

# Supporting Information

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## SI Materials and Methods

**Data Set Acquisition and Filtering.** All data sets were downloaded from the GEO database, and consisted of experiments run on either mouse or human brain tissue (Fig. 1A). We filtered out all but a core collection of data sets that were similar enough for useful bioinformatic comparison. First, we removed all data sets that were not run on an Affymetrix platform, leaving three platforms in human (HG-U95A, HG-U133A, HG-U133 Plus 2) and two in mouse (MG-U74A, MG-U430A). Second, we excluded all samples in each data set that were not taken from brain tissue (for example, in one expression atlas study, more than 80% of the samples were excluded). Third, to make the correlations between genes more comparable across studies, we omitted all data sets with fewer than 20 samples and split data sets with more than 40 samples into subsets when a biologically meaningful splitting parameter was available (i.e., brain region, disease state, or mouse strain). Finally, data sets were preprocessed identically (as detailed later) and all data sets with average within-species expression correlation (correlation between expression ranks of genes in two studies) and connectivity correlation (correlation between connectivity ranks of genes in two studies) that were disproportionately low were excluded. For the connectivity correlation assay, test networks were made for each data set with a power of five using WGCNA (see refs. 1 and 2 for more details). After filtering, a total of 18 data sets in human and 20 in mouse remained for our analysis (Table S1).

**Preprocessing and Network Formation.** An initial expression matrix was either downloaded from GEO and scaled such that the average intensity was 200 (if no .cel files were available), or created from Affymetrix .cel files. These .cel files were downloaded, read into R, and preprocessed using the “expresso” function and the MAS5 method of preprocessing. We chose MAS5 based on a study by Lim et al. (3), which benchmarked four commonly used normalization procedures (MAS5, RMA, GCRMA and Li-Wong) in the context of established algorithms for the reverse engineering of protein-DNA and protein-protein interactions (PPIs). Using replicate sample, randomized, and human B-cell data sets as input, their study suggests that MAS5 provides the most faithful cellular network reconstruction. We then calculated the correlation of gene expression between samples, and outliers with mean sample correlations more than two to three SDs below average (exact value specific to each study) were omitted until no outliers remained (as described in ref. 2). After performing quantile normalization on the filtered data, probe sets that were not present were excluded from the analysis either by using the “pma” function in R and excluding probe sets that were called “absent” in more than 90% of the samples (in the data sets where .cel files were available), or by removing a comparable number of probe sets (approximately 40%) with the lowest 90% quantile of expression. To allow comparison across Affymetrix platforms, only a single probe set for each gene was kept—for genes with two corresponding probe sets we chose for each sample the probe set with highest expression, whereas for genes with three or more probe sets we chose the probe set with the highest connectivity across samples. To make the final expression file for each data set, all probe sets without associated genes were omitted and all remaining probe sets were reassigned the name of their corresponding gene symbol. In mouse network, mouse gene symbols were converted to human orthologues using data from Jackson Laboratory Mouse Genome Informatics (August 2006). The result of this step was 18 human expression

files with 20 to 40 samples and 5,629 to 9,731 genes each and 20 mouse expression files with 18 and 44 samples and 5,176 to 6,157 genes each. All preprocessed data files (as well as the resulting network data and some associated code and support files) are available at the WGCNA group Web site ([www.genetics.ucla.edu/labs/horvath/CoexpressionNetwork/MouseHumanBrain](http://www.genetics.ucla.edu/labs/horvath/CoexpressionNetwork/MouseHumanBrain)).

From these preprocessed expression files we created a human and a mouse consensus network (method modified from ref. 4). For each consensus network we first created correlation matrices from each data set (obtained by calculating the Pearson correlations between all variable probe sets across all subjects in each data set), and then weighted them based on the number of samples used in that data set. Each data set was weighted as follows:

$$W_k = 0.5 * \left[ \sqrt{N_k} / \left( \sum (\sqrt{N_a}) + 1/S \right) \right] \quad [S1]$$

where  $W_k$  is the weight of the  $k$ th expression matrix,  $N_k$  is the number of samples in the  $k$ th data set, and  $S$  is the number of data sets. Expression matrices where a given gene was not considered present were omitted from this calculation and genes that were present in fewer than 50% of data sets were excluded from the consensus network, leaving a total of 9,778 genes in the human network and 6,368 genes in the mouse network. Networks were formed from the weighted correlation matrices following the protocols of WGCNA, as previously described (1, 2). In short, the adjacency matrices were calculated by raising the absolute values of the weighted correlation matrices to a power of five. Finally, topological overlap (TO), a measure of node similarity (i.e., how close the neighbors of gene 1 are to the neighbors of gene 2) that has proven biologically meaningful, was then calculated as described previously (1, 5). We compared TO with known PPIs for both human and mouse in two different databases (6, 7) by placing all of the TO values into 100 bins representing the percentile of ranked values from largest to smallest, and determined what percentage of known PPIs were present in each bin (Fig. S2).

**Module Formation, Characterization, and Preservation.** For the initial module identification, all but 5,000 of the most connected genes in the human network (3,000 in mouse) were excluded to decrease noise. This filtering step left genes with high intramodular connectivity in any module as part of the network while omitting genes with weak membership in all modules. Omitted genes are included in the gene by eigengene table, which is used for many of the comparisons in this paper (as detailed later). Genes were hierarchically clustered using  $1 - TO$  as the distance measure and modules were determined by using a dynamic tree-cutting algorithm (8). Module identifiers in the mouse network were then changed to match the modules in the human network with the most significant gene overlap (Fig. 1B and C) (3). Each gene’s module membership (MM) for a given module was then estimated as the average Pearson correlation between that gene and the five genes in that module with the highest within-module connectivity ( $k_{in}$ ), which has been shown to be a good approximation of the module eigengene (ME) (2, 9).  $P$  values were obtained by (i) averaging the T-score from gene-eigengene Pearson correlation across data sets, (ii) scaling to the square root of the number of data sets per gene, and (iii) calculating a  $P$  value from the T-distribution of the resulting scaled T-score. For the final module characterizations, all genes with MM values of  $R > 0.2$  and with  $P < 10^{-13}$  were assigned to that module, leaving an average of approximately 5% of all of the genes in each

module, with some genes assigned to multiple modules. Although these values represent one of many possible sets of module-thresholding parameters, the results were relatively robust to changes in module size. We also used enrichment analysis by way of Expression Analysis Systematic Explorer (10) and IPA to characterize modules based on gene ontology (GO). Finally, modules were graphically depicted using VisANT (11) as previously described (12, 13).

For unbiased disease gene (DG) characterization we used an annotated list of approximately 5,000 orthologous mouse and human genes, for which mutations in the gene were known to produce disease phenotypes for any human or mouse disease (Jackson Laboratory) (14). This list of “all DGs” was curated from the literature in an unbiased manner and distinguishes genes causing human-specific disease phenotypes from those causing similar phenotypes in both mouse and human. We created a list of “dementia DGs” by taking the subset of DGs that was associated with dementia-related disorders. Dementia-related disorders were defined as the list of all disorders returned in a search of Online Mendelian Inheritance in Man (ncbi.nlm.nih.gov/omim) for the term “brain AND (“dementia” OR “neurodegenerative” OR “neurodegeneration”)”. Overall, we found that approximately 20% of all genes in our networks were DGs and approximately 3% of the genes in our network were dementia DGs.

Finally, we used a variety of strategies to measure module preservation. First, we used a permutation test procedure implemented in the WGCNA R package, which produces a summary preservation Z-score (Table 1) (15). Second, we assessed the significance of module overlap between genes in corresponding mouse and human modules (Table 1). Third, we estimated the similarity of module annotation both by showing that most corresponding human and mouse modules show significant overlap with the same module from ref. 2 (Table 1), as well as by showing that these module pairs share similar annotations as measured by GO and Ingenuity Pathway Analysis (IPA; [www.ingenuity.com](http://www.ingenuity.com)) (Table S2).

## SI Results and Discussion

This article provides a case study regarding metaanalysis on the level of coexpression networks. Among other things, the article shows (i) how to successfully reduce potential biases from individual studies, (ii) how to weigh the information from different data sets, and (iii) how to compare the resulting networks between species. Our results illustrate that our method for compiling multiple data sets into a single correlation matrix allows across-experiment and between-species comparisons.

### Linear Relationship Between TO and PPIs in Both Mouse and Human.

We and others have previously shown that our measure of gene coexpression, TO, predicts many biologically meaningful relationships. For example, across multiple species such as yeast (16) and human (2, 17), highly coexpressed genes are more likely to interact on the protein level than genes with low coexpression. Therefore, to provide another level of systematic network validation, we determined the relative likelihood that gene pairs of specific TO would also have PPIs (Fig. S2) (6, 7). For positively correlated genes, there was a strong, positive linear relationship between TO and PPIs in both networks. In contrast, we observed a similar negative linear relationship between negatively correlated gene pairs, which fits expectations (18). We also find strong relationships in the mouse network, despite the fact that these genes are actually mouse homologues of the genes in both PPI databases.

**Networks Are Robust to Choice of Data Sets.** We next determined the robustness of our networks to choice of data set. To do this, we randomly split the mouse and human data into two groups of nine

data sets (approximately 250 arrays), creating new networks for each of these grouping as described earlier in the *SI Text*. For each network we then calculated both the average expression rank across data sets, as well as the connectivity rank for each gene in the network, and correlated these two measures within species (Fig. S1). There was nearly perfect expression correlation between both the human ( $R = 0.94$ ;  $P < 10^{-1,900}$ ) and the mouse ( $R = 0.98$ ;  $P < 10^{-2,700}$ ) group pairs, suggesting that our choice of data sets has minimal impact on gene expression ranking or levels. There was lower, but still highly significant, connectivity correlation between the human ( $R = 0.76$ ;  $P < 10^{-700}$ ) and the mouse ( $R = 0.62$ ;  $P < 10^{-400}$ ) group pairs, suggesting a high preservation of the gene coexpression relationships in networks made from different data sets, consistent with previous studies (2, 18, 19). Finally, to ensure that module selection is robust to our choice of data set, we performed WGCNA following the procedure outlines in Fig. 1A on each of these human and mouse subnetworks, defining modules by using the same characterization as in Fig. 1B and C. This network formation schema resulted in networks highly overlapping with those created using all data sets. Taken together, these results show that there is no significant within-species bias in the data and suggest that the composition of brain-specific data sets used in this analysis does not significantly impact the results.

