"Functional Organization of the Transcriptome in Human Brain"

Michael C. Oldham, Steve Horvath, Genevieve Konopka, Kazuya Iwamoto, Peter Langfelder, Tadafumi Kato, and Daniel H. Geschwind

Nature Neuroscience

Supplementary Figure 1: Pairs of proteins that physically interact have higher topological overlap in gene coexpression networks than randomly selected pairs

Comparison of mean topological overlap (TO) for interacting protein pairs versus mean TO for randomly selected pairs in (**a**) CTX, (**b**) CN, and (**c**) CB. A set of experimentally validated interacting human protein pairs was obtained from ref. 26. Mean TO was calculated in each brain region for all expressed, interacting protein pairs ($\text{CTX} = 5,980$ pairs; $\text{CN} = 4,901$ pairs; $\text{CB} = 5,347$ pairs). For genes represented by multiple probe sets, the average was taken. The mean TO for interacting protein pairs was then compared to the mean TO for randomly selected pairs of probe sets in each network (n = 50,000). Data were highly skewed and log-transformed. Significance was assessed using the Kruskal-Wallis test.

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Supplementary Figure 2: Module summaries

Summaries for all modules from CTX (**a–s**), CTX_95 (**t–aj**), CN (**ak–bg**), and CB (**bh–cc**). Top left: heat map of gene expression levels for all genes assigned to the module in Fig. 1 (red = increased expression; black = neutral expression; green = decrease d expression). Genes were ranked from top to bottom by the absolute value of module membership (MM). Bottom left: barplot of th e module eigengene (ME; i.e. the first principal component following singular value decomposition). The ordering of samples in heat maps and ME barplots is identical for all modules in each network. Sample labels appear on the x-axis of the ME barplot (H1 = Human 1, etc.; BA = Brodmann area). Note that many samples from CTX, CN, and CB were taken from the same individuals (as denoted by sample labels). Right: log_2 -transformed expression levels for the top 10 genes selected by $|MM|$ (note: kme = MM). Some genes are represented by multiple probe sets.

Figure S2

Cortex

Figure S2A

CTX palegreen Top 10 genes by |kme|

Figure S2B

CTX midnightblue Top 10 genes by |kme|

Sample

Figure S2C

CTX greenyellow Top 10 genes by |kme|

Sample

Figure S2D

Sample

Figure S2E

Sample

Figure S2F

CTX darkolivegreen Top 10 genes by |kme|

Sample

Figure S2G

CTX honeydew Top 10 genes by |kme|

Sample

Figure S2H

CTX salmon Top 10 genes by |kme|

Sample

Figure S2I

CTX turquoise Top 10 genes by |kme|

Sample

Figure S2J

Figure S2K

Sample

Figure S2L

 $M12A$ (tan)

CTX tan Top 10 genes by |kme|

Sample

Figure S2M

CTX powderblue Top 10 genes by |kme|

Sample

Figure S2N

Sample

Figure S2O

CTX brown Top 10 genes by |kme|

Sample

Figure S2P

Sample

Figure S2Q

Sample

Figure S2R

Sample

Figure S2S

CTX red Top 10 genes by |kme|

Sample

Figure S2

Cortex (U95)

Figure S2T

CTX_95 orange Top 10 genes by |kme|

Sample

Figure S2U

CTX_95 ivory Top 10 genes by |kme|

Sample

Figure S2V

CTX_95 mediumseagreen Top 10 genes by |kme

Sample

Figure S2W

 \subseteq Expression level ∞ ESRRG
CDH12
EXTL2 IJ \mathbf{r} PCP4
PVALB
BTBD3 $\overline{}$ 37788_at
PENK
DCAMKL1
CAMTA1 \boldsymbol{A} \ldots $\overline{}$

CTX_95 tomato Top 10 genes by |kme|

Sample

Figure S2X

CTX_95 dodgerblue Top 10 genes by |kme|

Sample

Figure S2Y

CTX_95 firebrick Top 10 genes by |kme|

Sample

Figure S2Z

CTX_95 papayawhip Top 10 genes by |kme|

Sample

Figure S2AA

Figure S2AB

Sample

Figure S2AC

 \subseteq Expression level $\rm \omega$ ANTN1
RGS4
YWHAZ
PITPNA
PRKACB
PRKACB \overline{a} PCMT1
GNAQ $\overline{4}$ ATP5A1
CALM1 \sim \sim \sim $\overline{}$

CTX_95 blue Top 10 genes by |kme|

Sample

Figure S2AD

CTX_95 green Top 10 genes by |kme|

Sample

Figure S2AE

CTX_95 brown Top 10 genes by |kme|

Sample

Figure S2AF

 -0.4

 $rac{8}{2}$

 $H(02)$

TMF1
NELL2
KIF3C
MTF2
ASXL1
SLC4A7
MBLIQCL

SFPQ
UPF3A
GOSR1

MPHOSPH9

44 الأمالا ۰-

- -. . . ۰.
Figure S2AG

CTX_95 salmon Top 10 genes by |kme|

Sample

Figure S2AH

 \overline{C} $\sum_{\mathbf{q}}$ -0.3 - BA44 RH
- BA44 RH
- H104 BA9
- H105 BA9
- H106 BA9 $rac{8}{2}$ $H(02)$

Sample

Figure S2AI

CTX_95 darkred Top 10 genes by |kme|

Sample

Figure S2AJ

Sample

Figure S2

Caudate nucleus

Figure S2AK

Sample

Figure S2AL

CN purple Top 10 genes by |kme|

Sample

 Δ

A
CLAPTM5
CO53
FCGR3A /// FCGR3B
ALOX5AP
CLY86
LY86
LY86

HLA-DRA
CD74
HLA-DRA
C1QA

ولاوة $\overline{}$

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 $\hspace{1.0cm} \rule{1.5cm}{0.15cm} \hspace{1.0cm} \rule{1.5cm}{0.15cm}$

. . . г.

