stone in building arches. Perhaps the closest analog to the information entity

we are now constructing, (the super-brain?) is a city. Cities are constructed by the long term and large scale combined efforts of people. Cities are not explicitly designed, but they grow as a result of numerous mostly independent efforts. Even without explicit design cities normally have a number of design elements in common, such as neighborhoods, or sidewalk cafes ([Alexander et al. 1977](#)).

Major elements in all cities are places to get things. These are often the end points of complex webs of activity. An example could be a bakery, which combines efforts by fertilizer providers, seed salesmen, farmers, millers, truckers, and others to provide bread. Major elements in the information structure we are building are places to get information. These also are the end points of complex webs of activity. An example could be the Smithsonian/NASA Astrophysics Data System (ADS; [Kurtz et al. 1993, 2000, 2005](#)). The ADS combines the efforts of lens designers, rocket scientists, astronomers, publishers and others to provide astrophysics research information.

There are substantial differences in how these design elements are instantiated. There can be bakeries, hardware stores, dress shops, toy stores, etc.; and there can be Wal-Mart or Target. Both systems have their advantages. In the world of information there can be specialized providers, such as ADS, PubMed, The Internet Movie Database, Flightstats, etc; and there can be Google or Bing. Again both systems have advantages.

## 4 Vectors of the Mind

Context is an important criterion; asking to get one's tank filled will get an altogether different result at Diver Jim's Belmont Scuba Co than it will if asked at the gas station next door. Likewise the query "plasma diagnostics" will get a different result on PubMed than on ADS.

Even when one can narrow down a request, for a product, or information, to a specific realm, context is still important. A typical hardware store, for example, will have hundreds, if not thousands of different fasteners (nails, screws, glue, tape, . . .); which product to purchase depends critically on exactly what the current problem is. Likewise the ADS has thousands of papers on a topic such as "weak lensing," which paper to read depends critically on the exact current problem.

Context is usually provided by people. A customer chooses to go to a hardware store (instead of, say, a cheese shop) to solve some problem, which is described to a clerk. The clerk has substantial expertise in the specific problem domain, and suggests one, or several possible solutions, taking into account the actual needs and abilities of the customer.

In the information world the customer still chooses between providers, ADS or PubMed, for example, but there is no equivalent to the clerk; this function is performed by the information service. Because the actual needs and abilities of each "customer" vary greatly for the exact same query (a beginning

student will often be better served by different information than would be best for a world renowned expert) the information system will need to be able to adapt to, and perhaps sense, the larger context of queries.

## 4.1 Global Measures

### Linear Algebra Techniques

Clearly information systems perform functions which were previously performed by humans, or by groups of humans. This requires techniques to model the thoughts and behavior of people and groups of people. Psychologists and Sociologists have been developing these techniques for decades.

[Thurstone \(1934\)](#) used eigenvector techniques to build an orthogonal vector space model for human thought. These techniques have become very widely used; psychometrics and marketing for example depend heavily on them. They have also been used to model the idea space of documents. [Ossorio \(1966\)](#) used a psychological testing approach to model individual opinions concerning the relevance of documents. [Kurtz \(1993\)](#) reverse engineered a set of classified documents to build a model of the thought process of a librarian classifier. Perhaps the most successful of these methods is latent semantic analysis (LSA; [Deerwester et al. 1990](#)) which builds the vector space based on the co-occurrence of words in documents.

These eigenvector techniques have also been used in many different classification problems ([Murtagh and Heck 1987](#)); such as with astronomical spectra. [Kurtz \(1982\)](#) first applied the method to stellar spectra, and [Connolly et al. \(1995\)](#) rediscovered it for galaxy spectra. While the methods have been used, they have not found great success, compared to partitioning line ratio diagrams ([Baldwin et al. 1981](#)) or color-magnitude diagrams ([Golay et al. 1977](#)). This is likely because, while the techniques are linear, the underlying physics is highly non-linear ([Kurtz 1982](#)).

