Neurotree: A Collaborative, Graphical Database of the Academic Genealogy of Neuroscience

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Abstract

Neurotree is an online database that documents the lineage of academic mentorship in neuroscience. Modeled on the tree format typically used to describe biological genealogies, the Neurotree web site provides a concise summary of the intellectual history of neuroscience and relationships between individuals in the current neuroscience community. The contents of the database are entirely crowd-sourced: any internet user can add information about researchers and the connections between them. As of July 2012, Neurotree has collected information from 10,000 users about 35,000 researchers and 50,000 mentor relationships, and continues to grow. The present report serves to highlight the utility of Neurotree as a resource for academic research and to summarize some basic analysis of its data. The tree structure of the database permits a variety of graphical analyses. We find that the connectivity and graphical distance between researchers entered into Neurotree early has stabilized and thus appears to be mostly complete. The connectivity of more recent entries continues to mature. A ranking of researcher fecundity based on their mentorship reveals a sustained period of influential researchers from 1850–1950, with the most influential individuals active at the later end of that period. Finally, a clustering analysis reveals that some subfields of neuroscience are reflected in tightly interconnected mentor-trainee groups.

Introduction

Neuroscience is a highly interdisciplinary field that draws researchers from a variety of backgrounds ranging across the sciences and humanities. Understanding how ideas are drawn into neuroscience from other fields and how they interact is of central interest to the history of science. Given the large size of the field (the annual meeting of the Society for Neuroscience regularly draws over 30,000 attendees), it is becoming increasingly difficult even for active neuroscientists to simply observe and describe the trends governing the field. These problems are ripe for computational tools that enable systematic organization and study of large data sets containing information about individual neuroscience researchers.

An academic mentorship database provides several additional benefits to a research community, allowing new members to learn the lay of the land and to place themselves within the context of their field. Several fields of science have published their own mentorship history in some form or another, including mathematics, computer science, primatology and physics [1–3]. Analysis of academic genealogies has provided useful insight into training environments that produce the most productive researchers in their later careers [4].

This report describes Neurotree [5], an online database that documents mentor relationships within the field of neuroscience and with scientists in related fields. Information about mentorship is presented in an intuitive family tree format that enables straightforward visualization and navigation of the database [3]. Data in Neurotree have been provided by several thousand volunteer users since the site went live in 2005, and the database continues to grow daily. In addition to traditional neuroscientists, Neurotree contains information about physiologists, philosophers, physicists, computer scientists, economists and others who have either trained neuroscientists or performed neuroscience research themselves. Some users have expanded the historical reach of the database, allowing the majority of researchers in the database to trace their mentorship in several chains back to the earliest days of the University in the twelfth century or earlier.

The dataset contained in Neurotree provides a valuable resource for quantitative study of the individuals and disciplines that have influenced neuroscience throughout its development. Because mentors often train multiple students, understanding academic mentorship also allows one to follow the divergence of theories and techniques through different descending branches of the tree. Here we describe the data that constitutes Neurotree, assess how completely and accurately it documents mentorships, and illustrate how it can be used to understand large-scale trends in the field of neuroscience.

Methods

Neurotree is accessed through a public website at http://neurotree.org/ [5]. The site is built using a set of custom-programmed scripts that present information about mentor relationships between neuroscience researchers and allow site visitors to edit and add to that information. Mentor relationships
are presented graphically in a tree format (Figure 1) and in a more detailed biographical format (Figure 2). In addition to the database itself, Neurotree contains a search feature, a FAQ, a discussion board, and dynamically updated analyses of the database contents. As a service to the neuroscience community, we have made the data in Neurotree available to interested researchers (see below).

Database architecture

The core of Neurotree is a relational database consisting of two main tables (Figure 3A). Each row in the person table contains information about an individual researcher (name, most recent institution, research areas), identified by a numerical index, pid. Mentorship relationships between two people are then recorded in the connection table. Each row of the connection table links to two nodes by pid1 and pid2. The nature of the relationship is identified by a connection type. For example, a connection type of 1 indicates that node pid1 was a graduate student of pid2. Implicit in the relationship code is directionality, indicating that pid1 was the trainee of pid2 (Figure 3B). The types of relationship are detailed in Table 1.

Additional database tables are designed to link researchers to a set of institutions and research areas. We have imposed no restrictions on the contents of these auxiliary tables. Thus if a new institution or research area is entered by a user, this will result in the addition of a new entry to the respective table.

The simple architecture of the tree reflects an attempt to incorporate information into the Neurotree database using an organic, unrestricted approach. The field defining an individual’s research area is not restricted to a fixed set of terms and, instead, can be whatever the user adding data to the site considers appropriate. This approach leads to an obvious potential for lack of consistency, but at the same time permits a very flexible and dynamic catalog of research areas in neuroscience, which evolve rapidly. Most importantly, the flexible structure of the Neurotree database means that future researchers can amend, improve, and augment this structure in the future.