Figure S2AM

CN black Top 10 genes by |kme|

Sample

Figure S2AN

CN palevioletred Top 10 genes by |kme|

Sample

Figure S2AO

CN mistyrose Top 10 genes by |kme|

Sample

Figure S2AP

CN darkgreen Top 10 genes by |kme|

Sample

Figure S2AQ

CN aliceblue Top 10 genes by |kme|

Sample

Figure S2AR

Sample

Figure S2AS

CN turquoise Top 10 genes by |kme|

Sample

Figure S2AT

Sample

Figure S2AU

CN sandybrown Top 10 genes by |kme|

Sample

Figure S2AV

CN powderblue Top 10 genes by |kme|

Sample

Figure S2AW

Sample

Figure S2AX

CN seashell Top 10 genes by |kme|

Sample

Figure S2AY

CN maroon Top 10 genes by |kme|

Sample

Figure S2AZ

CN aquamarine Top 10 genes by |kme|

Sample

Figure S2BA

CN royalblue Top 10 genes by |kme|

Sample

Figure S2BB

Sample

Figure S2BC

Sample

Figure S2BD

CN lavenderblush Top 10 genes by |kme|

Sample

Figure S2BE

CN orange Top 10 genes by |kme|

Sample

Figure S2BF

CN brown Top 10 genes by |kme|

Sample

Figure S2BG

CN mintcream Top 10 genes by |kme|

Sample

Figure S2

Cerebellum

Figure S2BH

CB palegreen Top 10 genes by |kme|

Sample

Figure S2BI

Sample

Figure S2BJ

Sample

Figure S2BK

CB darkgoldenrod Top 10 genes by |kme|

Figure S2BL

CB yellow Top 10 genes by |kme|

Sample

Figure S2BM

CB cornflowerblue Top 10 genes by |kme|

Figure S2BN

CB chocolate Top 10 genes by |kme|

Sample
Figure S2BO

Sample

Figure S2BP

Sample

Figure S2BQ

CB violetred Top 10 genes by |kme|

Sample

Figure S2BR

 \overline{Q}

 -0.3

 $H42$ _{-CB}- $H43$ _CB- $H44$ CB-H45_CB-H46_CB-

Sample

Figure S2BS

Sample

Figure S2BT

Sample

Figure S2BU

CB honeydew Top 10 genes by |kme|

Sample

Figure S2BV

CB darkblue Top 10 genes by |kme|

Sample

Figure S2BW

CB wheat Top 10 genes by |kme|

Sample

Figure S2BX

CB darksalmon Top 10 genes by |kme|

Sample

Figure S2BY

Sample

Figure S2BZ

CB lemonchiffon Top 10 genes by |kme|

Sample

Figure S2CA

CB turquoise Top 10 genes by |kme|

Sample

Figure S2CB

Sample

Figure S2CC

Sample

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Supplementary Figure 3: Module membership is correlated in multiple human brain datasets (additional conserved modules)

Comparison of module membership between networks for M4 (**a**), M18 (**b**), and M19 (**c**). Data are presented as described in Fig. 3 of the journal article. Note that for smaller modules (e.g. M4), most genes were not significantly correlated with the module eigengene.

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Supplementary Figure 4: Module visualizations

150 pairs of genes with the highest topological overlap in each module are depicted for CTX (**a–s**), CN (**t–ap**), and CB (**aq–bl**) (Supplementary Methods). Genes with expression levels that were negatively correlated are connected by black lines. Where gene symbols are unknown, Affymetrix probe set IDs are shown (e.g. 214903_at). Numbers appended to gene symbols denote the rank |module membership| (RMM) for the corresponding probe set (some genes are represented by multiple probe sets). For example, *KIAA0103* exhibited the strongest membership of any gene for M10A (**j**). Genes with >= 20 depicted connections appear as large nodes, followed by genes with 10–19 connections that appear as medium nodes, followed by genes with < 10 connections that appear as small nodes.

Figure S4

Cortex

Figure S4A

M1A

Figure S4B

 $M2$

Figure S4C

M3

Figure S4D

M4A

Figure S4E

M5A

Figure S4F

M₆A

Figure S4G

M₇A

Figure S4H

M8A

Figure S4I

M9A

Figure S4J

$M10A$

Figure S4K

M11A

Figure S4L

M12A

Figure S4M

M13A

Figure S4N

M14A

Figure S4O

M15A

Figure S4P

M16A

Figure S4Q

M17A

Figure S4R

M18A

Figure S4S

M19A

Figure S4

Caudate nucleus

Figure S4T

M1C

Figure S4U

M4C

Figure S4V

M5C

Figure S4W

M8C

Figure S4X

M9C

Figure S4Y

M₁1C

Figure S4Z

M₁₃C

Figure S4AA

M15C

Figure S4AB

M16C

Figure S4AC

M18C

Figure S4AD

M19C

Figure S4AE

Figure S4AF

Figure S4AG

Figure S4AH

Figure S4AI

Figure S4AJ

Figure S4AK

Figure S4AL

Figure S4AM

Figure S4AN

Figure S4AO

Figure S4AP

Figure S4

Cerebellum

Figure S4AQ

M1D

Figure S4AR

M4D

Figure S4AS

M₆D

Figure S4AT

M7D

Figure S4AU

M9D

Figure S4AV

$M10D$

Figure S4AW

$M11D$

Figure S4AX

$M12D$

Figure S4AY

M14D

Figure S4AZ

M15D

Figure S4BA

M16D

Figure S4BB

M18D

Figure S4BC

M19D

Figure S4BD

Figure S4BE

Figure S4BF

Figure S4BG

Figure S4BH

Figure S4BI

Figure S4BJ

Figure S4BK

Figure S4BL

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Supplementary Figure 5: *In situ* **hybridization confirms cellular/regional specificity of gene coexpression modules**

Mouse *in situ* hybridization (ISH) data for genes from M6D (**a–j**) and M13C (**k–t**). ISH data were downloaded from the Allen Brain Atlas³¹ (ABA) for available genes with the strongest membership for each module. Juxtaposed for each gene are the ISH image and corresponding expression level analysis (as calculated by the ABA). For genes in M6D, expression was strongest and most consistent in Purkinje neurons. For genes in M13C, the highest and most consistent expression levels in caudate nucleus were found in or near the subventricular zone.

Sample

Figure S5A

M6D: CALB1

Figure S5B

M6D: PVALB

Figure S5C

M6D: ITPRI

Figure S5D

M6D: PLXDC1

Figure S5E

M6D: LPL

Figure S5F

$M6D: PCP4$

Figure S5G

M6D: LARGE

Figure S5H

M6D: CHST2

Figure S5I

M6D: LRP8

Figure S5J

M6D: SLC1A6

 P

 \mathcal{E}

Sample

Figure S5K

M13C: PLTP

Figure S5L

M13C: CD24

Figure S5M

M13C: CD24

Figure S5N

M13C: GJA1

Figure S5O

M13C: BBOX1

Figure S5P

M13C: SPFH2

Figure S5Q

M13C: DPYSL3

Figure S5R

M13C: SPAG6

Figure S5S

M13C: TSPAN6

Figure S5T

M13C: ANGPT1

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Supplementary Figure 6: Module eigengene networks and comparisons between brain regions

Pearson correlation coefficients and corresponding p-values for all module eigengene (ME) comparisons in CTX (**a**), CTX_95 (**b**), CN (**c**), and CB (**d**). Red and green denote positive and negative correlations, respectively. MEs in each network were ordered to facilitate visual interpretation of the networks (Supplementary Methods). ME network comparisons between CTX and CN (**e**), CTX and CB (**f**), and CN and CB (**g**) were restricted to conserved modules and performed as described in Supplementary Methods.