### Cortex/Control Networks and Overall Brain Networks Are Equally Comparable.

One key idea in our analysis is that we include only arrays from brain, to reduce noise generated from samples in which we are not interested. One possible problem with this approach is that there are relatively few data sets in mouse and human brain that both have data publicly available and also include enough samples to perform viable coexpression analyses. As such, our mouse and human data sets might not be completely matched; for example, most human samples are quite region-specific, with several data sets acquired via laser capture microdissection, whereas many mouse data sets are from larger regions or even whole brain. It is therefore possible that resulting network differences could be a result of differences in data set selection rather than differences between species. To address this issue, we created separate “C/C” networks in mouse and human that included only cortex samples from control subjects, removing bias caused by brain area, disease, or treatment state, thus making our networks more directly comparable. We included whole brain samples along with cortex samples in mouse because (i) the mouse brain largely consists of cortex and (ii) we would not have had enough samples to perform such a comparison using only mouse control samples from cortex. This filtering step left three mouse data sets (57 arrays) and five human data sets (137 arrays) in our analysis (Table S1), which we compared following the same procedures outlined in the text for the original networks (e.g., Table 1 and Fig. S1).

We find that the two analyses (C/C and all brain) produce highly similar networks, suggesting that our between-species analysis using all available brain tissue is not biased by networks specific to brain region, disease states, or to medications that may be taken by human subjects. At the global level, we find similar preservation between mouse and human expression in the all-brain analysis compared with the C/C analysis ( $R = 0.60$  vs.  $R = 0.64$ ), whereas node connectivity preservation is actually better in the all-brain analysis ( $R = 0.27$  vs.  $R = 0.15$ ), consistent with the notion that connectivity measures are more sensitive to the amount of data than to the precise matching of data sets. In the case of module comparison, although we find highly similar results at the level of module overlap (nearly all modules in both networks show gene overlap between analyses with significance levels of  $P < 10^{-40}$ ), in the case of module preservation, most modules show lower preservation Z-scores in the C/C networks compared with the overall networks. In fact, modules for oligo-

dendrocytes (M2h) and multiple cellular components (M5h, M8h, M14h) that were significantly preserved in the overall network no longer show significant preservation between the C/C networks. In short, we find that networks made using data sets from all reliable brain samples are more comparable than networks made using fewer, but better-matched data sets.

These C/C networks can also be used to further address the issue of how sensitive networks are to data set selection. To do so, we measured within-species module preservation in our original networks compared with the C/C networks. For all modules, we found similar average preservation Z-scores (as a typical example, module M1h in the original and C/C analyses have  $Z = 6.08$  and  $Z = 5.77$ , respectively), suggesting that both networks are robust to removal of a large percentage of the data.

**Minimal Effects of Agonal State on Between-Species Transcriptional Changes.** Many genes are known to change expression levels with death. It is therefore important to rule out agonal state as a prominent cause of between-species coexpression differences. First, gene expression levels show high preservation between human and mouse, which points to minimal effects of agonal state in general between species. Furthermore, others have shown that, despite the relatively large number of affected genes, agonal state has a minimal (if any) effect on differential expression analyses (20)—in other words, changes in expression with death are disease and region blind. Finally, we used the hypergeometric distribution to measure overlap between each module in both networks and a core set of human genes previously shown to be related to agonal state (either showing increased or decreased expression in autopsy vs. biopsy tissue) (20). Consistent with results from this group, we found that modules associated with mitochondria and ribosome were enriched with genes showing decreased expression after death (for M4h,  $P < 10^{-43}$ ; for M5h,  $P < 10^{-9}$ ; for M8h,  $P < 10^{-20}$ ), whereas M14h (nucleus) contained excess genes showing increased expression with death ( $P < 10^{-9}$ ). As these are among the most preserved modules between the species, and the corresponding mouse modules showed comparable enrichments (for M4m,  $P < 10^{-48}$ ; for M5m,  $P < 10^{-38}$ ; for M8m,  $P < 10^{-16}$ ; for M14m,  $P < 10^{-12}$ ), agonal state does not appear to play different roles between mouse and human. Although there is weak enrichment for genes increasing with agonal state in M9h ( $P < 10^{-3}$ ), this enrichment is much less significant than in the highly preserved cellular component modules and is almost entirely caused by genes not present in the mouse network. Thus, although we cannot rule out the fact that agonal state may partially underlie some species differences in this poorly preserved module, it is highly unlikely that this effect is substantial.

**Preservation of Modules Associated with General Cellular Components.** Although the thrust of our research is brain-specific, confirmation of basic cellular biology is a key validation of our method. Orthologous ribosomal, mitochondrial, and other ubiquitous cellular components are found in nearly all known species, with high conservation between species as distant as yeast, fly, and human (19, 21). Furthermore, previous studies of general transcriptional similarities between mouse and human have found multiple common modules of coexpressed genes—including the ribosomal subunits (22, 23). Our metaanalyses uncovered similarities between many global network properties, including general measures of gene expression, connectivity, and module preservation, with genes involved in basic cellular components showing the highest level of preservation. In our human network, within-species preservation can be most clearly seen in module M12h, which contains 64 of the 71 ribosomal subunits present in the human network (Table S2), whereas between-species preservation is most obvious in M4h, which shows the most highly significant module preservation Z-score ( $Z = 17.21$ ).

Replication of these relatively well established coexpression links is an important step toward confirming the validity of our methods, and demonstrating the reliability of our results.

To further flesh out the mitochondrial result, we compared M4 and M5 with validated lists of genes transcribed in somatic versus synaptic mitochondria (24). M4 showed enrichment over M5 for somatic mitochondria in both mouse ( $P < 10^{-6}$  vs.  $P < 10^{-3}$ ) and human ( $P < 10^{-12}$  vs.  $P < 10^{-7}$ ). Conversely, although there was equal enrichment for synaptic mitochondria in both modules, we found higher significance for glutamatergic synapse genes (M10 from the CTX network in ref. 2) in M5 relative to M4 for both species ( $P < 10^{-26}$  vs.  $P = 10^{-3}$  in mouse;  $P < 10^{-240}$  vs.  $P < 10^{-83}$  in human). As a specific example, we find that cyclin-dependent kinase 5 (CDK5) is the top interspecies marker for M5 (Table S4). Although cytoplasmic, CDK5 inhibition has been shown to rescue mitochondrial damage occurring from neurotoxic insults (25); therefore, the role of CDK5 as a mitochondrial hub, particularly one also highly coexpressed with glutamatergic synapse genes, is not unreasonable. Furthermore, unlike most other AD-related genes, CDK5 overexpression can result in similar disease phenotypes in mouse and human, causing neurodegeneration in mice (26) and playing a role in a number of neurodegenerative human diseases. These results suggest that, although the two mitochondrial modules are highly overlapping in both species, they represent separate, evolutionarily conserved biological components.

**Networks Correctly Sort Known Marker Genes by Cell Type.** In addition to being a useful resource, our list of interspecies marker genes (Table S3) provides an important validation for our methods. For example, although there may be some biological differences between cell types in mouse and human, we should find that a majority of known highly specific marker genes for cell type show strong coexpression with modules corresponding to relevant cell types. To address this issue, we measured the correlation of 40 highly cell type-specific markers for neurons, astrocytes, and oligodendrocytes in mouse (figure 3 in ref. 27) and 10 in human (figure 4 in ref. 2) against each ME in both network. We then calculated for which module each marker gene showed the highest correlation and where each gene ranked in that module by significance of MM (Table S5). In the case of oligodendrocytes, our network precisely matched expectations: nearly all known oligodendrocyte markers were reproduced in both our mouse and human networks, with known mouse markers tending to be hubs in our mouse network and known human markers tending to be hubs in our human network. Similarly, we found that the majority of known neuronal markers showed the highest correlation with neuron-associated modules, although not necessarily the module chosen for Table S3 (M13), consistent with the diverse neuronal populations throughout the brain. Although the results for astrocyte markers were less clear, the hubs between the network of Oldham et al. (2) and our human network were highly reproducible. Overall, these results suggest that our method can sort genes by cell type in both species to a relatively high degree of accuracy, and that lists of marker genes from our networks may provide valuable biological insight.

**Mouse Models in the Study of Human Disease.** Animal models are essential tools in the study of human disease, and have led to breakthroughs in nearly every area of medical science. As a result of their relative ease of genetic manipulation and short life spans, mice present especially useful animal models (28–30). Given the widely varying success of mouse models at mimicking human disease phenotypes, having a method to more accurately predict the effectiveness of model systems would be extremely useful. One possible strategy for predicting the effectiveness of specific mouse models in disease is to compare and contrast the human and mouse transcriptome. For example, coexpression preservation has been successfully used as a restrictive filter for predicting



which are the relevant human genes in disease loci (31). Furthermore, transcriptional analyses in human have found that genes causing the same disease tend to have shared expression patterns, a finding that is enhanced when data from other species are also included (32). Finally, phenotypic information from mouse homologues has been shown to improve DG prioritization beyond that which can be obtained using human expression data and associated categorization databases (e.g., GO and Kyoto Encyclopedia of Genes and Genomes) (33). By restricting our analysis to brain data and including the aforementioned modifications to standard transcriptional analysis, we believe that our results will be particularly useful in DG prioritization for neurological and neurodegenerative disorders, such as AD.

**DGs Show Differential Expression and Connectivity Patterns in Mouse and Human Brain.** Comparison of transcriptional programs across species has previously demonstrated that core metabolic functions and cellular structures are highly conserved between human and species as distant as *Escherichia coli* (19, 21). Similar gene expression preservation studies have been used to gain significant insight into disease in myriad cases, including in sleep and circadian rhythm biology (34, 35), in neurodegenerative disease (36), and as a filter for predicting DGs under a linkage peak (31), and is often a basic assumption of such work. We hypothesize that the opposite is also true. That is, we expect genes showing poor expression and connectivity preservation between species to be enriched for DGs associated with human-specific disease phenotypes. To assess the viability of this hypothesis, we first identified the sets of genes showing significantly high expression or node connectivity in mouse or human, but not both (genes in the upper left and lower right of Fig. S1 A and B). Unbiased GO annotation found enrichment for such disease-related genes: the top GO hit for genes with high connectivity in mouse, but not human was “disease mutation” (uncorrected  $P < 0.005$ ) (10), whereas three of the main players in AD—apolipoprotein E, mitochondrial associated protein tau (MAPT), and PSEN1—have high connectivity in human, but not mouse.