Ambiguities in cataloging an academic discipline

As it has grown, Neurotree has been confronted with ambiguities over the precise definition of mentoring relationships, relying on modern terms such as “research assistant” and “postdoctoral fellow.” Such designations have evolved over the course of history, and differences persist between countries today. In addition, many influential individual careers have taken idiosyncratic paths that do not reduce easily to a simple set of relationships. Our preference is to be pragmatic and suggest that contributors use the term that seems most appropriate based on the stage of an individual’s career and to document all relationships that substantially influenced the trainee’s work (see Table 1).

Another technical problem is that some scientists have multiple home institutions. We have adopted a policy that the most recent home institution should be the official institution. We acknowledge that this leads to some confusion, as when a scientist is closely associated with one location and then, near retirement, moves to...
Reliability of Neurotree

Like Wikipedia and other crowd-sourced projects, Neurotree is publicly editable, and, as a consequence, is not guaranteed to be accurate. Formal documentation is not required for submissions, but we have implemented a simple reporting system for flagging and resolving possible errors. Error reports can be submitted by any site visitor. A volunteer group of editors validates these reports and makes appropriate changes to the database. Generally error reports can be checked against information publicly available on the Internet. If the need arises for a more extensive discussion, editors may choose to contact the individuals who entered the information in question or to open the discussion with other editors. In the case of discrepancies that cannot be definitively resolved (typically in the case of historical figures whose biographies may be incomplete), the information in the tree is labeled as potentially unreliable.

In addition to inaccuracies in data, an additional issue is that information in the database may not be complete, as only a subset of mentors or trainees may be listed for any given individual. In this study, we explore how several statistical properties of the tree

Figure 2. Example biographical information page. Information about each researcher in Neurotree can also be displayed in a more detailed format, as in the example of Robert Yerkes shown here. Detailed information, when available, includes a photo or drawing, links out to various analyses on the Neurotree site, biographical notes and a link to a relevant off-site web page. In addition, dates and locations of mentor relationships are provided when available.

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Robert Mearns Yerkes (Tree - Distance to... - Nearest Nobel - Oldest ancestor - Extended family)

| Institution          | Yale University          |
|----------------------|--------------------------|
| Area                 | Primatology              |
| Mean distance        | 7.42 (cluster 6)         |
| Home page            | http://psychclassics.asu.edu/Yerkes/murchison.htm |
| Pub med              | Yerkes+RM                |
| Cross-listed         | PsychTree - Primatology Tree |

Parents

| Hugo Munsterberg     | grad student 1897-1902 Harvard University |
| Elmer E Southard     | research scientist 1913-1917 Harvard Medical School |

Children

| M E Haggerty         | grad student               |
| Kenneth W. Spence    | grad student 1928 Yale University |
| Chauncy McKinley Louttit | grad student 1917-1918 University of Minnesota |
| Karl Spencer Lashley | grad student 1937-1940 Yale University |
| Solly Zuckerman      | post-doc Stanford University |
| Clarence "Ray" Ray Carpenter | post-doc Stanford University |

Collaborators

Added by: hayden (2005-01-16 10:57:10)
Graphical analysis of the Neurotree database

Neurotree can be described as a graph composed of nodes (researchers) and directional edges (mentor relationships, Figure 3B). This very simple model permits a number of analytical approaches based on graph theory. Here we describe examples of analysis that can be applied to the data. The results described in this study are based on the contents of the Neurotree database as of March 31, 2012, 87 months after the database was established.

Distance metrics. The distance, \( d(a, b) \) between researchers \( a \) and \( b \) can be measured as the smallest number of edges between nodes, either in a signed direction (e.g., mentor to trainee) or independent of direction. Most nodes are connected in a single graph, but if a connection does not exist, then the distance is defined as infinite. In order to factor in infinite distance, the average distance between one node and \( N \) other nodes is defined as the mean of reciprocals,

\[
da = \frac{1}{N!} \left( \frac{1}{d_{a1}} + \frac{1}{d_{a2}} + \cdots + \frac{1}{d_{an}} \right)
\]

For infinite \( d \), the reciprocal is defined as zero and permits a numerical solution for average distance.

Fecundity. In order to characterize how prolific one individual has been in training researchers who have themselves been productive, it is possible to count offspring using the directional information in the graph. A mentorship tree is defined as the graph of nodes along the mentor-to-trainee axis from an individual researcher. In this way, the total impact, \( I \), with \( n_1 \) trainees, can be measured recursively by traveling down the mentorship tree,

\[
I = n_1 + \gamma n_2 + \cdots + \gamma^m n_m + \cdots
\]

where \( n_2 \) is the total number of trainees of the \( n_1 \) trainees, and \( n_m \) is the number of trainees stepping down through \( m \) successive generations. In the case that the normalization factor, \( \gamma \), is 1, this simply reduces to counting the total number of offspring. For \( \gamma = 1/2 \), trainee counts from subsequent generations are weighted.