Figure S6A

MIA

PMP

Correlation and p-values in CTX

PALLA

MB

County

Figure S6C

Correlation and p-values in CN

M33 M16C **N3A** 430 4490 4110 4110 4132 41180 41130 41190

M31

Figure S6D

Correlation and p-values in CB

Eigengene correlation in CN -1.0 M19 -1.0 $M₄$ M₅ -0.5 -0.5 M15 M11 -0.0 0.0 M₉ $M₁$ M13 -0.5 -0.5 M18 M16 -1.0 $M8$ **M15** MIS **41, 41,3 41,8 41,6 SA** M11 MA 129

Eigengene dendrogram

 -1.0

MB

Correlation preservation

Eigengene dendrogram

Correlation preservation

Eigengene dendrogram

Correlation preservation

M15	1	.48	.74	.74	.73	.88	90	98
M9	.48	J.	.81	.78	.78	95	.69	93
M11	.74	.81	♦	93	.86	.85	88	.77
M ₁	.74	.78	93	۹.	87	97	.88	94
M18	.73	.78	86	97	\mathbf{I}	98	94	98
M ₄	88	95	.85	97	98	1	.88	.83
M16	90	.69	.88	.88	94	.88	۹	93
M19	98	.93	.77	94	98	.83	93	٦
	MIS	MB	M11	My	MIS	MA	416	MIS

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Supplementary Figure 7: Relationships between modules in cortical networks are highly reproducible

Heat maps depicting Pearson correlation matrices (PCMs) of module eigengenes (MEs) for modules found in both CTX (**a**) and CTX 95 (b). Red and green denote positive and negative correlations, respectively. MEs in each network were ordered to facilitate visual interpretation of the networks (Supplementary Methods). (**c**) Correlation preservation for each pair of MEs (1 = perfect preservation; Supplementary Methods). (**d**) Average linkage hierarchical clustering of MEs based on the average of the PCMs depicted in (**a**) and (**b**). Three main clusters were evident in the consensus dendrogram, corresponding to modules that were primarily glial, synaptic/membranal, or neuronal in nature.

Figure S7

96 .74

.68

 94

.77

 $.82$

.86

.89

96

95 94

97 .86

.80 .79

 $.84$

MIB **MIT**

98 .83

.88

95

94

.73

 $.82$.86 $.91$

90

280

.80

92

98

90

.84

 $.63$

96 .86

93 .73

.77

98 .88

.83

 92

20 \mathbf{z}

.68

96 95

 96 94

 $M₄$ $.76$

 $M5$

M19 .73 97 $.87$

M₁₀ 94

M16

 $M8$.74

 $M18$

M17

 $.91$

 0_f

.89

 $.80$

MIS

.86

.80

98

94

95

MS

 $.87$

 $.80$

 91

 $.73$

94

97

.86 .79 $.91$

MIS

.73

98

.91 .73

.77

.73

.80

MIO MIG

Supplementary Methods

Michael C. Oldham, Steve Horvath, Genevieve Konopka, Kazuya Iwamoto, Peter Langfelder,

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Microarray data processing

Microarray data generated from control samples of human cerebral cortex, caudate nucleus, and cerebellum were gathered from nine published studies¹⁻⁹. Four datasets were assembled. Gene coexpression analyses are particularly sensitive to the presence of outlier samples and systematic biases in microarray data. Therefore, rigorous quality control procedures were implemented to ensure the highest possible level of quality for each dataset. First, non-specific and mis-targeted microarray probes were masked prior to generating expression values¹⁰. Second, outlier samples were identified and removed from each dataset. Third, data were normalized to eliminate systematic biases introduced by combining data from different studies ("batch effects")¹¹.

Prior to removal of outlier and duplicate samples, dataset 1 ("CTX") consisted of 104 samples from various cortical areas^{3,4,8}, dataset 2 ("CTX 95") consisted of 82 samples from various cortical areas^{1,2,5-7,9}, dataset 3 ("CN") consisted of 32 samples from the head of the caudate nucleus³, and dataset 4 ("CB") consisted of 27 samples from cerebellar hemisphere³. To eliminate non-specific and mis-targeted probes prior to generating expression values, mask files were obtained for both microarrays (http://masker.nci.nih.gov/ev/)¹⁰ and applied to the raw data using GCOSv1.2 or the R package "ProbeFilter" (http://arrayanalysis.mbni.med.umich.edu/MBNIUM.html#ProbeFilter)¹². After applying the mask files, only probe sets with at least seven (HG-U133A) or ten (HG-U95A/v2) remaining probes were retained for further analysis ($n = 18,631$ and $n = 10,553$, respectively).

 Expression values for CTX, CN, and CB were generated using GCOSv1.2. All arrays were scaled to the same average intensity (200). For CTX 95, expression values were generated in R using the "expresso" function of the "affy" package (http://www.bioconductor.org/)¹³ with "mas" settings and no normalization, followed by scaling of arrays to the same average intensity

(200). Scaled expression values were imported into R for outlier detection and removal prior to normalization. A detailed supplement containing all of the relevant R code and corresponding figure images that were used to guide our decisions to remove outlier samples in each of the four datasets analyzed in this study is available on our web page (http://www.genetics.ucla.edu/labs/horvath/CoexpressionNetwork/HumanBrainTranscriptome/). For each dataset, samples were correlated with one another using expression levels for all probe sets. These inter-array correlations (IACs) were averaged for each array and compared to the resulting distribution of IACs for the dataset. In general, samples with an average $IAC < 2.0$ standard deviations below the mean IAC for the dataset were removed. Samples were also hierarchically clustered using average linkage and 1-IAC as a distance metric to identify outliers. This process was repeated for each dataset until no outliers were evident. This approach constitutes an unbiased method for the identification and removal of samples with aberrant gene expression levels. In practice, such samples often possess long postmortem intervals or low pH values, which have been shown to alter the expression levels of certain classes of genes¹⁴. However, these variables are not perfect predictors of sample quality¹⁵, and in many cases the underlying causes of aberrant gene expression levels are unknown. The number of samples identified as outliers in each dataset was as follows: 14 (CTX), 36 (CTX 95), 5 (CN), and 3 (CB). Following outlier removal, technical replicates were averaged (CTX_95). For CTX, additional samples were removed to account for the fact that many samples from refs. 4,8 were taken from the same individuals. 23 pairs of such samples were identified; for each pair, the sample with the lower average IAC was removed from the dataset. These samples were removed from CTX to ensure a 1:1 ratio of samples to unique individuals for this dataset, which was also the case for CN and CB. However, an interesting biological question concerns the extent to

which gene coexpression patterns are preserved across cortical areas within the same individual. It would have been difficult to interpret the extent of such preservation in CTX had these samples been retained, since a) each unique individual would have been represented by no more than two cortical areas, and b) the effect of regional variability would have been confounded by potential batch effects. However, the composition of the dataset from ref. 6 presented a tractable opportunity to explore this question in CTX_95, as each individual from this study was represented by six cortical areas.