Similar between-species differences in gene expression patterns can be seen at the level of modules. Apolipoprotein E shows high expression correlation with the astrocyte module (M3h) in the human network ( $R = 0.43$ ), but not the mouse network ( $R = -0.01$ ). As mentioned in the main text, glycogen synthase kinase-3 $\beta$  (GSK3B), a key protein involved in abnormal tau phosphorylation (37), is a hub gene for the poorly characterized, yet highly human-specific module M7h, which also contains MAPT (Fig. 3E). In contrast, CDK5—another AD-related kinase—shows different expression patterns (as described earlier). This is especially interesting given the recent evidence that GSK3B plays a dominant role in overall tau phosphorylation, whereas the main effects of CDK5 in AD progression are in the regulation of amyloidogenic APP processing (38) in addition to tau phosphorylation. Finally, there several other modules that are human specific, including one related to AD progression in humans (M9h; as detailed later). Given the human predilection for this disease, such genes and modules with divergent expression patterns become important candidates for studying the pathophysiology of AD in humans, and suggest that there may be a lot of information in control transcriptional networks regarding AD—as well as other neurodegenerative disorders—that has yet to be uncovered.

**Module M9h Is of Particular Interest in AD and Aging.** Interestingly, we found replication of the red module (12) in the human network in our current analysis. Not only does module M9h show very high within-species module preservation in human, in the sense that four of the hubs are replicated in both modules and further confirmed in the Celsius database (Fig. 3 A and B), but M9h also shows low between-species module preservation (Table 1), increasing the plausibility of its role in human-specific

brain disease. To follow up on this finding, we performed WGCNA (*Materials and Methods*) on two additional large data sets in human, which were recently deposited in GEO (39, 40). The first study compared the relationship between gene expression and genomics in AD, finding that relative transcript levels are a good endophenotype for disease (40). From these data, which were run on the Illumina Human Refseq-8 microarray platform, we used 118 control and 95 AD samples from temporal cortex in our analysis. The second study compared gene expression changes between male and female across a wide range of ages in four different brain regions (hippocampus, entorhinal cortex, superior frontal gyrus, and postcentral gyrus) (39). This study on aging was run using the Affymetrix HG-U133 Plus 2.0 array and had 32 to 43 control samples for each brain region, all of which we used in our analysis.

In the AD study (40), we performed WGCNA using only the 118 control samples, and found a total of 24 modules, most of which showed either a significant increase or decrease in expression between control and AD. The black module showed significant overlap with M9h ( $P < 10^{-4}$ ), including the common hub gene CXXC1 (Fig. S3A). Furthermore, when we compared the ME values between control and AD, we find that this module showed a significant increase in expression with AD progression ( $P < 10^{-11}$ ; Fig. 3C). Thus we find modules from two separate data sets (40, 41) that both show increased expression in AD as well as significant overlap with M9h. Also, taking into consideration the fact that these studies were run in different laboratories, on different microarray platforms, and using tissue from different areas of the brain, we are confident that our result is biologically meaningful. To assess whether this module is unique to AD or whether it may also play a role in normal aging, we performed a second WGCNA analysis using aging data (39). In this analysis, one of the 10 modules we found (the yellow module) showed significant overlap with M9h ( $P < 10^{-14}$ ; Fig. S3B) as well as positive correlation with age across all four brain regions ( $P < 10^{-5}$ ; Fig. 3D). Therefore, in addition to the role of M9h in AD progression, M9h may also be involved in normal aging and possibly other neurodegenerative disorders. Finally, to assist other groups who may wish to follow up the results from this analysis, we have compiled a ranked list of 50 genes that show high MM in M9h and all comparative modules (Table S7).

**Glossary of WGCNA and Comparative Network Terms.** Between-species preservation is any measure of preservation comparing data from human to data from mouse (e.g., Fig. S1 A and B)

A (coexpression) network is an undirected, weighted network with nodes corresponding to genes and edges based upon gene-gene coexpression levels. To evaluate coexpression levels between genes, Pearson correlations are taken and then weighted by raising their absolute value to a power. This weighting emphasizes strong correlations at the expense of weak ones.

A consensus network is a single network defined from multiple sources of data (in this case created from the weighted average of the correlation matrices from each human or mouse data set).

Expression preservation is the Pearson correlation between the ranked average expression value of genes across two sets of studies. Although this type of preservation is independent of network formation, it is useful in assessing the comparability of data sets across species (e.g., between the 18 human and 20 mouse data sets used in this analysis).

A hub is any highly connected gene. A hub can be characterized by high MM, high intramodular connectivity, or a strong presence in network depictions (e.g., circled genes in Fig. 3A).

Intramodular connectivity ( $k_{in}$ ) is a measurement of network position that reflects how connected a given gene is with respect to the genes of a particular module. The higher the  $k_{in}$ , the more central a gene is to the network.

A module is a group of genes with strong sharing of co-expression relationships as measured by high TO. Modules are identified via hierarchical clustering (Fig. 1 B and C) using a measure of dissimilarity (i.e.,  $1 - TO$ ). Genes in a module show much higher coexpression with each other (either positive or negative) than with genes outside the module.

Module characterization is a short descriptive term characterizing genes in a module based on GO or IPA annotation, module overlap with experimentally derived gene lists, and module overlap with modules previously characterized and published.

The ME is the first principal component of a module. The ME summarizes the characteristic expression pattern of a module.

MM is the Pearson correlation between the expression level of a given gene and a given ME. This quantity describes the extent to which a gene “belongs” to a module, and is used in the final module definitions.

Module (or list) overlap is the number of common genes between one module (or list) and a different module (or list). The significance of module overlap can be measured using the hypergeometric test.

Module preservation is any of a number of tests that measure how well characteristics of a module in one network are

reproduced in another network. As the particulars of module preservation are beyond the scope of this article, we present a single Z-score that summarizes a variety of preservation measures (15).

(Node) connectivity preservation is the Pearson correlation between the ranked connectivities of genes common to two networks (e.g., the mouse and human networks).

(Overall) connectivity is the sum of connection strengths (adjacency matrix values) with all other network genes. The connectivity measures how correlated a gene is with all other genes in a network.

TO is a quantity describing gene pair similarity by comparing the weighted correlation of these genes with all other genes in the network.

(Weighted) adjacency matrix is a symmetric matrix whose off-diagonal elements lie between 0 and 1. The adjacencies measure the connection strength between pairs of nodes. In correlation networks, the adjacency between two genes is a power of the Pearson correlation between their expression profiles.

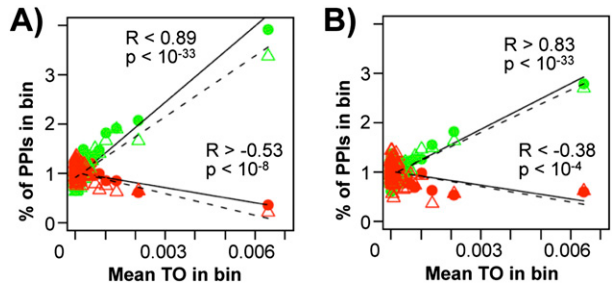
Within-species preservation is any measure of preservation comparing two sets of data in the same species (e.g., Fig. S1 C–F).

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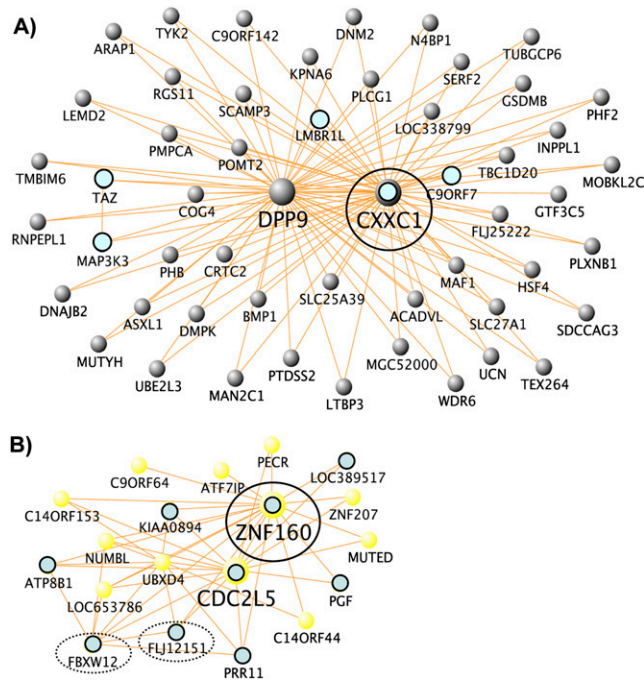






**Fig. S2.** TO reflects PPIs in both the human (A) and mouse (B) networks, with positively correlated (green) and negatively correlated (red) genes showing opposite effects. This result was replicated in both the HPRD (solid points and lines) (1) as well as the IntAct (hollow points and dashed lines) databases (2). The y axis represents the percent of all interactions from a given comparison contained in each of 100 bins of gene pairs sorted based on TO, whereas the x axis represents the average TO of each bin.

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2. Hermjakob H, et al. (2004) IntAct: An open source molecular interaction database. *Nucleic Acids Res* 32(database issue):D452–D455.



**Fig. S3.** M9h is preserved across studies. (A) Network depiction of a subset of the black module from ref. 1 shows that this module shares a common hub (CXXC1) with M9h. Labels as in Fig. 3A, except only approximately 100 connections are shown. (B) Network depiction of a subset of the yellow module from ref. 2 shows that this module contains multiple hub genes of M9h (i.e., ZNF160). Labels as in Fig. 3A, except only approximately 60 connections are shown.

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2. Berchtold NC, et al. (2008) Gene expression changes in the course of normal brain aging are sexually dimorphic. *Proc Natl Acad Sci USA* 105:15605–15610.