Table 1. Connection types (stored in the connection table, Figure 3A) defining mentor relationships between pairs of researchers in Neurotree.

| Connection type | Description |
|-----------------|-------------|
| 0               | Research assistant. Undergraduate, pre-bachelor’s degree. |
| 1               | Graduate student. Work lead to master’s or doctoral dissertation. |
| 2               | Postdoctoral fellow. Short-term employment after earning doctorate. |
| 3               | Research scientist. Long-term employment after doctorate. |
| 4               | Collaborator. Non-directional, work together influenced each other’s thinking. |

*Table 1.* Connection types (stored in the connection table, Figure 3A) defining mentor relationships between pairs of researchers in Neurotree.

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by one-half, allowing for a more balanced comparison between researchers at different points in the past. Mentorship trees are often interconnected (i.e., in biological terms, incestuous), and individuals may appear multiple times in a single tree. To avoid bias from such repeats, individuals are counted only once, at the point of closest proximity to a.

An alternative metric has been proposed for studying fecundity based on the researchers trained directly by a mentor rather than iteratively across generations [4], equivalent to $\gamma = 0$ here. Both metrics are helpful for understanding the impact of a researcher on a field. The iterative statistic used here is specifically helpful as a measure of long-term impact on the field, as it accounts for whether the mentorship was effective enough to produce trainees with a high impact of their own.

**Clustering.** Given that neuroscience, like any academic discipline, contains a number of sub-fields, one might expect clustering, in which researchers tend to train others who continue work within their subfield rather than in a new, completely unrelated field. We studied this problem by clustering the Neurotree database according to mentorship relationships. A sparse connection matrix was defined, $(c_{ab})$, with a value of 1 when a relationship existed between researchers $a$ and $b$, and a value of 0 otherwise. The matrix was divided into 60 partitions using spectral factorization, an effective algorithm for clustering large, sparse data sets [6]. This procedure computed the 60 largest eigenvectors of the matrix and then applied $k$-means clustering (cosine distance) to the projection of $C$ into the eigenvector space. The $k$-means algorithm produces clusters with minimum distance between each researcher and the centroid of their cluster in the eigenvector subspace.

Clusters were assigned numbers based roughly on chronology, ordered by the average generation of each group. In order to characterize their basic features, each cluster was labeled with two representative researchers (the two individuals with shortest distance to other members of the cluster) and two representative research areas (the most common research areas across all members of the cluster). The clusters were plotted using open source software (Graphviz, [7]). An interactive version of the cluster map is available on the Neurotree web site.

The single parameter required by the spectral factorization algorithm, cluster count, was not identified by objective criteria. The value of 60 produces a number of clusters that could be plotted on a single graph and which demonstrated the variable topology of clusters identified by spectral factorization (large versus small, tightly versus loosely connected, etc., see Results). Changing the number of clusters over a range of 40–80 did not have a major impact on the patterns observed in these properties.

It is likely that other, more advanced clustering algorithms may provide cleaner and more interpretable results. We chose the spectral factorization method for this study as a compromise between a more standard $k$-means analysis and several more complex possibilities. The $k$-means algorithm was unable to converge to a stable solution, given the sparse structure of the connection matrix. More complex algorithms may prove effective at elucidating important clusters. However, differences between such algorithms effectively represent hypotheses about the structure of the mentorship network. The comparison of different clustering algorithms is an important problem in itself that should be addressed in future studies. The analysis in this study provides a demonstration that clustering can reveal structure in the Neurotree graph.

**Tracking tree features over time.** Neuroscience is an evolving field, and many features of the graph are likely also to evolve over time. Thus to understand the tree, it can be helpful to measure statistics as a function of the time at which researchers performed their work. The database has a capacity for logging the dates of mentor relationships, but this information is often incomplete. As an alternative to using absolute dates, we labeled each researcher with their generation, which counted the minimum number of steps from one individual back to their oldest ancestor. The majority of researchers in the tree could trace their mentorship directly back to a single individual (Florentius Radewyns). Thus we could align researchers in this group along a single temporal axis. The analysis of historical dynamics focused on this subset of the Neurotree database.

**Citations and data export**

Data contained in Neurotree are available for export under the Creative Commons License 3.0. The data may be used freely by other researchers, and publications using the data should cite this publication as a source. Instructions for requesting the data are included in the site FAQ at http://neurotree.org/neurotree/faq.php [5].

**Ethics statement**

Data in Neurotree are collected from publicly available web sites and databases. Thus this study represents an analysis of information in the public domain. In order to respect potential privacy concerns, we have given individuals the opportunity to have their information removed from the Neurotree simply by submitting an error report or contacting the site administrators.