Following outlier removal, quantile normalization¹⁶ was performed for each dataset in R. Average linkage hierarchical clustering using 1-IAC as a distance metric revealed that most samples clustered by study (data not shown), indicating the presence of significant batch effects in the data. To eliminate batch effects, additional normalization was performed using the R package "ComBat" (http://statistics.byu.edu/johnson/ComBat/)¹¹ with default parameters. Within each dataset, each study was assigned a single batch number with the exception of ref. 3, which was assigned two batch numbers (samples from this study exhibited a batch effect that reflected country of origin [U.S. vs. New Zealand; data not shown]). ComBat successfully eliminated batch effects in each dataset as evidenced by hierarchical clustering and significant improvement of mean IAC (data not shown). Negative expression values introduced by ComBat $(-0.01\%$ of all expression values) were replaced with the median for the corresponding probe set.

 Following microarray data processing, CTX consisted of 67 samples from 67 individuals representing four cortical areas (mean inter-array correlation $[IAC] = 0.970$), CTX 95 consisted of 42 samples from 32 individuals representing six cortical areas (mean IAC = 0.975), CN consisted of 27 samples from 27 individuals (mean IAC = 0.972), and CB consisted of 24 samples from 24 individuals (mean $IAC = 0.975$). Combined, these datasets comprised 160 samples from 106 individuals (CTX, CN, and CB samples from ref. 3 often represented the same individual). Additional sample information can be found in Supplementary Table 1.

Choice of genes for network analysis

For each dataset, WGCNA was performed on all expressed genes. (Note: although some genes are represented by multiple probe sets and other probe sets are not fully annotated, for consistency we refer to probe sets as "genes" throughout the journal article, unless otherwise noted.) A gene was considered expressed if it was called "present" or "marginal" in at least half of all samples in a given dataset. In CTX, a gene was also considered expressed if it was called present or marginal in at least three quarters of all samples from one cortical area. Finally, genes that were consistently called present or marginal in either males or females were also included in the analysis. Present/marginal/absent calls were determined using GCOSv1.2 (CTX, CN, and CB) or the "mas5calls" function (Bioconductor "affy" package) in R (CTX_95). The total number of expressed probe sets in each dataset was as follows: 10,865 (CTX), 5,392 (CTX 95), 9,363 (CN), and 9,714 (CB). These "brain-expressed" probe sets are indicated in the "BE" column of Supplementary Tables 3-6 (1 = expressed, $0 =$ not expressed).

Weighted gene coexpression network construction and module detection

Several alternative network approaches have been proposed for analyzing microarray data¹⁷⁻²³. For example, graphical Gaussian models have been proposed for inferring gene association networks²⁴⁻²⁷. A comparison of these alternative methods is beyond the scope of this article, but will be important for future development of network approaches.

The use of weighted networks constitutes an improvement over unweighted networks produced by dichotomizing the Pearson correlation matrix, since a) the continuous nature of gene coexpression information is preserved, and b) the results of weighted network analyses are highly robust with respect to the choice of the parameter β (where connection strength = $|correlation|^{\beta}$), whereas unweighted networks display sensitivity to the choice of cutoff²⁸. Gene coexpression networks, like many other types of biological networks, have been found to exhibit an approximate scale-free topology²⁸⁻³⁰. Zhang and Horvath²⁸ proposed a scale-free topology criterion for choosing β. Here, a power of $β = 4$ was chosen for both CTX and CTX 95, while slightly higher powers were chosen for CN ($\beta = 6$) and CB ($\beta = 5$) due to the smaller sizes of these datasets.

Unlike correlation, which considers each pair of genes in isolation, topological overlap (TO) considers each pair of genes in relation to all other genes in the network. TO thus serves as a filter to exclude spurious or isolated connections during network construction (see Figures S1 and S2 from ref. 31). Due to the large number of genes analyzed, we performed an additional step to enrich each network with genes with high TO. A dynamic tree-cutting algorithm³² was used to "cut" each dendrogram and define an initial set of modules for each network (the minimum module size was arbitrarily set to ten probe sets). This algorithm uses the structure of a dendrogram to iteratively decompose and combine branches until the number of clusters stabilizes³². The density of the resulting modules (defined as the average intramodular TO) was compared to the density of modules of equivalent size selected randomly from the network ($n =$ 5,000 permutations). Density p-values were determined for each initial module by calculating the percentage of trials in which the density of the "random" modules exceeded the density of the initial module. Modules for which this p-value exceeded 0.01, along with genes that were not assigned to any initial modules, were removed from the network. This filter reduced the number of probe sets in each network to 5,549 (CTX), 3,203 (CTX_95), 4,050 (CN), and 4,029 (CB). Using only these probe sets, a new TO matrix was calculated for each network and average linkage hierarchical clustering was performed to group genes based upon the TO dissimilarity measure. The dynamic tree-cutting algorithm³² was again used to identify modules in each network. To ensure the consistency of coexpression patterns within modules, the algorithm was tuned to first identify small modules, which were then progressively merged based on similarities in gene expression profiles. To assess similarities in gene expression profiles, singular value decomposition $(X = UDV^T)$ was performed for all modules and the values of the module eigengenes, V_1 (i.e. the first principal components), were correlated with one another. In general, modules with highly correlated eigengenes (Pearson correlation >= 0.8) were merged. This process was performed iteratively until merging was no longer necessary. Small modules that consisted primarily of probe sets for a single gene (e.g. protocadherin, hemoglobin) were removed. Lastly, modules with a final density $P > 0.1$ (calculated as described above, but using random samples from the second [filtered] TO matrix instead of the first) were also removed. Genes belonging to each of the remaining modules were labeled by color (one color per module), while genes from modules that were removed and genes that were not assigned to modules were denoted with the color grey. Following these steps, the number of modules identified in each network was as follows: 19 (CTX), 17 (CTX 95), 23 (CN), and 22 (CB). Summaries of all modules are presented in Supplementary Figure 2.