**Table S1. Data sets used in the human and mouse networks**

Species	GEO no.	Index	Arrays	Used*	Chip	Cel	Description	Subset/Comment	Refs.
Human	GSE1133	1	158	22	HG-U133A	Y	Samples from multiple brain/CNS regions of controls	Cortex, GP, caudate, medulla, thals, cingulate, pons	42
Human	GSE1297	2	28	26	HG-U133A	Y	AD at various stages of severity in CA1	Used all data	41
Human	GSE1572	3	30	24 (24)	HG-U95A	Y	FC of controls aged 26–106 y	Used all data	43
Human	GSE3526A	4	353	33	HG-U133 Plus 2	Y	Samples from multiple brain/CNS regions of controls	VTA, medulla, SN, corpus callosum, thals, midbrain, VN	—
Human	GSE3526B	5	353	25 (21)	HG-U133 Plus 2	Y	Samples from multiple brain/CNS regions of controls	Mostly cortex, (2 × HP, 2 × amygdala)	—
Human	GSE4036	6	28	24	HG-U133 Plus 2	Y	CB of schizophrenia patients and controls	Used all data	—
Human	GSE4757	7	20	20	HG-U133 Plus 2	Y	LCM of NFT-laden and NFT-free pyramidal cells in entorhinal cortex of mid-AD patients	Used all data	—
Human	GSE5281A	8	161	34	HG-U133 Plus 2	Y	LCM of pyramidal cells from HP, EC, MTG, PC, SFG, and PVC	Controls (only 2 × EC, 2 × MTG)	44,45
Human	GSE5281B	9	161	34	HG-U133 Plus 2	Y	LCM of pyramidal cells from HP, EC, MTG, PC, SFG, and PVC	AD subjects (only 3 × MTG, 0 × EC)	44,45
Human	GSE5392A	10	82	34 (34)	HG-U133A	Y	OFC and DLPFC prefrontal cortex from controls	Controls	46
Human	GSE5392B	11	82	31	HG-U133A	Y	OFC and DLPFC from adults with bipolar disorder	Bipolar subjects	46
Human	GSE9770	12	34	29	HG-U133 Plus 2	Y	LCM of pyramidal cells from 6 brain regions of patients with MCI	Used all data	—
Human	GSE2164B	13	87	40 (40)	HG-U95A	Y	Male and female DLPFC, ACC, and CB	DLPFC and ACC	47
Human	GSE3790A	14	202	27	HG-U133A	N	CB, FC [BA4, BA9] and CN from HD patients and controls	CN	48
Human	GSE3790B	15	202	38 (18)	HG-U133A	N	CB, FC [BA4, BA9] and CN from HD patients and controls	FC	48
Human	GSE3790C	16	202	38	HG-U133A	N	CB, FC [BA4, BA9] and CN from HD patients and controls	CB	48
Human	GSE7621	17	25	23	HG-U133 Plus 2	Y	Substantia nigra from PD patients	Used all data	49
Human	GSE8397	18	47	27	HG-U133A	Y	SFG and SN of PD patients and controls	SN only (mostly med/lat SN of PD patients)	50
Mouse	GSE1482	1	30	29	MG-U74A	Y	HP of control and NF1 <sup>+/-</sup> mice between 10 and 32 d postnatal	Used all data	—
Mouse	GSE1782A	2	64	18	MG-U74A	N	CA1 and DG of mice in control and fear conditioned situations	CA1	51
Mouse	GSE1782B	3	64	21	MG-U74A	N	CA1 and DG of mice in control and fear conditioned situations	DG	51
Mouse	GSE2392	4	22	22	MG-U74A	Y	Whole brain 0, 4, 8, 24, 72 h post traumatic brain injury	Used all data	52
Mouse	GSE3248	5	48	44	MG-U74A	Y	CB of control and HD mutant mice	Used all data	53
Mouse	GSE3327A	6	87	24	MG-U74A	Y	Samples from 7 brain regions of 6 inbred strains	Amygdala and cingulate cortex	54
Mouse	GSE3327B	7	87	34	MG-U74A	Y	Samples from 7 brain regions of 6 inbred strains	BN, HP, hypothalamus	54
Mouse	GSE3594C	8	150	21 (15)	MG-U74A	N	Samples from 24 neural and 10 nonneural tissues	Amygdala and cortex	55
Mouse	GSE3963A	9	48	22	MG-U74A	N	HP and amygdala of fear conditioned and control mice	HP	56
Mouse	GSE3963B	10	48	20	MG-U74A	N	HP and amygdala of fear conditioned and control mice	Amygdala	56
Mouse	GSE4269	11	36	26	MG-U74A	N	Time course: PVC of light deprived/nondeprived mice	Used all data	57
Mouse	GSE4734	12	61	34	MG-U430A	N	Mouse strain and brain region comparison	BN, hypothalamus, and PG	58
Mouse	GSE5429	13	32	29	MG-U74A	Y	HP from 8 inbred strains	Used all data	59
Mouse	GSE6285	14	24	22 (22)	MG-U430A	Y	Whole brain of mice fed 4 different diets	Used all data	60
Mouse	GSE6514A	15	90	37 (20)	MG-U430A	Y	Cerebral cortex/hypothalamus during spontaneous sleep and prolonged wakefulness	Cortex	61

**Table S1. Cont.**

Species	GEO no.	Index	Arrays	Used*	Chip	Cel	Description	Subset/Comment	Refs.
Mouse	GSE6514B	16	90	42	MG-U430A	Y	Cerebral cortex/hypothalamus during spontaneous sleep and prolonged wakefulness	Hypothalamus	61
Mouse	GSE9444A	17	113	21	MG-U430A	Y	Sleep deprivation and the brain (omit 850-867 -> liver)	AKR/J mice	62
Mouse	GSE9444B	18	113	23	MG-U430A	Y	Sleep deprivation and the brain (omit 850-867 -> liver)	C57BL/6J mice	62
Mouse	GSE9444C	19	113	23	MG-U430A	Y	Sleep deprivation and the brain	DBA/2J mice	62
Mouse	GSE10263	20	26	25	MG-U430A	Y	Mutant HD on striatal gene expression in mice	Used all data	63

Data sets used in the human and mouse networks. A list and extended summary of all of the data sets, as well as the number of samples listed on GEO vs. the number used in each data set in the meta-analysis, and whether or not cel files (raw data) was available. For subsetted data sets and data sets where a large portion of the samples were omitted, the "Subset/Comment" column summarizes which phenotypes are included in the final expression file. References for each data set, when listed on the GEO website, are presented in the *S1 Text*. ACC, anterior cingulate cortex; BN, bed nucleus of stria terminalis; CB, cerebellum; CN, caudate nucleus; CNS, central nervous system; DG, dentate gyrus; DLPC, dorsolateral prefrontal cortex; EC, entorhinal cortex; FC, frontal cortex; GP, globus pallidus; HP, hippocampus; LCM, laser capture microdissection; MCI, mild cognitive impairment; MTG, medial temporal gyrus; NFT, neurofibrillary tangles; OFC, orbitofrontal cortex; PC, posterior cingulate; PD, Parkinson disease; PG, periaqueductal gray; PVC, primary visual cortex; SFG, superior frontal gyrus; thals, thalamus, subthalamus, and hypothalamus; VN, vestibular nucleus; VTA, ventral tegmental area.

\*In the "Used" column, the number in parentheses represents the number of samples included in the "cortex/control only" analysis.

Table S2. Selected GO and IPA annotations for each module

Module	Network	Gene category	List hits	List total	Population hits	Population total	EASE score	Bonferroni correction
M1h	Human	<u>Mitochondrion</u>	60	363	445	5,952	4.12E-09	1.14E-05
M1h	Human	<u>NADH dehydrogenase (ubiquinone) activity</u>	12	363	29	6,071	3.81E-07	1.05E-03
M1h	Human	<u>CNS-specific functions</u>	24	90	168	1,671	8.81E-06	2.44E-02
M1h	Human	<u>Hs_glycolysis and gluconeogenesis</u>	11	79	27	849	5.66E-05	1.57E-01
M2h	Human	Short-chain dehydrogenases/reductases family signature	6	93	12	1818	1.78E-04	5.13E-01
M2h	Human	Myelin	5	112	7	1987	2.84E-04	8.17E-01
M2h	Human	<u>Cytoskeleton organization and biogenesis</u>	23	360	166	6,014	3.15E-04	9.07E-01
M3h	Human	Homeostasis	17	422	55	6,014	5.87E-07	2.05E-03
M3h	Human	<u>Amino acid metabolism - Homo sapiens</u>	29	82	170	1,168	2.13E-06	7.42E-03
M3h	Human	Copper ion homeostasis	7	422	9	6,014	7.96E-06	2.78E-02
M4h	Human	<u>Mitochondrion</u>	125	474	445	5,952	4.70E-40	1.53E-36
M4h	Human	<u>NADH dehydrogenase (ubiquinone) activity</u>	27	482	29	6,071	3.63E-26	1.18E-22
M4h	Human	<u>Proteasome</u>	16	397	34	4,833	1.69E-08	5.52E-05
M4h	Human	<i>Homo sapiens</i> 19	65	507	408	6,518	2.12E-08	6.91E-05
M4h	Human	<u>Acetylation</u>	28	397	120	4,833	8.10E-07	2.64E-03
M4h	Human	<u>Mitochondrial ribosome</u>	8	474	20	5,952	5.95E-04	1.00E+00
M4m	Mouse	<u>Mitochondrion</u>	77	259	334	3,963	6.71E-25	1.29E-21
M4m	Mouse	<u>NADH dehydrogenase (ubiquinone) activity</u>	18	261	28	4,043	3.75E-14	7.20E-11
M4m	Mouse	<u>Mitochondrial ribosome</u>	14	259	23	3,963	1.79E-10	3.43E-07
M4m	Mouse	<u>Ribosome - Homo sapiens</u>	17	95	26	862	2.54E-10	4.87E-07
M4m	Mouse	<u>Acetylation</u>	23	200	96	3,350	1.85E-08	3.55E-05
M4m	Mouse	RNA binding	34	261	219	4,043	2.28E-06	4.38E-03
M4m	Mouse	<u>Proteasome</u>	11	200	32	3,350	8.92E-06	1.71E-02
M5h	Human	<u>Mitochondrion</u>	109	670	445	5,952	4.26E-16	1.70E-12
M5h	Human	<u>Coated vesicle</u>	30	670	57	5,952	1.17E-13	4.67E-10
M5h	Human	<u>NADH dehydrogenase (ubiquinone) activity</u>	19	686	29	6,071	7.41E-11	2.95E-07
M5h	Human	<u>ATP synthesis</u>	16	557	21	4,833	1.93E-10	7.66E-07
M5h	Human	<u>Clathrin coat</u>	12	670	17	5,952	2.19E-07	8.72E-04
M5h	Human	<u>Synapse</u>	14	670	24	5,952	3.13E-07	1.25E-03
M5h	Human	<i>Homo sapiens</i> 19	78	723	408	6,518	1.05E-06	4.18E-03
M5h	Human	<u>Proteasome subunit</u>	15	334	35	2,897	1.30E-05	5.17E-02
M5m	Mouse	<i>Homo sapiens</i> 19	47	265	280	4,290	2.25E-10	5.00E-07
M5m	Mouse	<u>Mitochondrion</u>	51	238	334	3,963	2.86E-10	6.35E-07
M5m	Mouse	Primary active transporter activity	22	251	112	4,043	3.17E-06	7.04E-03
M5m	Mouse	<u>Proteasome</u>	11	199	32	3,350	8.52E-06	1.89E-02
M6h	Human	<u>Coated vesicle</u>	19	349	57	5,952	1.57E-09	4.36E-06
M6h	Human	<u>Neuronal transmission</u>	27	107	144	1,671	2.66E-07	7.38E-04
M6h	Human	<u>Neurogenesis</u>	39	360	275	6,014	7.15E-07	1.98E-03
M6m	Mouse	<i>Homo sapiens</i> 19	49	241	280	4,290	4.39E-13	8.78E-10
M6m	Mouse	<u>Synapse</u>	8	221	17	3,963	1.78E-05	3.57E-02
M6m	Mouse	<u>Coated vesicle</u>	12	221	47	3,963	3.55E-05	7.10E-02
M6m	Mouse	<u>neurogenesis</u>	26	221	199	4,002	6.62E-05	1.32E-01
M7h	Human	<u>mRNA binding</u>	7	77	73	6,071	2.76E-04	2.79E-01
M7h	Human	<u>Nucleus</u>	36	78	1,622	5,952	4.34E-04	4.38E-01
M7h	Human	Neuronal cell recognition	3	79	4	6,014	9.80E-04	9.91E-01
M8h	Human	<u>Defense response</u>	67	299	373	6,014	4.26E-21	1.13E-17
M8h	Human	Glycoprotein	100	278	1,045	4,833	1.98E-08	5.27E-05
M8h	Human	<u>Regulation of cell proliferation</u>	22	299	150	6,014	1.30E-05	3.46E-02
M8m	Mouse	Heat shock protein activity	8	107	20	4,043	4.09E-07	5.45E-04