**Results**

**Neurotree’s seeding and growth**

Neurotree [5] was born out of the authors’ attempt to map out the mentoring relationships in the subfield of visual systems neuroscience. Although its original form was a large piece of paper, the problem turned out to be too complex for paper and was translated in 2005 into a relational database (Figure 3A) that could be displayed dynamically in a family tree format through a set of PHP scripts (Figure 1). Because the information was thought to be of interest to a broader community, the initial database of several hundred researchers was made publicly accessible online, with an interface for adding data.

As the site was indexed by search engines and subsequently discovered by researchers with related interests, the scope of the database grew unexpectedly beyond its original focus. An example illustrates how the tree filled in around one researcher in the database, Robert Yerkes, a comparative psychologist (Figure 1). As is typical for neuroscience, the number of trainees is larger than the number of mentors, reflecting the expansion of the field in recent decades. More detailed information can also be displayed in a biographical format that includes links to additional information on the Internet and dates of mentor relationships, when this information is available (Figure 2).

The site has also taken on a number of new functions in addition to its original design as an education resource. Neurotree can serve as a tool for disambiguating between researchers with the same name, a problem that occurs frequently in such a large field. It is also used as a professional networking tool, enabling journal editors, employers and potential collaborators to learn more about individuals they encounter in the community.

As the site has grown, we have taken a broad view of the term “neuroscience”, and have chosen to err on the side of inclusiveness. Neuroscience has been and continues to be a highly interdisciplinary field, and maintaining information about the relationship between neuroscience and related fields is valuable in
and of itself. Thus we have deliberately encouraged people to submit information about connections between neuroscientists and well-known individuals in other fields. This information provides insight into connections across a broader academic community and with the historical roots of the field.

The site continues to grow and, as of January 2012, draws an average of 25,000 unique visitors each month. The original database was seeded with about 500 researchers and has since grown to 35,000, with about 300 added each month (Figure 4).

Basic graphical properties

One of the benefits of any genealogical database is the ability to map the connections linking members of the tree. Neurotree can be described mathematically as a graph, with nodes (researchers) connected by edges (mentor relationships, Figure 3B). Currently, 30055/35953 (84%) of researchers in the tree are linked in a single large graph, and 22970 of those researchers (64%) can trace their academic roots directly back to a single ancestor (Florentius Radewyn of Deventer, Holland). As discussed in the Methods, it is sometimes difficult to make an exact designation of neuroscientist versus philosopher. Regardless of his field of study, a clear line of mentorship can be drawn to this individual (and back many more generations in other fields). The difference between the total number of linked researchers versus the number of direct descendents reflects individuals who are linked to the main graph as mentors (arrows going down, Figure 3B), but who themselves do not currently have a record of their mentorship linking back to the main graph (arrows arriving from above).

The graphical structure of Neurotree permits a number of analyses, some of which we demonstrate below. Because the database depends on contributions of volunteer users, however, the results of any analysis must be interpreted with the caveat that information in the database is not complete. As the tree matures and fills in, we expect the data to become increasingly more reliable.

Accuracy and completeness of the Neurotree database

In order to assess the reliability of the current database, we performed simple spot checks on its content. First we examined the accuracy of 100 randomly selected researchers in Neurotree compared to information available elsewhere on the Internet. Of these, 72 were verified to have correct institutional affiliation, 13

| Department                  | Count | Listed in Neurotree | Correct institution |
|-----------------------------|-------|---------------------|---------------------|
| Hebrew University, ICNC    | 27    | 22                  | 20                  |
| Reed College, Psychology   | 9     | 6                   | 6                   |
| University of Michigan, Neuroscience | 114   | 67                  | 58                  |
| Totals                      | 150   | 95/150              | 84/95               |
| Percent                     |       | 63%                 | 88%                 |

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had positively identified errors, and no information was available about the accuracy of the final 15. Given that information is subject to change sporadically during a career, one less stringent concern is that information be accurate for researchers who are retired or no longer active in research. Of the 85 individuals identified outside of the database, 13 were no longer active, and 12 of these were accurately documented in Neurotree.

To assess how completely Neurotree represents the field, we also compared faculty rosters between Neurotree and three departmental web sites in institutions that varied in size and geography (Table 2). In all three cases, about two-thirds (63%) of departmental faculty were listed in Neurotree. Of those listed, 88% had correct institutional affiliation. Because departmental web sites are generally kept up to date, this analysis is likely to provide a reasonably accurate measure of representation of researchers in Neuroscience-oriented departments.

Finally, we assessed how accurately and completely mentorship records were documented for five research groups by comparing trainee lists from public web pages and information in Neurotree (Table 3). For these groups, 75% of trainees listed on the web sites appeared in Neurotree. Of trainees listed in Neurotree, 30% did not appear on the lab websites. In all the cases studied, these mentor relationships could be verified by identifying at least one publication in Medline for which the mentor and trainee were co-authors. These results should be interpreted with caution. Because labs that maintain training records online might be more likely to also maintain Neurotree records, there may be a bias toward more complete representation of mentor relationships for these research groups. However, it is interesting to note that in many cases, Neurotree contained more up-to-date information than the most accurate alternative resource.