Topological overlap of interacting protein pairs

To assess whether proteins that physically interact have higher TO in gene coexpression networks than proteins that do not, we downloaded a database of experimentally validated interacting protein pairs from EBI (European Bioinformatics Institute)/IntAct (http://www.ebi.ac.uk/intact/site/index.jsf)³³. Analysis was restricted to interacting human protein pairs for which both gene symbols were known. After excluding self-self and duplicate interacting pairs, a total of 17,540 interacting human protein pairs were obtained. Using the TO matrices for all expressed genes in CTX, CN, and CB, we calculated the mean TO of all interacting protein pairs for which both members were present in the matrix ($\text{CTX} = 5,980 \text{ pairs}$, $CN = 4,901$ pairs, and $CB = 5,347$ pairs). For genes represented by multiple probe sets, the average was taken. The mean TO for interacting protein pairs was then compared to the mean TO for randomly selected pairs of probe sets in each network ($n = 50,000$).

Module comparisons between networks

The overlap and corresponding significance for all pairwise comparisons of networks and modules can be found in Supplementary Table 2, and all of the information necessary for the calculation of the hypergeometric p-values can be found in Supplementary Tables 2-6. The "Module" column of Supplementary Tables 3-6 denotes the module assignments of all probe sets used to construct the networks depicted in Figure 1; probe sets that were not used for network construction are denoted by NA ("not available"). For example, 5,549 probe sets were used to construct the CTX network (Supplementary Table 3) and 4,050 probe sets were used to construct the CN network (Supplementary Table 5). Intersecting these lists identifies 2,542 probe sets common to CTX and CN network construction. Comparing M4 (purple), we find 30 probe sets

assigned to this module in CTX (Supplementary Table 3), 22 of which were represented among the probe sets used for CN network construction (Supplementary Table 5); in CN, we find 62 probe sets assigned to this module (Supplementary Table 5), 38 of which were represented among the probe sets used for CTX network construction (Supplementary Table 3). In total, 19 probe sets were shared in M4 between CTX and CN (Supplementary Table 2). The statistical significance of the reported overlap for this example corresponds to a one-sided p-value of 1.39e–34. After correcting for multiple comparisons, the adjusted p-value is 3.19e–33 (Supplementary Table 2).

Defining a measure of module membership (k_{ME})

In our study, we defined the module membership for each gene with respect to each module as the Pearson correlation between the expression level of the gene and the $ME³⁴$. This quantity, which we refer to here as k_{ME} , is a natural summary of the extent to which a gene conforms to the characteristic expression pattern of a module. However, we note that other summary measures are possible. One advantage of using the ME is that it satisfies an optimality criterion: by definition, it provides the best summary of variation in gene expression within a module. The ME also has an intuitive interpretation when it is juxtaposed with the more familiar "heat map" depicting the expression levels of genes within a module (Supplementary Figure 2). On the other hand, the ME is not a real gene; it is a centroid of a module. Because modules have varying extents of heterogeneity in gene expression, not all modules are represented equally well by the ME. Summaries of such modules may benefit from the use of additional components.

Module characterization

Modules were characterized using several complementary approaches. One primary approach involved cross-referencing gene sets describing pertinent cellular or functional phenotypes with module composition. Lists of genes known to be preferentially expressed in mouse oligodendrocytes, astrocytes, and neurons were obtained from Tables S4-S6 of ref. 35 and Table S1 of ref. 36. For data from ref. 35, analysis was restricted to genes with at least threefold enrichment in a given cell type. A third list of astrocyte markers was obtained from Table S7 of ref. 37, and a list of markers for Purkinje cells was obtained from Table 3 of ref. 38. We also generated a list of genes with increased expression in differentiated rat oligodendrocytes relative to oligodendrocyte precursors by analyzing data from ref. 39. Raw data (.CEL files) were obtained from Gene Expression Omnibus (http://www.ncbi.nlm.nih.gov/geo/query/acc.cgi?acc=GSE5940) for nine samples (five precursor, four differentiated) analyzed on Affymetrix, Inc. RAE230A microarrays. Data were imported into R and processed as described above but without probe masking or batch normalization. To identify differentially expressed (DE) genes, a Bayesian t-test was applied using the R package "bayesreg"⁴⁰ with the following parameters: betaFit = 1, bayes = TRUE, winSize = 101 , conf = 10 . Genes with higher expression in differentiated oligodendrocytes relative to oligodendrocyte precursors and a posterior probability of differential expression (PPDE) > 0.999 were used for cross-referencing. Similarly, lists of genes up-regulated in mouse glutamatergic cortical neurons, GABAergic cortical neurons, or layer 4-6 interneurons were obtained by analyzing data from ref. 41. Raw data (.CEL files) were obtained from Gene Expression Omnibus (http://www.ncbi.nlm.nih.gov/geo/query/acc.cgi?acc=GSE2882) for 42

samples analyzed on Affymetrix, Inc. MG-430A microarrays. Non-specific and mis-targeted probes were masked using the R package "ProbeFilter"12 prior to generation of expression values and normalization in R as described above (no batch normalization was necessary). DE genes were identified as described above. All comparisons were restricted to cortical neurons. For genes up-regulated in glutamatergic or GABAergic cortical neurons, PPDE > 0.999 was chosen as the threshold for differential expression. For genes up-regulated in layer 4–6 interneurons, a threshold of PPDE > 0.99 was chosen. For cross-referencing with the synaptic proteome, a list of proteins enriched in the post-synaptic density was obtained from the Genes2Cognition $Consortium^{42}$ (http://www.genes2cognition.org/cgi-

bin/browser?action=bydataset;proteomics id=psp_member;proteomics_value=Y), while a list of proteins enriched in synaptic vesicles and the pre-synaptic membrane compartment was obtained from ref. 43 (Tables 1 and 2). Finally, a list of genes with altered expression following ischemia and reperfusion in mouse hippocampus was obtained from Table 1 of ref. 44.

 Gene symbols were used as unique identifiers to cross-reference each set of genes with all modules in each network in an unbiased manner. For each module, these comparisons were restricted to genes with positive k_{ME} values ($P < 0.001$). The significance of module enrichment was assessed using Fisher's exact test (one-sided). To account for multiple comparisons, a Bonferroni correction was applied based upon the number of modules in the network. Complete cross-referencing results can be found in Supplementary Table 7.