Table S2. Cont.

Module	Network	Gene category	List hits	List total	Population hits	Population total	EASE score	Bonferroni correction
M8m	Mouse	<u>Regulation of transcription</u>	37	107	624	4,002	1.68E-06	2.24E-03
M9h	Human	Homo sapiens 19	20	134	408	6,518	5.65E-04	7.93E-01
M9h	Human	Nuclear division	8	120	93	6,014	2.31E-03	1.00E+00
M9h	Human	Alternative splicing	35	88	1,214	4,833	2.62E-03	1.00E+00
M9h	Human	<u>M phase</u>	8	120	99	6,014	3.30E-03	1.00E+00
M9h	Human	<u>Regulation of cell cycle</u>	14	120	283	6,014	3.71E-03	1.00E+00
M10h	Human	<u>Defense response</u>	80	244	373	6,014	4.34E-38	9.96E-35
M10h	Human	<u>Antigen presentation</u>	14	244	21	6,014	8.52E-14	1.96E-10
M10h	Human	Glycoprotein	96	222	1,045	4,833	2.33E-13	5.35E-10
M10h	Human	Polymorphism	79	222	894	4,833	9.74E-10	2.24E-06
M10h	Human	<u>Ribosome - Homo sapiens</u>	17	52	71	1,168	8.72E-09	2.00E-05
M10m	Mouse	Molecular function unknown	4	17	176	4,043	2.99E-02	1.00E+00
M10m	Mouse	<u>Development</u>	6	17	706	4,002	1.36E-01	1.00E+00
M10m	Mouse	Polymorphism	5	13	642	3,350	1.83E-01	1.00E+00
M11h	Human	<u>Mitochondrion</u>	115	682	445	5,952	2.63E-18	1.08E-14
M11h	Human	<u>Proteasome subunit</u>	21	357	35	2,897	2.12E-10	8.67E-07
M11h	Human	<u>Main pathways of carbohydrate metabolism</u>	27	685	61	6,014	4.51E-10	1.84E-06
M11h	Human	<u>ATP synthesis - Homo sapiens</u>	19	214	29	1,168	1.36E-07	5.58E-04
<b>M12h</b>	<b>Human</b>	<b><u>Ribosome - Homo sapiens</u></b>	<b>64</b>	<b>83</b>	<b>71</b>	<b>1,168</b>	<b>1.12E-77</b>	<b>1.51E-74</b>
M12h	Human	<u>Antigen presentation</u>	10	148	21	6,014	5.58E-10	7.51E-07
M12m	Mouse	<u>Mitochondrion</u>	74	298	334	3,963	9.58E-19	2.09E-15
M12m	Mouse	RNA binding	46	300	219	4,043	7.68E-11	1.68E-07
<b>M12m</b>	<b>Mouse</b>	<b><u>Ribosome - Homo sapiens</u></b>	<b>18</b>	<b>105</b>	<b>26</b>	<b>862</b>	<b>8.87E-11</b>	<b>1.94E-07</b>
M12m	Mouse	<u>Mitochondrial ribosome</u>	14	298	23	3,963	1.05E-09	2.30E-06
M12m	Mouse	<u>NADH dehydrogenase (ubiquinone) activity</u>	14	300	28	4,043	2.09E-08	4.56E-05
M12m	Mouse	Acetylation	22	237	96	3,350	1.76E-06	3.84E-03
M12m	Mouse	<u>Proteasome</u>	12	237	32	3,350	5.77E-06	1.26E-02
M13h	Human	<u>Transport</u>	142	561	1,026	6,014	1.99E-07	7.55E-04
M13h	Human	<u>Secretory pathway</u>	23	561	86	6,014	7.80E-06	2.96E-02
M13h	Human	<i>Homo sapiens Xq</i>	30	611	146	6,518	6.62E-05	2.51E-01
M13h	Human	<u>Mitochondrion</u>	67	557	445	5,952	6.90E-05	2.61E-01
M13m	Mouse	<u>Neuronal transmission</u>	22	71	96	1,175	2.56E-08	6.03E-05
M13m	Mouse	<u>Signal transduction</u>	86	226	924	4,002	2.37E-07	5.58E-04
M13m	Mouse	Acetylcholine receptor	7	95	9	1,660	2.06E-06	4.85E-03
M13m	Mouse	GTPase activity	17	227	97	4,043	7.29E-05	1.71E-01
M14h	Human	Intracellular	346	458	3,968	5,952	1.29E-05	4.08E-02
M14h	Human	<i>Homo sapiens 4q</i>	29	501	165	6,518	4.74E-05	1.50E-01
M14h	Human	Heterogeneous nuclear ribonucleoprotein complex	5	458	7	5,952	9.96E-04	1.00E+00
<i>M14h</i>	<i>Human</i>	<i><u>RNA-binding</u></i>	22	347	151	4,833	2.27E-03	1.00E+00
<i>M14h</i>	<i>Human</i>	<i><u>Nucleus</u></i>	148	458	1,622	5,952	8.87E-03	1.00E+00
M14m	Mouse	<u>6.3.2.19 [ubiquitin]</u>	8	68	12	807	1.14E-05	3.45E-02
M14m	Mouse	<u>Protein transport</u>	42	437	196	4,002	1.94E-05	5.87E-02
<i>M14m</i>	<i>Mouse</i>	<i><u>RNA-binding</u></i>	45	450	219	4,043	4.49E-05	1.36E-01
<i>M14m</i>	<i>Mouse</i>	<i><u>Nucleus</u></i>	156	427	1,131	3,963	1.22E-04	3.70E-01
<i>M15h</i>	<i>Human</i>	<i>Glycoprotein</i>	83	188	1,045	4,833	3.19E-12	6.93E-09
M15h	Human	<u>Signal transducer activity</u>	71	241	1,117	6,071	2.25E-05	4.90E-02
<i>M15h</i>	<i>Human</i>	<i><u>G protein coupled receptor</u></i>	17	188	128	4,833	2.74E-05	5.96E-02
M15h	Human	<u>Carcinoembryonic antigen</u>	6	99	10	2,228	3.15E-05	6.85E-02
M15h	Human	Homo sapiens 19	33	252	408	6,518	8.02E-05	1.74E-01
<i>M15m</i>	<i>Mouse</i>	<i><u>G protein coupled receptor</u></i>	21	242	84	3,350	1.05E-06	2.69E-03
<i>M15m</i>	<i>Mouse</i>	<i>Glycoprotein</i>	72	242	729	3,350	2.24E-03	1.00E+00

Selected GO categorizations for each module in the mouse and human networks. At least one GO category corresponding to each significant cellular process or component is included for each relevant module. Categories with significant overlap between matched modules in the mouse and human modules are highlighted in bold (corrected  $P < 0.05$ ) or italics (uncorrected  $P < 0.01$ ). GO categories were found using EASE (ref. 10), with the EASE score used as an approximation for  $P$  value. Categories confirmed using Ingenuity pathways analysis are underlined. EASE, Expression Analysis Systematic Explorer.

**Table S3. Interspecies marker genes for brain cell types**

Marker	References
<b>Oligodendrocyte (M2h)</b>	
MOG	2, 27, 64
EVI2A	2, 27
MAG	2, 27, 64
GPR37	2, 27, 64
MBP	2, 27, 64
RNF20	2, 27, 64
SCD	2
PLP1	2, 27
CLDN11	27
CSRP1	64
FNBP1	2
TMEM 39	2
<b>Neuron (M13h)</b>	
SNX10	2, 27
HMP20	27, 64
PGRMC1	2, 27
GUCY1B3	2, 27
MAPK1	2, 27
PPP3CB	27
ACTR3	27
DLD	–
ARMCX2	27
SEH1L	27
SUMO3	2
MAP2K1	2, 64
<b>Astrocyte (M3h)</b>	
ZFP36L1	2, 27
SOX2	27
F3	2, 27
TOB1	2
HIF1A	2
TSPAN6	2
GJA1	2, 27, 64
ITGA6	2, 27
HRSP 3	2, 27
TJP1	27
MCL1	–
ZFP36L2	2, 27
<b>Microglia (M10h)</b>	
TYROBP	2, 65
ARHGDIB	2
LY86	2
S100A11	–
CD21	2, 66
FCGR1A	2, 66
CYBA	2
CSF1R	2, 66
TSPO	–
LAPTM3	2
HMOX1	66
GPX1	65

Genes were ranked based on interspecies hub status for the indicated cell-type related modules, omitting genes that showed high coexpression with multiple such modules. The “References” column indicates which studies have previously found these genes to be markers for their respective cell types, demonstrating that these genes show a high overlap with known markers ( $P < 10^{-10}$  for all cell types). In ref. 2, genes in modules M9A, M15A, M16A, and M4A with  $R > 0.5$  were considered markers of oligodendrocytes, astrocytes, neurons, and microglia, respectively. Neither refs. 27 nor 64 had microglia as a cell type, whereas refs. 65 and 66 only tested microglia in mouse and human, respectively.