Quantitative analysis of growth and connectivity

For a more quantitative analysis of the maturity of Neurotree’s connectivity, we measured on the temporal dynamics of three statistics: the fraction of researchers linked in the main graph (Figure 5A), the average distance between researchers (Figure 5B), and the average number of connections per researcher (Figure 5C). Because data about researchers added to the tree earlier are likely to be more complete than later entries, we compared these statistics for the first 1000 nodes entered into the tree and for the entire tree.

The trajectory of statistics for the first 1000 nodes follows a distinct pattern from that of the entire tree. The 1000th researcher was added when Neurotree had been online for 10 months. After that time, the fraction of these nodes connected to the main tree graph through mentor relationships, as a function of months since Neurotree was established. The blue line shows data for the subset of the first 1000 researchers added to the tree (starting in month 10, when the one-thousandth research was added) while the green line shows data for the entire tree. Error bars indicate one standard error on the mean, calculated by jackknifing. B, Mean distance between nodes over time, either within the subset of the first 1000 researchers or across the entire tree, plotted as in A. C, Average number of connections per node, plotted as in A.

### Table 3. Spot check of trainee listing accuracy for individual mentors.

| Mentor              | Institution                          | In lab web site | In Neurotree | In Neurotree, not lab site |
|---------------------|--------------------------------------|----------------|--------------|----------------------------|
| C. Daniel Salzman   | Columbia University                  | 14             | 8            | 0                          |
| Patricia Kuhl       | University of Washington             | 15             | 5            | 1                          |
| Barbara Chapman     | University of California, Davis      | 7              | 8            | 2                          |
| Robert Malenka      | Stanford University                  | 15             | 25           | 14                         |
| Lynn Robertson      | University of California, Berkeley   | 16             | 11           | 0                          |
| Totals              |                                      | 67             | 40/67        | 17/57                      |
| Percent             |                                      | 75%            | 30%          |                            |

Lists of trainees (postdoctoral fellows only for Malenka, graduate students and postdoctoral fellows for all others) were compared between the websites of principal investigators who publish this information and mentorship data in Neurotree. In a few cases, Neurotree documented relationships that did not appear in the lab web sites (right column). All of these relationships were confirmed as accurate by a Medline publication record.

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Figure 5. Basic connection properties of Neurotree. A, Fraction of researchers (nodes) connected to the main tree graph through mentor relationships, as a function of months since Neurotree was established. The blue line shows data for the subset of the first 1000 researchers added to the tree (starting in month 10, when the one-thousandth research was added) while the green line shows data for the entire tree. Error bars indicate one standard error on the mean, calculated by jackknifing. B, Mean distance between nodes over time, either within the subset of the first 1000 researchers or across the entire tree, plotted as in A. C, Average number of connections per node, plotted as in A.

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also reached an asymptote at 5.5 steps. The average number of connections per researcher to other researchers, finally, stabilized at 2.5. A slight ongoing rise in number of connections appears to reflect new connections that continue to form between members of the group. The fact that the number of connections within the first 1000 entries has stabilized does not mean that connections of these nodes with the rest of the tree have done the same. The average number of connections from this group to the entire tree has grown to 10, and continues to grow at a rate of 0.8 connection per year (data not shown). This ongoing growth likely reflects both the entry of new researchers into the field as well as the filling in of earlier connections.

In contrast to the first 1000 entries, we observed that the statistics of the full tree have remained more or less flat since the first year online. The fraction of nodes connected to the main graph has remained stable at about 80%. The mean distance between nodes has very slowly risen from 10 to 11 steps. Finally, the average number of connections per node has remained nearly constant at 2.2. This suggests a balance between the rate at which new entries are added and connections between older entries are filled in more completely.

### Identifying the founders of neuroscience

As illustrated by the example tree (Figure 1), individual researchers, through their trainees and the subsequent trainees of those trainees, can influence a large number of subsequent researchers. Measuring the fecundity of researchers according to their number of trainees provides a means of comparing their relative influence and determining which individuals have had the greatest influence on the field. Of course, fecundity is not a direct measure of influence, but rather a useful and readily quantifiable proxy.

We measured a fecundity index by counting iteratively the number of trainees and trainees of those trainees, normalized exponentially by the number of steps from the original mentor (see Methods, $\gamma = 1/2$). Normalization was critical to prevent attributing the most influence to the very earliest researchers, who would always have the most offspring in a non-normalized count (i.e., $\gamma = 1$). At the other extreme, a strong normalization factor (e.g., $\gamma \leq 1/10$) would place the most weight on the mentor’s immediate trainees and would simply equate fecundity with large research groups.