Human thought is also highly non-linear; representing it by a linear vector space is bound to cause problems. Although the success of LSA as an indexing method for text demonstrated that very local measures of nearness can be effectively defined, more generally these are not metric spaces. As an example, human perceptions do not follow the Schwartz or triangle inequality. The perceptual distance between a dog and a vacuum cleaner is made shorter by the introduction of a third point, a mechanical dog; a mechanical dog is a kind of dog, and a mechanical dog is a kind of vacuum cleaner ([Kurtz 1989](#)).

### Social Network Techniques

By analyzing the connections between entities (people, documents, molecules, traffic jams, ...) one can build powerful descriptive and predictive models ([Barabasi 2003; Newman 2003](#)). Many of the techniques were developed for the social sciences ([Wassermann and Faust 1994](#)) and are now widespread. Fifteen

percent of the papers published in 2009 by *Physical Review E* address aspects of network problems, as do 26% of papers published in *PLOS Computational Biology*, for example.

The structure of information networks contains information about the intelligent processes which created them. Obtaining the underlying structure from the network is called community detection, and is similar to techniques for cluster analysis or classification.

[Fortunato \(2010\)](#) reviews these methods. Currently the most popular method is that of [Girvan and Newman \(2002\)](#) and the “best” (according to [Lancichinetti and Fortunato 2009](#)) is that of Rosvall and Bergstrom (RB [2008](#)). RB have used their algorithm on citation data to show the interrelationships between the major fields of science; their map may very profitably be compared with the similar map of [Bollen et al. \(2009a\)](#) who show a similar structure based on usage data and *pre-existing* field classifications.

The RB algorithm has been used by [Kurtz et al. \(2007\)](#) and [Henneken et al. \(2009\)](#) to map the subfields of astronomy, based on both citation data and on shared keywords for journal articles. Attempts to build a similar map from usage data have not, thus far, been successful, perhaps because of the very broad readership patterns of many astronomers.

Another measure obtainable from a network graph is the “importance” of the individual nodes. Importance is normally called centrality in this context, and there are several different centrality measures. In a friendship network, where people are the nodes and they are linked to other people by friendship, the person with the most friends would be the person with the highest degree centrality. Note that friendship is directional: I may consider you my friend, but that does not mean that you consider me a friend; thus the concepts of in-degree and out-degree. In a citation network the paper with the highest in-degree is the most cited paper, while review articles would have very high out-degree.

Betweenness centrality is another “importance” measure. In a friendship network the most central people are those with friends in many different, otherwise autonomous cliques; in a journal to journal citation network the most central journals are the interdisciplinary journals ([Leydesdorff 2007](#)), like *Science* or *Nature*, which are between otherwise autonomous fields, such as astronomy and neuroscience. Betweenness centrality is a key measure in an information flow network; the high betweenness centrality nodes facilitate information transfer between fields.

The currently most used centrality measure is the expected occupation time for each node when visited by a random walk, where the agent randomly follows links from node to node. This is normally called eigenvector centrality, as the result is the same as the first eigenvector of the node-node connectivity matrix ([Bonacich 1972](#)). Google’s famous Page-Rank algorithm ([Brin and Page 1998](#)) is essentially eigenvector centrality, with clever implementation details.

There are several other centrality measures. [Kurtz and Bollen \(2010\)](#) give a brief introduction; [Koschützki et al. \(2005\)](#) a detailed discussion.

## 4.2 Local Measures

While measures which solve for globally optimum measures are clearly desirable and useful, they are often not feasible. This is especially true in situations where the data is inherently highly multipartite. Journal articles, for example, may be connected by citations, but they may also be connected by having the same author, or having been read by the same reader, or concerning the same subject matter, or the same astronomical object, or ....

An interesting question is how much is lost if one uses local measures, instead of attempting a global solution. Some recent work discusses this.