 Another approach to module characterization involved searching for over-represented categorical systems using $EASE^{45}$ (p-values cited in the journal article refer to EASE scores from Supplementary Table 8). For module characterization using EASE, analysis was restricted for each module to genes with positive k_{ME} values ($P < 0.001$). Population files were comprised of

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probe sets retained following mask application ($n = 18,631$ [HG-U133A] and $n = 10,553$ [HG-U95A/v2]). All available categorical systems were searched. To control for multiple comparisons, the global false discovery rate (FDR) was calculated for all systems in each module (1000 iterations). Categorical systems with a global FDR \leq 0.05 were deemed significantly enriched and are reported in Supplementary Table 8.

Modules were also characterized by correlating MEs with available sample information such as age, gender, and cortical area (Supplementary Table 1). For example, to determine whether any MEs in CTX 95 were significantly correlated with expression in primary visual cortex, an indicator variable was created $(1 =$ primary visual cortex samples, $0 =$ all other samples). This indicator variable was then correlated (Pearson) with all MEs. A Bonferroni correction was applied based on the number of modules in the network. Finally, modules were also characterized through visual inspection using $VisANT^{46}$.

Module visualization

Visualizations of all modules from CTX, CN, and CB are presented in Supplementary Figure 4. For each module, pairwise TO values were calculated for the top 1% of all probe sets based on $|k_{\text{ME}}|$. A second filter was applied to select only those gene pairs for which both members exhibited higher $|k_{ME}|$ for the module in question than for any other module in the network. From this list, 150 pairs of genes with the greatest TO were depicted using VisANT (http://visant.bu.edu/)⁴⁶. The "Spring Embedded Relaxing" layout algorithm was used to confer partial network structures, which were then manually adjusted for clarity. In these visualizations, modular structure is defined by the connections between genes; distances are irrelevant. Genes with expression levels that were negatively correlated are connected by black lines; all other genes were positively correlated (except for the black module [M11], where red lines denote negative correlations). Numbers appended to gene symbols denote the $|k_{\text{ME}}|$ rank (i.e. RMM) for the corresponding probe set (some genes are represented by multiple probe sets). Genes with \ge = 20 depicted connections appear as large nodes, followed by genes with 10–19 connections that appear as medium nodes, followed by genes with < 10 connections that appear as small nodes.

Module eigengene network comparisons

To explore the higher-order structure of gene coexpression networks and the relationships between modules, module eigengene (ME) networks⁴⁷ were created. An ME network describes the relationships between modules based on the correlations between MEs^{47} . For each dataset, Pearson correlation coefficients were calculated for all pairwise comparisons of MEs. Comparisons of ME networks between datasets were restricted to conserved modules. Correlation preservation between MEs *I,J* in networks k_1 and k_2 was assessed using the following formula 47 :

$$
CP_{IJ}^{(k_1,k_2)} = 1 - \left(\begin{array}{c} \frac{|R_{IJ}^{(k_1)} - R_{IJ}^{(k_2)}|}{2} \end{array}\right) \tag{1}
$$

where $R^{(k)}$ _{*IJ*} is the ME Pearson correlation matrix for all conserved modules (labeled by indices *IJ*) in network k_1 , and similarly for network k_2 . In addition, average linkage hierarchical "consensus" clustering of eigengenes in ME networks k_1 and k_2 was performed using the following dissimilarity measure⁴⁷ (I, J) again label eigengenes):

$$
DM_{IJ}^{(k_1,k_2)} = 1 - \left(\begin{array}{c} R_{IJ}^{(k_1)} + R_{IJ}^{(k_2)} \\ 2 \end{array}\right) \tag{2}
$$

ME networks were depicted as heat maps using the "image.plot" function in R, with red corresponding to positive correlations and green corresponding to negative correlations (Supplementary Figure 6). To facilitate visual evaluation of ME network heat maps, MEs were ordered using average linkage hierarchical clustering with 1-correlation as the dissimilarity measure, followed by re-ordering of branches within the restrictions imposed by the dendrogram such that the correlation of adjacent MEs was maximized.

Comparisons of module membership (k_{ME}) between brain regions

Because k_{ME} is itself a correlation, comparisons of k_{ME} between networks (e.g. brain regions) is equivalent to assessing the significance of differences in correlations from samples of different sizes. To compare k_{ME} values for probe set *i* relative to module *j* in network k , we first normalized these values using the Fisher transformation:

$$
z_{ijk} = 0.5 * \log\left(\frac{1 + k_{ME_{ijk}}}{1 - k_{ME_{ijk}}}\right) \tag{3}
$$

For comparison between networks *k*1 and *k*2, the difference between the resulting z scores for probe set *i* relative to module *j* was divided by the joint standard error:

$$
zdiff = \frac{z_{ijk1} - z_{ijk2}}{\sqrt{1/(n_1 - 3) + 1/(n_2 - 3)}}
$$
(4)

where *zijk*1 and *zijk*2 represent the normalized correlations for probe set *i* relative to module *j* in network *k*1 and network *k*2, respectively, and n1 and n2 represent the sample sizes. This z-score was converted into a two-sided p-value based upon the normal distribution. These p-values and their corresponding z-scores are reported for all probe sets for all pairwise comparisons of conserved modules between CTX, CN, and CB in Supplementary Table 11, along with mean expression levels and differential expression (DE) p-values. To assess the significance of DE, scaled expression data from CTX, CN, and CB were pooled and normalized as described above. For batch normalization¹¹, samples from each study were assigned to a single batch, with tissue

(CTX, CN, or CB) designated as a covariate. DE p-values were calculated using a Bayesian ttest from the R package bayesreg⁴⁰ as described above.

Immunohistochemistry

Postmortem human brain tissue samples were obtained through the UCLA Pathology Department under the UCLA human subject guidelines. Individuals did not have evidence of neuropathological conditions and four of five patients died from non-CNS complications; the fifth patient died from a brain infarct that did not compromise the area of interest. Tissue was used from five individuals aged 51 to 81 y.o. The region of the subventricular zone at the head of the caudate was excised from formalin-fixed brain under the direction of a neuropathologist. Tissue was embedded in paraffin and sectioned at 7 μM intervals. Sections were rehydrated, boiled in citric acid buffer for antigen retrieval, and incubated in 0.3% hydrogen peroxide following standard procedures. Non-specific binding was blocked using PBS containing 5% milk, 0.2% triton-X, and 2% normal goat serum at room temperature for 1h. Tissue was incubated with primary antibody diluted in blocking solution at 4°C overnight. The following antibodies and dilutions were used: ALDH1L1 mouse monoclonal (Abcam, ab56777; 1:500), ASCL1 rabbit polyclonal (Abcam, ab38556; 1:50), CD24 mouse monoclonal (Abcam, ab19704; 1:100), connexin 43 (GJA1) rabbit polyclonal (Santa Cruz, sc-9059; 1:100), DPYSL3 rabbit polyclonal (Chemicon, AB5454; 1:1500), GFAP rabbit polyclonal (Dako, Z0334; 1:10,000), PLTP rabbit polyclonal (Abcam, ab18990; 1:100), neuronal class III beta-tubulin (TuJ1) mouse monoclonal (Covance, MMS-435P; 1:5000). Appropriate biotinylated secondary antibodies diluted in blocking solution were applied to slides for 1h at room temperature. The chromagens 3,3'-diaminobenzidine (DAB) or Vector® SG (Vector Laboratories) were used following the