The 25 researchers with the highest fecundity index appear in Table 4. On this list are a number of individuals typically.

#### Table 4. The founders of neuroscience, as ranked by fecundity measured from the Neurotree database (normalization factor, $\gamma = 1/2$, see Methods).

| Rank (1/2) | Name                  | Institution                  | Year | Gen | Rank (Alt $\gamma$) 1 1/4 1/10 |
|------------|-----------------------|------------------------------|------|-----|----------------------|
| 1.         | John Eccles           | Australian National University | 1937 | 20  | 153                  1 11      |
| 2.         | Charles Sherrington   | University of Oxford         | 1901 | 19  | 117                  8 168     |
| 3.         | Stephen Kuffler       | Harvard University           | 1962 | 21  | 167                  2 26      |
| 4.         | Karl Lashley          | Harvard University           | 1924 | 20  | 159                  5 80      |
| 5.         | John Langley          | University of Cambridge      | 1900 | 19  | 113                  111 849   |
| 6.         | Michael Foster        | University of Cambridge      | 1870 | 18  | 109                  162 1342  |
| 7.         | Edgar Adrian          | University of Cambridge      | 1923 | 20  | 155                  43 273    |
| 8.         | Donald Hebb           | McGill University            | 1952 | 21  | 199                  9 58      |
| 9.         | Robert Yerkes         | Yale University              | 1918 | 19  | 154                  105 645   |
| 10.        | Johannes Müller       | Humboldt Universität zu Berlin | 1842 | 16  | 75                   81 178    |
| 11.        | Wilhelm Wundt         | University of Leipzig        | 1886 | 17  | 111                  106 206   |
| 12.        | Bernard Katz          | University College London    | 1952 | 21  | 204                  19 82      |
| 13.        | Torsten Wiesel        | Rockefeller University       | 1974 | 22  | 267                  4 14       |
| 14.        | Keith Lucas           | University of Cambridge      | 1904 | 19  | 136                  236 1826  |
| 15.        | Hans- Lukas Teuber    | Mass. Inst. of Technology    | 1965 | 21  | 231                  13 85      |
| 16.        | John Black Johnston   | University of Minnesota      | 1907 | 22  | 157                  231 2077  |
| 17.        | John Watson           | Johns Hopkins University     | 1916 | 19  | 158                  234 2095  |
| 18.        | Clinton Woolsey       | University of Wisconsin      | 1964 | 21  | 230                  25 141     |
| 19.        | Philip Bard           | Johns Hopkins University     | 1928 | 20  | 197                  77 701     |
| 20.        | Hugo Munsterberg      | Harvard University           | 1902 | 18  | 137                  193 738   |
| 21.        | John Fulton           | Yale University              | 1932 | 20  | 168                  62 255     |
| 22.        | Wilder Penfield       | McGill University            | 1952 | 20  | 181                  91 535     |
| 23.        | Hallowell Davis       | Harvard University           | 1935 | 21  | 170                  118 598   |
| 24.        | Archibald Hill        | University College London    | 1915 | 20  | 171                  82 264     |
| 25.        | Julius Axelrod        | National Inst. of Mental Health | 1962 | 22  | 255                  12 44      |

Year refers to first year a degree was awarded to a trainee of this mentor. Generation (Gen) refers to the number mentorship steps back to the oldest common ancestor. Rankings for these individuals based on measures with alternative (Alt) normalization factors appear in the columns at right. At the extremes, $\gamma = 1$ weighs all offspring equally, regardless of generation, and $\gamma = 1/10$ counts primarily the number of direct trainees and gives very little weight to later generations.

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associated with critical advances in the field. The majority of these individuals were active mentors (based on their first mentoring year, i.e., the first year a student of theirs was awarded a degree) between 1900 and 1950, though the remainder range broadly across years. The differences are not so extreme for a less strict adjustment, γ = 1/4. It is interesting to note, however, that even for this adjustment, historical figures who did not themselves have large groups but did train a small number of influential researchers (e.g., Michael Foster, Wilhelm Wundt) fall substantially in rank.

Growth and development of the field of neuroscience

One challenge to precise interpretation of the temporal features of these data is that does not account for a substantial number of connections in Neurotree. In order to include a larger pool of researchers in the analysis of temporal dynamics, we computed the mentorship generation for each researcher by counting the number of steps back directly to their oldest ancestor. As discussed above, 64% of researchers in Neurotree can trace their mentorship back to a single individual. When we compared generation versus first mentoring year for the subset of researchers with appropriate data, we found a very strong correspondence (Figure 6A).

Using mentorship generation as a proxy measurement for time, we could then study the timecourse of fecundity across the field (Figure 6B). This analysis shows that average fecundity was greatest around generation 16, although the researchers with greatest fecundity tended to fall later, in generations 19–21. At these influential researchers largely predate the vast expansion of the field, which was just beginning in generation 21 (green line, Figure 6B).