Eigenfactor ([West et al. 2010a](#)) is a useful measure of scholarly journals; it is available in the Thompson-Reuters Web of Science, and finds frequent use by librarians in making purchasing decisions. The Eigenfactor is essentially eigenvector centrality, measured on the journal to journal citation graph.

[Davis \(2008\)](#) pointed out that the Eigenfactor journal rankings in a subfield (medicine is what Davis used) are very similar to rankings derived from simple citation counts. In their two dimensional comparison of 39 different network measures [Bollen et al. \(2009b\)](#) showed eigenvector centrality near to in-degree, but not identical. [West et al. \(2010b\)](#) showed convincingly that the Eigenfactor produces rankings which are significantly different from plain citation counts.

While eigenvector centrality is clearly different from simple in-degree, and in cases such as Eigenfactor likely better, the fact remains that the differences are small. This suggests that in many instances very similar results may be had using much simpler measures.

The ADS second order operators (SOO: [Kurtz 1992](#); [Kurtz et al. 2002](#)) make use of local measures in the multipartite space to achieve specific results. The SOO are not a ranking or clustering methodology, per se, rather the SOO are relational operators which one uses to build custom rankings. Two examples of their use, both taken from the ADS Topic Search ([adsabs.harvard.edu/cgi-bin/TopicSearch](http://adsabs.harvard.edu/cgi-bin/TopicSearch)), will serve as an illustration. Here we will use the language of networks, [Kurtz et al. \(2005\)](#) use the language of lists of attributes. Both examples find information about a technical topic, while this can be almost anything, for concreteness we'll use the topic "weak lensing."

Example 1 starts by taking the article to article citation graph, where articles (nodes) are (directionally) connected by citations (links). First we take the subset of nodes which concern the topic, weak lensing; next we sort the nodes in the subset by their in-degree centrality, and retain only the top N (say 200). Next we form a super-node which is the sum of the individual top 200 nodes, and we sort the entire graph on the out-degree centrality to the super-node. The top of this list are articles which cite a large number of

articles on weak lensing which are, themselves, highly cited. In other words we have found review articles on weak lensing.

Example 2 starts with the article-reader bipartite graph, where an article is connected to a reader if that person has read that article. Again we initially restrict the articles to ones concerning the topic weak lensing, then we sort that list on an attribute of the article (now that attribute is the publication date), and take the most recent 200. Again we form a super-node with the 200 articles, and sort the reader nodes by out-degree to this super node. We take the readers with high out-degree to the article super-node (persons who have read recent papers on weak lensing) and form a reader super-node. Finally we sort all the articles in the (non restricted) graph on in-degree from the reader super-node. The top of this list are the currently most popular papers among persons working in the field of weak lensing.

Notice how these constructions solve many of the problems associated with trust ([Josang et al. 2007](#)). Only directly relevant, and well regarded papers and individuals are used; ADS further restricts the readers by removing persons who come from external search engines, who usually do not share the goals of professional researchers ([Kurtz and Bollen 2010](#)).

The SOO were first implemented in the ADS in 1996; they are used throughout the system, and form much of the basis for the myADS notification service ([myads.harvard.edu](#)).

### 4.3 Recommender Systems

If direct queries to an information system, such as ADS, can be viewed as consciously recalling data from the collective memory, then recommender systems might be likened to having memories pop into your head. Recommender systems as a research and application field cover an enormous range of different areas (cf. [recsys.acm.org](#)) focusing mainly on commercial uses; here we will concentrate on the recommender systems for scholarly literature.

In a scholarly field, such as astrophysics, the information is denser, and the use sparser, than in many other fields. For example *The Videohound's Golden Movie Retriever* lists about 30,000 movies; the ADS contains more than four times this number of papers which contain the word cosmology in the abstract. The peak usage for a scholarly article is usually the first day it becomes available (so there can be no usage information) and decreases rapidly. The typical 10 year old article from a major journal is downloaded once per month.