manufacturer's instructions (Vector Laboratories, VECTASTAIN ABC kits). Substitution of either chromagen for each antibody gave similar results. Due to the availability of a mouse monoclonal antibody for CD24, double labeling was performed for CD24 together with ASCL1, GJA1, or PLTP. For double-labeling experiments, slides were processed with the first primary and secondary antibody and chromagen followed by the second primary and secondary antibody and contrasting chromagen. Hematoxylin staining was conducted following standard procedures after the blocking step. Most antibodies were used on two or more individuals and yielded similar expression patterns. Two different antibodies for CD24 and GJA1 gave similar results. Omission of primary antibody did not result in detectable staining.

Identification of candidate genes with expression patterns that distinguish SVZ astrocytes from mature astrocytes

To identify candidate genes with expression patterns that distinguish SVZ astrocytes from mature astrocytes, we calculated the difference in membership for M13C and M15C (MM_{diff}) for all genes in CN ($n = 18,631$). We limited our search to genes with strong membership for either module (MM > 0.7) and $|MM_{diff}| > 0.4$. For genes meeting these criteria with MM15C $>$ MM13C, we also required evidence of expression in astrocytes across brain regions (MM15 > 0.5 in CTX and CB). For genes meeting these criteria with $MM13C > MM15C$, we required evidence of absence of expression in astrocytes across brain regions (MM15 < 0.5 in CTX, CN, and CB).

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Supplementary Network Analysis - Illumina

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"Functional Organization of the Transcriptome in Human Brain"

Summary

To provide further validation for the reproducibility of gene coexpression relationships across individuals and microarray platforms, we applied weighted gene coexpression network analysis $(WGCNA)^1$ to a dataset ("CTX_ILMN") generated from human cerebral cortex samples using Illumina HumanRefseq-8 microarrays². The resulting gene coexpression network was compared with the "CTX" network, which was generated from human cerebral cortex samples using Affymetrix U133A microarrays and is described in detail in the journal article. A summary of these datasets is presented in Table 1.

Table 1: Summary of CTX_ILMN and CTX datasets. ^IAC = inter-array correlation. ^^Overlap = the percentage of unique gene symbols in a given network that were present in the other network.

In addition to the expected discrepancies in gene expression measurements introduced by differences in platform design between Illumina and Affymetrix microarrays, differences in the sample characteristics and representation of genes in the CTX ILMN and CTX datasets also presented substantial heterogeneity (Table 1). Despite this heterogeneity, a majority of gene coexpression modules identified in CTX in the journal article revealed significant evidence of overlap in CTX ILMN, and vice versa. We show that modules corresponding to the major cell classes of human cerebral cortex were present in CTX_ILMN, as they were in each of the four Affymetrix datasets analyzed in our study. Furthermore, we show that membership for the same modules was highly correlated between CTX and CTX_ILMN, as was the case for comparisons between CTX and CTX 95 (Fig. 3 from the journal article). These results are described below and provide additional evidence that conserved gene coexpression modules reflect consistent underlying sources of variation in microarray data generated from human cerebral cortex.

Microarray data processing

Because raw data from ref. 2 were unavailable, previously normalized expression values for 5,269 transcripts that were detected in all 193 samples of the original study (and therefore had no missing values) were used as the starting point for this analysis (National Center for Biotechnology Gene Expression Omnibus: accession code GSE8919). Beginning with these data, outlier samples in CTX ILMN ($n = 34$) were identified and removed. A detailed supplement containing all of the relevant R code and corresponding figure images that were used to guide our decisions to remove outlier samples in this dataset is available on our web page (http://www.genetics.ucla.edu/labs/horvath/CoexpressionNetwork/HumanBrainTranscriptome/). Briefly, inter-array correlations (IACs) were calculated by correlating samples with one another using expression levels for all 5,269 probe sets. Samples were hierarchically clustered using average linkage and 1-IAC as a distance metric to identify outliers. IACs were also averaged for each array and compared to the resulting distribution of IACs for the dataset, and samples with low average IACs relative to the distribution were removed. This approach constitutes an unbiased method for the identification and removal of samples with aberrant gene expression levels. Following outlier removal, quantile normalization³ was performed in R, resulting in a mean IAC of 0.943 for CTX ILMN. Because raw data from ref. 2 were unavailable, no batch normalization was performed.

Weighted gene coexpression network construction and module detection

WGCNA was applied to CTX ILMN using $\beta = 6$ as described in the journal article (Methods). A single topological overlap (TO) matrix (5,269 x 5,269) was constructed for CTX_ILMN and average linkage hierarchical clustering was performed to group genes based upon the TO dissimilarity measure. Using a dynamic tree-cutting method⁴, 28 gene coexpression modules were identified (Fig. 1).

Figure 1: Illumina human cerebral cortex (CTX_ILMN) gene coexpression network. Dendrogram produced by average linkage hierarchical clustering of genes based upon topological overlap (see Methods from journal article). 28 modules of coexpressed genes in CTX_ILMN were assigned colors as indicated by the horizontal bar beneath the dendrogram. Modules with the most significant overlap between CTX_ILMN and CTX (corrected hypergeometric p-value < 0.05) were assigned the same colors and numbers as in the CTX network, with asterisks denoting modules with less significant overlap. CTX_ILMN consists of data from Illumina HumanRefseq-8 microarrays measuring expression levels in 159 human cortical samples with 5,269 probe sets.

Cross-platform validation of gene coexpression relationships

To determine whether modules from CTX and CTX_ILMN were composed of the same genes, we calculated the overlap and corresponding hypergeometric probability for each possible pair of modules in the two networks (using gene symbols as unique identifiers; see Methods from the journal article). As seen in Figure 2, a majority of gene coexpression modules identified in CTX revealed significant overlap with modules identified in CTX_ILMN, with seven of these modules showing > 50% overlap.