To confirm that mentorship generation captures the essential features of a more strictly defined temporal analysis, we repeated the analysis of fecundity over time, but now focused only on the subset of 4654 researchers for which mentorship dates were available (Figure 6C). This analysis, while noisier, revealed similar trends. The period of greatest fecundity ranged from 1840–1950, with the most influential individuals appearing at the later end. The huge growth of the field can also be observed in the spike in the number of newly documented mentors that currently peaks for the period 2005–2010.

Mentorship-based cluster analysis

In order to study the relationship between mentorship groups and research areas within neuroscience, the entire set of connected nodes (30055/35953 researchers) was clustered into 60 groups based on the strength of mentorship connections (see [6] and Methods). Results are plotted (Figure 7), sorted on the y-axis roughly by time (i.e., by the mean generation of researchers contained in each cluster). An interactive version of this analysis is available online at http://neurotree.org/neurotree/clusters.php [5].

Each cluster was labeled with the names of the two researchers with the lowest mean distance to other researchers in that cluster and by the two research areas most frequently occurring across the clusters. Despite being derived through independent metrics, research areas representing a cluster typically show an obvious relationship to the representative researchers. For example, in cluster 10, Donald Hebb and Richard Thompson are both associated with the study of memory. Likewise, for cluster 13, Terrence Sejnowski and Torsten Wiesel are associated with visual and systems neuroscience. The information in Neurotree about research areas is not complete, as it depends on unconstrained choices by users entering the data. This incomplete information could lead to some of the apparent discrepancies (e.g., cluster 26, Rakic and Greenberg are not immediately associated with pain research).

Some neighboring clusters identify logical divisions between research areas. For example, cluster 15 (Schiller/Merzenich) captures a number of researchers who study sensory processing in non-human primates while cluster 23 (Gabrielli/D’Esposito) includes researchers who study similar problems of representation in humans.

When the clusters were studied more quantitatively, a few additional features were noteworthy. First, the size of clusters varied substantially (Figure 8A). This distribution suggests that...
some subfields of neuroscience may partition off more easily than others. Very large clusters are problematic, as they encompass a large variety of work and may require more elaborate procedures in order to be segmented effectively.

A more informative analysis may be to study how tightly coupled clusters are, relative to their average distance from other clusters (Figure 8B). Small within-cluster distance and large between-cluster distance represent highly interconnected and easily partitioned groups. The most striking examples of these appear to be more clinically-oriented groups. For example, cluster 14 (mean distance within 3.1, between 9.2) focuses on neuropathology and cluster 32 (within 3.7, between 9.8) focuses on neuropsychology. Groups with large within-cluster distances can result from number of factors. Clusters 1 and 2 are likely to have large within-cluster distance simply because they contain researchers spread out over long historical periods.

**Discussion**

Data documenting the tradition of academic mentorship naturally provoke curiosity to most people who have participated in the system. Each of us has received training from someone, who in turn was trained by someone else, and the whole process continues, iteratively, into the unknown past. An understanding of one’s academic mentorship allows one to connect oneself to the historical development of a field. A genealogical tree also provides the opportunity to see otherwise invisible links between ourselves and our colleagues, our friends, and important figures in the field. For these reasons, academic genealogies have been created for many fields. Neurotree is an attempt to do so for the large and diverse field of neuroscience.

Good mentoring is a skill that can differentiate successful from unsuccessful lab leaders. As of yet, very little is known about how important mentorship skills are in producing successful progeny [4]. Although most experts rely on judgments informed by anecdotal evidence, it is difficult to separate out the effects of
Neurotree graph. distance indicate groups that were well partitioned from the main nodes within each cluster (blue) and with nodes in other clusters to partition with the current algorithm.

Figure 8. Quantitative analysis of mentorship clusters. A, Curve shows the number of researchers in clusters 1–60, plotted on a logarithmic axis. The very large clusters (>3000 researchers) suggest that some groups, which often appear centrally in Figure 6, are difficult to partition with the current algorithm. B, Average distance between nodes within each cluster (blue) and with nodes in other clusters (green). Small within-cluster distance and large between-cluster distance indicate groups that were well partitioned from the main Neurotree graph.

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We argue that Neurotree has a specific role in the field of neuroscience. It provides a single repository for valuable information that is both highly specific and well-defined (such as mentor-trainee relationships) and that is more open-ended (such as field of interest). Additionally, Neurotree presents an opportunity to sort ideas and trends that make good mentors, which can in turn be used to direct training of mentors, guide hiring decisions, and help students choose mentors.

More generally, Neurotree provides an important tool for the study of the birth, life, and death, of ideas. Central to the function of academic mentorship is the transmission of ideas from mentor to trainee. Thus having a clear and full database of individuals and their relationships can serve as a tool for studying the life cycle of ideas.