Table S4. Top 20 interspecies marker genes for each module

Module	Gene	P value rank	
		Mouse	Human
M1	<i>SNAP91</i>	11	5
M1	<i>GUCY1B3</i>	10	15
M1	<i>TRIM37</i>	15	2
M1	<i>SCN1A</i>	18	4
M1	<i>NPTN</i>	29	10
M1	<i>ITPR1</i>	35	23
M1	<i>GABRG2</i>	41	17
M1	<i>SNAP25</i>	5	44
M1	<i>SERPINI1</i>	20	72
M1	<i>SH3GL2</i>	74	35
M1	<i>GABRA1</i>	6	76
M1	<i>PLCB1</i>	37	89
M1	<i>FBXW7</i>	58	90
M1	<i>MAT2B</i>	1	92
M1	<i>RNF11</i>	28	93
M1	<i>CCNI</i>	22	94
M1	<i>NARS</i>	99	22
M1	<i>USP33</i>	8	115
M1	<i>OLFM1</i>	116	48
M1	<i>CAB39</i>	25	144
M2	<i>MOG</i>	6	18
M2	<i>EVI2A</i>	5	25
M2	<i>MAG</i>	13	34
M2	<i>GPR37</i>	35	5
M2	<i>RDX</i>	41	40
M2	<i>SYPL1</i>	4	44
M2	<i>MBP</i>	25	49
M2	<i>RNF13</i>	19	50
M2	<i>SCD</i>	30	51
M2	<i>PLP1</i>	57	11
M2	<i>SEPT4</i>	21	58
M2	<i>STXBP3</i>	17	61
M2	<i>CLDN11</i>	28	62
M2	<i>CSRP1</i>	11	89
M2	<i>S100B</i>	66	93
M2	<i>LITAF</i>	108	38
M2	<i>GSN</i>	111	48
M2	<i>FNBP1</i>	116	31
M2	<i>LAMP2</i>	123	7
M2	<i>SPG20</i>	92	129
M3	<i>ZFP36L1</i>	10	26
M3	<i>TMEM123</i>	28	35
M3	<i>SOX2</i>	9	36
M3	<i>PCAF</i>	67	42
M3	<i>F3</i>	75	57
M3	<i>TOB1</i>	13	78
M3	<i>HIF1A</i>	51	92
M3	<i>TSPAN6</i>	109	99
M3	<i>SEPT2</i>	110	61
M3	<i>GJA1</i>	142	1
M3	<i>ITGA6</i>	146	82
M3	<i>HRSP12</i>	147	60
M3	<i>MAPRE1</i>	156	76
M3	<i>TJP1</i>	160	126
M3	<i>ZFP36L2</i>	171	113
M3	<i>PTTG1IP</i>	177	24
M3	<i>SERP1</i>	151	188
M3	<i>TRAM1</i>	143	195
M3	<i>TMED10</i>	55	208



Table S4. Cont.

Module	Gene	P value rank	
		Mouse	Human
M3	<i>ABCA1</i>	27	219
M4	<i>TCEB2</i>	3	13
M4	<i>SNRPD2</i>	2	20
M4	<i>UQCRQ</i>	27	12
M4	<i>NDUFA7</i>	33	10
M4	<i>CCDC56</i>	5	37
M4	<i>NDUFA8</i>	15	39
M4	<i>DDT</i>	6	40
M4	<i>NDUFB2</i>	42	17
M4	<i>C14orf156</i>	45	29
M4	<i>NDUFV2</i>	47	27
M4	<i>VPS28</i>	22	49
M4	<i>NEDD8</i>	34	51
M4	<i>NDUFB7</i>	49	53
M4	<i>PSMD4</i>	55	7
M4	<i>PSMB3</i>	16	57
M4	<i>NDUFC1</i>	4	62
M4	<i>EIF3K</i>	70	4
M4	<i>HSPC171</i>	56	70
M4	<i>MGST3</i>	12	71
M4	<i>NDUFB11</i>	51	75
M5	<i>CDK5</i>	1	3
M5	<i>GNG3</i>	12	5
M5	<i>UCHL1</i>	6	19
M5	<i>ACOT7</i>	20	1
M5	<i>SULT4A1</i>	21	16
M5	<i>EEF1A2</i>	22	9
M5	<i>ACTL6B</i>	18	24
M5	<i>PKM2</i>	35	23
M5	<i>SLC4A3</i>	43	20
M5	<i>PLD3</i>	47	6
M5	<i>ATP6V0A1</i>	42	51
M5	<i>RABAC1</i>	53	33
M5	<i>ATP6V0B</i>	39	55
M5	<i>SNCB</i>	55	4
M5	<i>ARHGDIG</i>	61	28
M5	<i>TAGLN3</i>	73	39
M5	<i>ASNA1</i>	27	77
M5	<i>UQCRC1</i>	78	7
M5	<i>PFKM</i>	24	79
M5	<i>PCSK1N</i>	56	80
M6	<i>CPNE6</i>	7	5
M6	<i>ICAM5</i>	1	11
M6	<i>HPCA</i>	12	7
M6	<i>PRKCG</i>	3	12
M6	<i>GRIA1</i>	13	2
M6	<i>EFNB3</i>	9	18
M6	<i>NELL2</i>	6	22
M6	<i>CAMK2B</i>	23	25
M6	<i>ARF3</i>	21	27
M6	<i>ST6GALNAC5</i>	26	28
M6	<i>SPTBN2</i>	18	31
M6	<i>RGS14</i>	4	34
M6	<i>SYN2</i>	5	39
M6	<i>NCDN</i>	31	49
M6	<i>CRMP1</i>	52	13
M6	<i>PTPRN</i>	56	16
M6	<i>SLC22A17</i>	62	62
M6	<i>CACNB3</i>	15	69

Table S4. Cont.

Module	Gene	P value rank	
		Mouse	Human
M6	<i>DLG3</i>	10	70
M6	<i>MAST3</i>	11	83
M7	<i>ZNF148</i>	1	1
M7	<i>UGCG</i>	36	47
M7	<i>TCF4</i>	53	14
M7	<i>NUCKS1</i>	57	19
M7	<i>GRIA3</i>	58	66
M7	<i>GRIA2</i>	17	82
M7	<i>NARG1</i>	83	49
M7	<i>RBBP6</i>	100	8
M7	<i>TNPO2</i>	112	45
M7	<i>PIK3R1</i>	133	6
M7	<i>PLEKHA5</i>	144	63
M7	<i>SFRS7</i>	92	164
M7	<i>KCNMA1</i>	46	171
M7	<i>ODZ3</i>	175	70
M7	<i>MEF2C</i>	187	153
M7	<i>SLC4A7</i>	73	190
M7	<i>PAPSS2</i>	160	202
M7	<i>KPNB1</i>	206	44
M7	<i>ZNF638</i>	212	189
M7	<i>PCYOX1</i>	30	217
M8	<i>CSDA</i>	1	1
M8	<i>SRGN</i>	20	4
M8	<i>CEBPD</i>	21	2
M8	<i>CDKN1A</i>	27	6
M8	<i>CEBPB</i>	32	10
M8	<i>MCL1</i>	7	36
M8	<i>FOS</i>	18	37
M8	<i>BCL6</i>	43	28
M8	<i>TGM2</i>	45	47
M8	<i>TIPARP</i>	47	35
M8	<i>CLDN5</i>	5	59
M8	<i>ANXA1</i>	9	62
M8	<i>ANXA2</i>	65	26
M8	<i>GADD45A</i>	69	20
M8	<i>MGP</i>	53	70
M8	<i>CDH5</i>	42	86
M8	<i>JUNB</i>	48	87
M8	<i>DUSP1</i>	11	95
M8	<i>S100A10</i>	95	83
M8	<i>ACTA2</i>	82	97
M9	<i>CXXC1</i>	1	2
M9	<i>PHF1</i>	6	11
M9	<i>CTTN</i>	41	45
M9	<i>ZNF444</i>	57	26
M9	<i>PCBP4</i>	132	89
M9	<i>AATK</i>	97	137
M9	<i>SIDT2</i>	165	76
M9	<i>SF3A2</i>	152	166
M9	<i>SFRS14</i>	167	101
M9	<i>NAGA</i>	34	170
M9	<i>RALGDS</i>	179	39
M9	<i>PIGT</i>	192	138
M9	<i>GGA1</i>	198	12
M9	<i>PGF</i>	199	1
M9	<i>ARHGEF1</i>	207	7
M9	<i>CSK</i>	208	189
M9	<i>NAP1L4</i>	33	223

Table S4. Cont.

Module	Gene	P value rank	
		Mouse	Human
M9	<i>RXRA</i>	151	227
M9	<i>EMID1</i>	201	232
M9	<i>METTL7A</i>	250	86
M10	<i>TYROBP</i>	1	4
M10	<i>ARHGDI3</i>	4	8
M10	<i>LY86</i>	2	9
M10	<i>S100A11</i>	9	7
M10	<i>CD14</i>	5	10
M10	<i>FCGR1A</i>	21	16
M10	<i>CYBA</i>	18	22
M10	<i>CSF1R</i>	36	18
M10	<i>TSPO</i>	3	37
M10	<i>LAPTM5</i>	40	1
M10	<i>HMOX1</i>	19	45
M10	<i>GPX1</i>	50	39
M10	<i>IFITM3</i>	20	50
M10	<i>IRF8</i>	53	26
M10	<i>ITGB2</i>	56	5
M10	<i>RAC2</i>	60	46
M10	<i>GFAP</i>	16	61
M10	<i>C1QB</i>	66	3
M10	<i>CTSS</i>	8	66
M10	<i>VAMP8</i>	68	27
M11	<i>HPRT1</i>	1	5
M11	<i>DLD</i>	4	26
M11	<i>ATP6AP2</i>	10	31
M11	<i>PCMT1</i>	33	8
M11	<i>ATP5C1</i>	45	22
M11	<i>G3BP2</i>	7	47
M11	<i>ATP6V1C1</i>	30	50
M11	<i>PREPL</i>	51	32
M11	<i>SERINC1</i>	52	34
M11	<i>PPP2CA</i>	59	57
M11	<i>SUCLA2</i>	60	3
M11	<i>GLRB</i>	69	15
M11	<i>TIMM17A</i>	72	38
M11	<i>PSMC6</i>	80	69
M11	<i>ITFG1</i>	81	63
M11	<i>UBE2V2</i>	3	82
M11	<i>TMEM30A</i>	29	89
M11	<i>SLC30A9</i>	95	37
M11	<i>ATP6V1D</i>	92	101
M11	<i>UBE2N</i>	91	105
M12	<i>RPS19</i>	1	1
M12	<i>RPS11</i>	2	7
M12	<i>RPS15A</i>	5	10
M12	<i>RPL7</i>	11	14
M12	<i>RPL7A</i>	7	15
M12	<i>RPL8</i>	17	5
M12	<i>BTF3</i>	3	21
M12	<i>SNRPG</i>	21	19
M12	<i>RPL13A</i>	25	4
M12	<i>RPL37</i>	10	26
M12	<i>RPL6</i>	26	24
M12	<i>RPS3</i>	29	2
M12	<i>RPL41</i>	34	13
M12	<i>RPLP1</i>	42	3
M12	<i>CHMP2A</i>	43	33
M12	<i>CNBP</i>	52	45



Table S4. Cont.