The ADS is building a set of recommenders based on the article currently being read, in the future we will also create recommenders based on the article viewing history of the reader. While the exact details are yet to be determined, the systems use nearly all the techniques described in this section, as well as the CLUTO ([Zhao and Karypis 2004](#)) clustering software. [Kurtz et al. \(2009\)](#) and [Henneken et al. \(2010\)](#) describe the initial implementation; which is intended for use by active researchers.

Briefly, we use the text and references in an article to find a set of recent articles which are very similar to the target article in subject matter. These articles are then used with the SOO to find recommendations using the words/keywords, citations, usage, authors, and astronomical objects.

## 5 The Scholarly Brain

In addition to having immensely enhanced memories, we now also have immensely enhanced perception. The new data intensive science ([Gray 2007](#)) rests not simply in the mechanical extension of our perception, as begun by Galileo and van Leeuwenhoek, but on the automated perception and analysis of huge data sets. The ATLAS experiment at CERN has a raw data rate of 60 TB/s ([Klous 2010](#)), about 50 trillion times the information handling capacity of humans ([Fitts 1954](#)).

The underlying technologies are being developed to satisfy the needs of huge systems, like the LHC experiments, but ever larger systems of sensor networks are being created to take advantage of the new capabilities. For these systems to combine their impact, they need to be able to communicate with each other; they need to share a language ([Kurtz 1989, 1992](#)). The shared language need not be native to any particular system or experiment ([Hanisch 2001](#)), but needs to be universally understood, like medieval Latin, or English today. This standardization is taking place across all scientific and technical fields, examples are the International Virtual Observatory Alliance's Simple Application Messaging Protocol (SAMP; [Taylor et al. 2009](#)) or the Open Access Initiative's Object Re-use and Exchange (OAI-ORE) protocol ([Van de Sompel et al. 2009](#)).

Automated memory and automated perception are combining to form automated ideas. Standardized data descriptors along with semantic tagging of text ([Accomazzi 2010](#)) produce a new environment, in which inference engines, similar to the stochastic/syntactic procedures used to analyze bubble chamber tracts ([Fu and Bhargava 1973](#)) are able to discover new, important associations and patterns.

These systems will be able to model and predict the behavior of humans ([Barabasi 2010](#)). Indeed [Ossorio \(1967, 1977\)](#) spent a good fraction of his career using his methods to model the behavior of specific humans. The role of these systems will not be to model individual human behaviors, but will be to act as the functional core for our collective intelligence.

This collection of machines will not provide the totality of the brain for the emergent super-organism which is human society; the higher functions, the cognitive layer, will be provided by the sum of all people. The machines will provide the core functionality, the lizard brain. Analogous with our own evolution there will be innate capabilities, like our instant reaction to heat, and anomalies, like our fear of snakes.

Individual scholarly disciplines have long functioned as semi-autonomous super-organisms. The memory function (on paper) being journal articles in university libraries. With the advent of the internet scholars are rapidly transforming their work habits to take advantage of the possibilities (Borgman 2007). New technologies effecting the speed of information transfer (Ginsparg 1994), and the ability to directly and effectively access huge datasets (Szalay and Gray 2001) have already been created, and more are coming daily. The scholarly literature has been fully digital for more than a decade. The idea that a discipline, such as astronomy, already functions as a coherent super-organism, with electronic memory and perception systems is not at all far fetched.

Millions of years before he imagined it would occur, we are beginning to implement Stapledon's (1930) *racial mind*, beginning first not with the human race, but with the sub races of astronomers, bio-chemists, economists, particle physicists, etc. With this scholarly brain we are achieving "*insight into many unsuspected and previously inconceivable features of the familiar world of men and things.*"

*Acknowledgement.* This essay is dedicated to the memory of two extraordinary scientists who showed me great kindness. Peter Ossorio's work continues to inspire me in several ways. Jim Gray's (2007) fourth Paradigm is the clearest exposition of how the new science will actually function.

Also Andre Heck has, through the years, provided me, and many others, with venues to discuss the deeper meaning of some current trends. The references to this paper alone list several.

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