We argue that Neurotree has a specific role in the field of neuroscience. It provides a single repository for valuable information that is both highly specific and well-defined (such as mentor-trainee relationships) and that is more open-ended (such as field of interest). Additionally, Neurotree presents an opportunity to sort out potential confusion regarding multiple researchers with the same name. While there is no current widely accepted unique identifier for individual scientists, the Neurotree database can help discriminate among individuals.

Maturing of Neurotree

As an experiment in crowd-sourcing the acquisition of data, Neurotree has been successful thus far. The Society for Neuroscience, whose academic focus encompasses a similar scope to that of Neurotree, lists 41,000 current members. This number does not include historical figures or neuroscientists who have not joined the Society, but the order of magnitude of this number matches that of the number of researchers listed in Neurotree. Given its record of growth, we expect Neurotree to develop a progressively more complete description of the field, thereby allowing reliable and unbiased sampling of mentorship relationships, and increasingly more accurate measures of progeny counts and connection distances. We have identified limitations to the scope of the dataset, both in its accuracy and completeness, and it remains an open question as to how completely these gaps can be filled with the current crowd-sourcing approach.

In addition to the general problem of sampling, crowd-sourcing efforts face the additional challenge of possible bias in how data is sampled [8]. Bias in gender, institution, geography, etc. can distort results in ways that are more difficult to correct than random sampling errors. Our initial analysis of accuracy revealed generally consistent levels of accuracy across institutions and labs, and Neurotree may benefit from the fact that a complete mentor-trainee record is well-defined. However, a more extensive analysis is required to determine if any systematic sampling bias exists.

Even with an incomplete data set, we have demonstrated approaches for approximating missing data from the database (e.g., using generation as a substitute for first year of mentoring). This has permitted us to include a much larger data set into the analysis of historically influential figures in the field.

Potential for expanded scope and depth

Neurotree can serve a number of functions, all of which would be improved if data in the tree were more complete and accurate. Substantial data sources exist in the public sphere online that could be used to automatically or semi-automatically fill in gaps in institutional affiliation, mentorship dates, and research areas in the current database. These resources include structured databases (e.g., [9]) and less structured on-line content such as departmental web sites and the CVs of individual researchers.

Numerous additional data resources exist that can be incorporated into Neurotree. Information about the contents of publications (methods, preparations, scientific questions) can be linked to individual researchers, providing a means of systematically studying the relationship between mentorship and the experimental approaches adopted by trainees. As expanded scientific content is linked to researchers, Neurotree will provide an increasingly powerful tool for studying the evolution of the field.

A complete, interdisciplinary academic genealogy

The software that forms the basis for Neurotree can be readily adjusted to make a database for any academic field. Based on unsolicited requests, we have created academic trees for other disciplines that, as far as we know, lack one of their own. These other trees include history, linguistics, and marine ecology, as well as a dozen others. Although they are given their own tree for display, they draw from the same database. This shared database permits cross-listing researchers between trees in different disciplines, so that, as the trees fill in, it will be possible to trace the larger-scale linkages between fields. Furthermore, it will be possible to study not only the graphical properties of mentor relationships within neuroscience but also how ideas and trends have traveled between fields.

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Author Contributions

Conceived and designed the experiments: SVD BYH. Performed the experiments: SVD BYH. Analyzed the data: SVD. Wrote the paper: SVD BYH.
References

1. Chang S (2003) Academic genealogy of American physicists. AAPPS Bulletin 13: 6–41.
2. Jackson A (2007) A labor of love: the mathematics genealogy project. Notices of the AMS 54: 1002–1003.
3. Kelley EA, Sussman RW (2007) An academic genealogy on the history of American field primatologists. American journal of physical anthropology 132: 406–425. doi:10.1002/ajpa.20532.
4. Malmgren RD, Ottino JM, Nunes Amaral L a (2010) The role of mentorship in protégé performance. Nature 465: 622–626. doi:10.1038/nature09040.
5. Neurotree website (2005). Available:http://neurotree.org/. Accessed 9 October 2012.
6. Hespanha P (2004) An Efficient MATLAB Algorithm for Graph Partitioning Technical Report Graph partitioning. October: 1–8.
7. Gansner ER, Gansner ER, Koutsofios E, North SC, Vo K (1993) A Technique for Drawing Directed Graphs. IEEE TRANSACTIONS ON SOFTWARE ENGINEERING 19: 214–230.
8. Lam S, Udawage A, Dong Z, Sen S, Musicant D, et al. (2011) WP:Clubhouse? An Exploration of Wikipedia’s Gender Imbalance. WikiSym 2011. Mountain View, CA: ACM.
9. Bandrowski A (2011) Biological resource catalog: NIF and NeuroLex. Nature Precedings. doi:10.1038/npre.2011.6238.1.