Module	Gene	P value rank	
		Mouse	Human
M12	<i>UBL5</i>	28	57
M12	<i>NACA</i>	66	11
M12	<i>SSR2</i>	72	64
M12	<i>C2orf28</i>	68	73
M13	<i>SNX10</i>	15	21
M13	<i>HMP19</i>	24	2
M13	<i>PGRMC1</i>	5	25
M13	<i>MAPK1</i>	4	37
M13	<i>PPP3CB</i>	54	38
M13	<i>ACTR3</i>	58	45
M13	<i>ARMCX2</i>	52	76
M13	<i>SEH1L</i>	21	77
M13	<i>SUMO3</i>	81	84
M13	<i>MAP2K1</i>	44	85
M13	<i>SLC1A1</i>	86	60
M13	<i>HTR2C</i>	90	22
M13	<i>KRAS</i>	78	90
M13	<i>GAP43</i>	97	95
M13	<i>RCN2</i>	80	98
M13	<i>TOMM70A</i>	101	73
M13	<i>GABRB3</i>	117	71
M13	<i>PTPRO</i>	131	33
M13	<i>GLOD4</i>	95	132
M13	<i>RTN1</i>	141	118
M14	<i>SH3BGRL</i>	7	17
M14	<i>USP1</i>	1	23
M14	<i>HNRPH2</i>	18	27
M14	<i>RAD21</i>	41	12
M14	<i>EIF1AX</i>	46	33
M14	<i>SMARCA5</i>	50	13
M14	<i>DDX5</i>	56	35
M14	<i>UBE2E1</i>	60	10
M14	<i>DEK</i>	67	73
M14	<i>FMR1</i>	10	79
M14	<i>PLS3</i>	80	21
M14	<i>SFRS11</i>	83	85
M14	<i>VBP1</i>	87	99
M14	<i>TCF12</i>	68	101
M14	<i>MGEA5</i>	96	108
M14	<i>OGT</i>	110	105
M14	<i>TTRAP</i>	111	29
M14	<i>TOP2B</i>	113	26
M14	<i>YTHDC1</i>	16	113
M14	<i>VPS4B</i>	33	121
M15	<i>GPR12</i>	2	15
M15	<i>DOLPP1</i>	10	53
M15	<i>DNPEP</i>	57	11
M15	<i>ZC3H3</i>	71	62
M15	<i>MVK</i>	79	4
M15	<i>FGF4</i>	56	101
M15	<i>KRT2</i>	121	21
M15	<i>BCAN</i>	74	122
M15	<i>HGS</i>	16	137
M15	<i>XPO6</i>	138	17
M15	<i>SPRR1B</i>	37	152
M15	<i>MYH14</i>	159	164
M15	<i>PRKACA</i>	170	72
M15	<i>PML</i>	173	87
M15	<i>G6PC3</i>	143	180

Table S4. Cont.

Module	Gene	P value rank	
		Mouse	Human
M15	<i>NUDCD3</i>	8	181
M15	<i>KLC2</i>	189	147
M15	<i>IMPDH1</i>	195	142
M15	<i>HTR4</i>	200	166
M15	<i>CCKBR</i>	154	204

Top 20 interspecies marker genes for each module. For each module, genes were scored based on maximum significance of MM between species (ranks close to 1 represent higher MM). Note that we expect some genes to show between-species preservation for all modules, both due to chance and because of the way mouse MEs were defined. Human-specific modules (i.e., M7 and M9) have the least significant preservation, as measured by the larger minimum ranks of the marker genes for these modules.

Table S5. Known highly specific marker genes confirmed in our network

Gene	List	Cell type	Top module		Top rank	
			Human	Mouse	Human	Mouse
<i>ALDOC</i>	Cahoy (M)	Astrocyte	<b>M3</b>	M9	544	648
<i>AQP4</i>	Cahoy (M)	Astrocyte	<b>M3</b>	M12	21	344
<i>ATP1A2</i>	Cahoy (M)	Astrocyte	<b>M3</b>	M6	4	264
<i>DIO2</i>	Cahoy (M)	Astrocyte	<b>M3</b>	<b>M8</b>	736	23
<i>F3</i>	Cahoy (M)	Astrocyte	<b>M8</b>	<b>M3</b>	45	75
<i>GFAP</i>	Cahoy (M)	Astrocyte	<b>M3</b>	<b>M10</b>	43	16
<i>HAPLN1</i>	Cahoy (M)	Astrocyte	M1	<b>M8</b>	664	412
<i>MERTK</i>	Cahoy (M)	Astrocyte	<b>M3</b>	M6	85	480
<i>PAPSS2</i>	Cahoy (M)	Astrocyte	M7	M7	202	160
<i>PLA2G7</i>	Cahoy (M)	Astrocyte	M7	<b>M2</b>	504	137
<i>PPP1R3C</i>	Cahoy (M)	Astrocyte	<b>M3</b>	<b>M8</b>	62	145
<i>SLC15A2</i>	Cahoy (M)	Astrocyte	<b>M3</b>	M5	314	1005
<i>SLC1A2</i>	Cahoy (M)	Astrocyte	M7	M6	46	619
<i>SLC4A4</i>	Cahoy (M)	Astrocyte	<b>M3</b>	M7	133	726
<i>AHCYL1</i>	Oldham (H)	Astrocyte	<b>M3</b>	M1	8	172
<i>EDG1</i>	Oldham (H)	Astrocyte	<b>M3</b>	M15	9	1048
<i>NTRK2</i>	Oldham (H)	Astrocyte	<b>M3</b>	M15	11	212
<i>PON2</i>	Oldham (H)	Astrocyte	<b>M3</b>	<b>M2</b>	2	345
<i>PPAP2B</i>	Oldham (H)	Astrocyte	<b>M3</b>	M6	17	245
<i>SDC4</i>	Oldham (H)	Astrocyte	<b>M3</b>	M4	39	504
<i>EPHA7</i>	Cahoy (M)	Neuron	<b>M13</b>	<b>M13</b>	344	28
<i>GABRA1</i>	Cahoy (M)	Neuron	<b>M1</b>	<b>M1</b>	76	6
<i>GABRG2</i>	Cahoy (M)	Neuron	<b>M1</b>	<b>M13</b>	17	30
<i>HTR2C</i>	Cahoy (M)	Neuron	<b>M13</b>	<b>M13</b>	22	90
<i>MEF2C</i>	Cahoy (M)	Neuron	M7	M7	153	187
<i>MYT1L</i>	Cahoy (M)	Neuron	<b>M1</b>	<b>M6</b>	16	168
<i>NEUROD6</i>	Cahoy (M)	Neuron	<b>M6</b>	<b>M1</b>	116	13
<i>NOV</i>	Cahoy (M)	Neuron	<b>M13</b>	<b>M6</b>	330	101
<i>PCSK2</i>	Cahoy (M)	Neuron	<b>M1</b>	<b>M5</b>	110	54
<i>SCG2</i>	Cahoy (M)	Neuron	<b>M13</b>	M3	20	144
<i>SLA</i>	Cahoy (M)	Neuron	M10	M15	17	389
<i>SLC12A5</i>	Cahoy (M)	Neuron	<b>M1</b>	<b>M6</b>	6	1244
<i>SNAP25</i>	Cahoy (M)	Neuron	<b>M11</b>	<b>M1</b>	17	5
<i>SSTR2</i>	Cahoy (M)	Neuron	<b>M6</b>	M8	314	175
<i>STMN2</i>	Cahoy (M)	Neuron	<b>M11</b>	<b>M5</b>	24	218
<i>SYT1</i>	Cahoy (M)	Neuron	<b>M11</b>	<b>M1</b>	51	63
<i>VIP</i>	Cahoy (M)	Neuron	<b>M13</b>	<b>M1</b>	505	421
<i>DNM1L</i>	Oldham (H)	Neuron	<b>M11</b>	<b>M13</b>	117	8
<i>FGF12</i>	Oldham (H)	Neuron	<b>M11</b>	M11	126	361
<i>GABRG2</i>	Oldham (H)	Neuron	<b>M1</b>	<b>M13</b>	17	30
<i>MAPK1</i>	Oldham (H)	Neuron	<b>M13</b>	<b>M13</b>	37	4
<i>NUDT21</i>	Oldham (H)	Neuron	<b>M11</b>	<b>M4</b>	121	391
<i>PITPNA</i>	Oldham (H)	Neuron	<b>M5</b>	M15	56	608

Table S5. Cont.

Gene	List	Cell type	Top module		Top rank	
			Human	Mouse	Human	Mouse
<i>RAB5A</i>	Oldham (H)	Neuron	M14	<b>M11</b>	509	26
<i>SYN2</i>	Oldham (H)	Neuron	M6	<b>M6</b>	39	5
<i>YWHAZ</i>	Oldham (H)	Neuron	<b>M13</b>	M7	7	280
<i>CLDN11</i>	Cahoy (M)	Oligoden.	<b>M2</b>	<b>M2</b>	62	28
<i>ERBB3</i>	Cahoy (M)	Oligoden.	<b>M2</b>	<b>M2</b>	9	212
<i>EVI2A</i>	Cahoy (M)	Oligoden.	<b>M2</b>	<b>M2</b>	25	5
<i>GSN</i>	Cahoy (M)	Oligoden.	<b>M2</b>	<b>M2</b>	48	111
<i>MAG</i>	Cahoy (M)	Oligoden.	<b>M2</b>	<b>M2</b>	34	13
<i>MAL</i>	Cahoy (M)	Oligoden.	<b>M2</b>	<b>M2</b>	4	153
<i>MBP</i>	Cahoy (M)	Oligoden.	<b>M2</b>	<b>M2</b>	49	25
<i>MOBP</i>	Cahoy (M)	Oligoden.	<b>M2</b>	<b>M2</b>	71	162
<i>MOG</i>	Cahoy (M)	Oligoden.	<b>M2</b>	<b>M2</b>	18	6
<i>PLA2G4A</i>	Cahoy (M)	Oligoden.	<b>M8</b>	<b>M3</b>	307	768
<i>PLP1</i>	Cahoy (M)	Oligoden.	<b>M2</b>	<b>M2</b>	11	57
<i>PRKCQ</i>	Cahoy (M)	Oligoden.	<b>M2</b>	M6	263	934
<i>SRPK3</i>	Cahoy (M)	Oligoden.	<b>M15</b>	M9	328	759
<i>UGT8</i>	Cahoy (M)	Oligoden.	<b>M2</b>	<b>M2</b>	17	335
<i>CRYAB</i>	Oldham (H)	Oligoden.	<b>M2</b>	<b>M10</b>	15	153
<i>ENPP2</i>	Oldham (H)	Oligoden.	<b>M2</b>	<b>M2</b>	1.5	302
<i>HSPA2</i>	Oldham (H)	Oligoden.	<b>M2</b>	M13	1.5	227
<i>MAL</i>	Oldham (H)	Oligoden.	<b>M2</b>	<b>M2</b>	4	153
<i>NPC1</i>	Oldham (H)	Oligoden.	<b>M2</b>	<b>M2</b>	8	200
<i>PMP22</i>	Oldham (H)	Oligoden.	<b>M2</b>	<b>M2</b>	3	272

Known highly specific marker genes confirmed in our network. The top marker genes for astrocytes, neurons, and oligodendrocytes in mouse (figure 3 from ref. 27) and human (figure 4 from ref. 2), which are also present in our networks, are listed in the "Gene" column. The "top module" column represents the module to which this gene has the most significant MM in each network. Genes in modules consistent with expectations are labeled in bold. The "Top Rank" columns list the ranked MM for each gene in its listed module, with lower ranks representing more significant MM values.

**Table S6. Human specific markers for major cell types**

Gene	Correlation in human	P-value in human	Correlation in mouse	P-value in mouse
<b>Oligodendrocytes</b>				
<i>ALCAM</i>	0.51	6.5E-85	-0.17	2.5E-01
<i>AMPD3</i>	0.38	3.0E-34	-0.06	1.5E-03
<i>ANGPTL2</i>	0.41	1.3E-25	-0.12	7.5E-05
<i>CBFB</i>	0.37	2.2E-38	-0.12	8.5E-09
<i>CDKN1B</i>	0.30	2.9E-59	-0.05	7.5E-02
<i>CHD1L</i>	0.32	1.8E-26	0.01	1.3E-00
<i>CLK1</i>	0.33	9.9E-54	-0.07	4.6E-03
<i>COL4A5</i>	0.65	2.7E-182	0.00	6.7E-01
<i>CSTF2T</i>	0.21	1.5E-22	-0.05	6.6E-09
<i>DYNC1I2</i>	0.48	6.0E-76	-0.10	6.4E-17
<i>ELOVL5</i>	0.30	4.8E-44	0.04	1.6E-01
<i>HSPA2</i>	0.80	0.0E+00	-0.07	2.6E-02
<i>INPP1</i>	0.44	5.4E-53	-0.05	1.5E-06
<i>IQGAP1</i>	0.31	9.4E-27	-0.08	5.7E-01
<i>IVNS1ABP</i>	0.31	2.7E-40	-0.07	2.8E-22
<i>LRP2</i>	0.44	5.9E-47	-0.03	2.4E-01
<i>MAN2A1</i>	0.58	6.4E-151	-0.06	7.0E-02
<i>MYLK</i>	0.45	1.9E-50	-0.02	1.0E-02
<i>NCAM1</i>	0.38	1.8E-33	-0.13	2.7E-06
<i>P2RX7</i>	0.41	9.7E-26	-0.09	6.9E-10
<i>PSEN1</i>	0.62	6.8E-177	0.03	6.8E-01
<i>PTP4A2</i>	0.45	1.9E-61	0.00	2.7E-10
<i>RNF103</i>	0.25	3.9E-19	-0.04	1.8E-12
<i>STAG2</i>	0.20	3.9E-23	-0.07	4.5E-02
<i>THBS2</i>	0.44	4.9E-50	-0.04	1.3E-01
<i>TXNIP</i>	0.25	1.9E-17	-0.06	1.0E-03
<i>ZFYVE16</i>	0.32	2.2E-37	0.00	8.7E-01
<i>HBEGF</i>	0.22	8.0E-14	-0.12	9.2E-05
<i>KIAA0174</i>	0.35	6.3E-27	-0.05	2.4E-08
<b>Microglia</b>				
<i>CD53</i>	0.49	2.1E-94	-0.05	1.4E-04
<i>CYFIP1</i>	0.41	3.1E-49	-0.12	3.4E-01
<i>ITGAM</i>	0.28	2.3E-26	0.00	1.7E-01
<i>KCTD12</i>	0.43	4.5E-53	-0.15	2.8E-04
<i>SLA</i>	0.50	6.2E-78	0.01	1.7E-01
<i>SLC2A5</i>	0.48	3.3E-86	0.03	8.6E-02
<i>STAB1</i>	0.43	7.2E-46	0.01	9.2E-01
<b>Astrocytes</b>				
<i>ABLIM1</i>	0.34	1.1E-35	-0.03	1.0E+00
<i>AQP1</i>	0.27	1.6E-38	0.00	3.1E-01
<i>CD99</i>	0.36	3.1E-70	-0.09	4.2E-01
<i>CRYL1</i>	0.29	2.5E-30	-0.05	8.1E-02
<i>FTH1</i>	0.21	9.8E-17	-0.05	2.1E-03
<i>FYN</i>	0.39	1.1E-44	0.04	6.1E-02
<i>GRAMD3</i>	0.63	1.2E-185	0.04	8.7E-01
<i>IGFBP7</i>	0.35	1.1E-42	-0.06	1.4E+00
<i>LEPROT</i>	0.31	1.1E-19	0.04	1.3E+00
<i>PIK3C2A</i>	0.53	2.5E-64	-0.02	7.7E-02
<i>PRKCA</i>	0.34	3.0E-54	-0.04	5.0E-02
<i>RAB31</i>	0.55	1.2E-107	-0.04	1.0E+00
<i>RYR3</i>	0.45	4.5E-73	-0.01	1.3E+00
<i>SRI</i>	0.42	7.0E-59	-0.08	9.0E-01
<i>TCF7L2</i>	0.45	2.1E-43	-0.01	1.9E-05
<i>TGFBR3</i>	0.41	1.1E-51	-0.01	3.2E-02
<i>UNG</i>	0.38	4.4E-47	-0.02	1.6E-12
<b>Neurons</b>				
<i>ACLY</i>	0.24	2.0E-20	0.02	1.3E+00
<i>ACP1</i>	0.29	5.0E-34	-0.03	2.8E-01

**Table S6. Cont.**

Gene	Correlation in human	P-value in human	Correlation in mouse	P-value in mouse
<i>ADK</i>	0.22	1.5E-15	0.04	4.6E-01
<i>CCDC6</i>	0.32	8.8E-36	-0.01	7.3E-01
<i>COPS8</i>	0.30	3.5E-34	-0.08	5.2E-01
<i>GHITM</i>	0.37	7.2E-66	-0.07	5.9E-04
<i>HSPA4L</i>	0.28	1.4E-24	-0.02	9.0E-03
<i>HSPA8</i>	0.25	1.1E-20	0.02	8.0E-01
<i>MCFD2</i>	0.39	2.1E-46	0.05	2.0E-01
<i>P15RS</i>	0.28	1.3E-22	-0.03	2.4E-03
<i>PEG10</i>	0.38	3.6E-84	0.01	3.4E-01
<i>PGK1</i>	0.24	3.5E-24	-0.04	1.0E+00
<i>PRKCI</i>	0.31	3.5E-22	-0.07	4.0E-02
<i>UQCRC2</i>	0.30	5.9E-37	0.01	1.2E+00

Human specific marker genes for four major cell types: oligodendrocytes, microglia, astrocytes, and neurons. All genes in these lists pass four criteria: (i) Member of the human module for the cell type, (ii) not significantly correlated ( $R < 0.05$ ,  $P > 0.05$ ) with the corresponding mouse module, (iii) validated in a human cortex network (2), and (iv) not validated in corresponding mouse comparison studies (27, 64, 65). SLA and STAB1 were further confirmed as markers for human microglia in ref. 66.

**Table S7. Top confirmed M9h genes**

Gene	Rank	Gene	Rank
<i>ZNF160</i>	1	<i>USP4</i>	26
<i>DCLRE1C</i>	2	<i>PRR14</i>	27
<i>SRRM2</i>	3	<i>SCAMP2</i>	28
<i>POGZ</i>	4	<i>ELAVL3</i>	29
<i>CLCN7</i>	5	<i>C21orf2</i>	30
<i>TAZ</i>	6	<i>TRIOBP</i>	31
<i>CXXC1</i>	7	<i>PIAS4</i>	32
<i>PRR11</i>	8	<i>ZNF688</i>	33
<i>WDR6</i>	9	<i>GAK</i>	34
<i>ZNF444</i>	10	<i>SORBS3</i>	35
<i>BRD3</i>	11	<i>PLCG1</i>	36
<i>CTDSP2</i>	12	<i>LMBR1L</i>	37
<i>CEP164</i>	13	<i>ZNF692</i>	38
<i>SAPS2</i>	14	<i>LAS1L</i>	39
<i>MAP3K11</i>	15	<i>RING1</i>	40
<i>FBXW4</i>	16	<i>PHF1</i>	41
<i>ZNF148</i>	17	<i>CELSR3</i>	42
<i>C9orf7</i>	18	<i>FLJ21865</i>	43
<i>ZBTB20</i>	19	<i>ECHDC2</i>	44
<i>MAP3K3</i>	20	<i>EFEMP2</i>	45
<i>DBT</i>	21	<i>GOSR1</i>	46
<i>TNS1</i>	22	<i>APBA3</i>	47
<i>EXOC7</i>	23	<i>MAML1</i>	48
<i>WHSC2</i>	24	<i>GLT25D1</i>	49
<i>AKAP8L</i>	25	<i>BCAT2</i>	50

Top confirmed M9h genes. Genes in this list are ranked based on high correlation with the ME of M9h and its corresponding confirmation modules (the red module from ref. 12, the black module from ref. 40, and the yellow module from ref. 39), and high correlation with M9h hubs in the Celsius database (ref. 67)