Figure 2: Gene coexpression modules in human cerebral cortex are preserved across individuals and microarray platforms. Comparison of the 19 gene coexpression modules identified in CTX with modules identified in CTX_ILMN. Modules with significant overlap (corrected hypergeometric p-value < 0.05) are depicted by horizontal colored bars. For example, M1 did not show significant overlap between CTX and CTX_ILMN, but M2 overlapped 71% with a module found in \overline{CTX} ILMN ($P = 5.9e-09$). Numbers in parentheses at right indicate the maximum possible number of shared genes per pair of modules (i.e. the denominator used to calculate percent overlap). NS = not significant.

 Module membership values were calculated for all genes relative to all modules in CTX_ILMN as described in the journal article (Methods). To explore the reproducibility of module membership for individual genes between CTX and CTX_ILMN, we directly compared this quantity between the two networks for conserved modules (Fig. 3).

Figure 3: Module membership in human cerebral cortex is highly correlated across individuals and microarray platforms. Comparison of module membership (MM) between CTX and CTX_ILMN for M9 (left), M15 (middle), and M16 (right). For each module, the correlation (Spearman) between MM for CTX and CTX_ILMN was assessed. MM was correlated for the intersection of all genes used to construct the CTX and CTX ILMN networks (1,598 genes).

As we observed in comparisons between Affymetrix microarray platforms (U133A $[CTX]$ vs U95A/v2 $[CTX 95]$; Fig. 3 from the journal article), module membership in human cerebral cortex was remarkably consistent between Affymetrix U133A (CTX) and Illumina HumanRefseq-8 (CTX ILMN) microarray platforms (M9: rho = 0.65 , $P = 1.6e-191$; M15: rho = 0.73, $P = 5.0e-264$; M16: rho = 0.61, $P = 3.0e-162$; Fig. 3), despite substantial heterogeneity between these datasets (Table 1). These results validate the reproducibility of module membership values for individual genes and indicate that conserved gene coexpression modules reflect consistent underlying sources of variation in microarray data generated from human cerebral cortex.

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Supplementary Note

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"Functional Organization of the Transcriptome in Human Brain"

Additional module characterization

Gene coexpression modules were characterized using five complementary approaches, as described in the journal article. To normalize comparisons across networks, module membership is reported below in terms of its rank $(RMM = rank |module | membrane)$. We focused primarily on characterizing modules with evidence of significant overlap across networks, but also characterized some modules found in only one network.

Interneurons: M6A, M23, M17

We observed that *PVALB*, a canonical marker of interneurons, exhibited strong membership for M6A (RMM = 8, *P* = 5.3e–15; Supplementary Table 3), M17A (RMM = 105, *P* = 2.0e–06; Supplementary Table 3), M17B (RMM = 4, $P = 1.5e-11$; Supplementary Table 4), and M23 (RMM = 17, $P = 3.2e-07$; Supplementary Table 4). These observations suggested that these modules might distinguish genes that are preferentially expressed in *PVALB*+ interneurons relative to other cell types in cerebral cortex. The two strongest members of M6A were *NEFH* and *VAMP1* (Supplementary Table 3 and Supplementary Fig. 4f), both of which were expressed significantly higher in a *PVALB*+ interneuron relative to pyramidal neurons in a single-cell microarray analysis of rat hippocampal $CA1¹$. Using raw data from ref. 2, we identified genes with higher expression in layer 4–6 interneurons relative to other neuronal cell types isolated from adult mouse forebrain. Both M6A ($P = 7.7e-03$) and M23 ($P = 8.7e-04$) were significantly enriched with genes from this list (Supplementary Table 7). Genes in M23 also showed increased expression in primary visual cortex relative to other cortical areas ($r = 0.57$, $P = 1.3e-$ 03; Supplementary Fig. 2y), as did genes in M17B ($r = 0.71$, $P = 2.5e-06$; Supplementary Fig. 2w). Collectively, these data support the conclusion that gene coexpression in these modules reflects the relative abundance of certain classes of *PVALB*+ interneurons in samples from different cortical areas.

Purkinje neurons: M6D

M6A also showed significant overlap with a module identified in cerebellum (M6D; Supplementary Table 2). The strongest members of M6D were *PVALB* and *CALB1* (Supplementary Table 6 and Supplementary Fig. 4as), both of which are highly expressed in Purkinje neurons in cerebellum³. These observations suggested that M6D might consist of genes that are preferentially expressed in Purkinje neurons relative to other cell types in cerebellum. Consistent with this hypothesis, Purkinje cell protein 4 (*PCP4*), considered a marker for Purkinje neurons, also exhibited strong membership for M6D (RMM = 9, *P* = 5.9e–09; Supplementary Table 6 and Supplementary Fig. 4as). *In situ* hybridization (ISH) data from adult mouse brain revealed elevated and often exclusive expression in Purkinje neurons for nine out of ten genes with the strongest membership for this module (Supplementary Fig. 5a–j). We also obtained a list of genes expressed in Purkinje neurons with significantly reduced expression levels in cerebella from Purkinje cell degeneration (pcd^{3J}) mice relative to wild-type littermates⁴. M6D was highly enriched with these genes $(P = 6.1e-23,$ Supplementary Table 7). These results indicate that M6D is comprised of genes that are preferentially expressed in Purkinje neurons relative to other cell types in cerebellum.

Microglia: M4, M5

EASE indicated that the gene ontology (GO) biological process "immune response" was significantly over-represented in M4 ($P = 2.6e-56$ [CTX]; $P = 8.4e-09$ [CTX_95]; $P = 1.3e-24$ [CN]; *P* = 1.5e–11 [CB]), along with numerous related categories such as "defense response", "response to wounding", and "response to stress" (Supplementary Table 8). Among those genes with the strongest membership for M4A were several members of the major histocompatibility class II complex, including *HLA-DRA*, *HLA-DPA1*, and *HLA-DMA*, as well as several members of the classical complement pathway, including *C1QA*, *C1QB*, and *C3* (Supplementary Table 3 and Supplementary Fig. 4d). In the brain, expression of these genes reflects the activation of microglia, the resident immune cells of the central nervous system⁵. M5 was also enriched for genes involved in the GO biological process "immune response" (*P* = 9.8e–42 [CTX]; *P* = 5.6e– 11 [CTX 95]; $P = 4.7e-04$ [CN]), as well as numerous related categories (Supplementary Table 8). Expression levels of many genes with strong membership for M5A have been shown to increase significantly in microglia in response to activation with interferon-gamma⁶, including *PSMB9*, *SERPING1*, *STAT1*, and *CASP1* (Supplementary Table 3). These data indicate that coexpression in M5, like M4, likely reflects activation of microglia in response to an immunogenic event. Consistent with this interpretation, coexpression in these modules was driven by a small number of individuals, some of who were represented by multiple brain regions (e.g. H46 in Supplementary Fig. 2d,al,bt), suggesting a global neuroimmunological response possibly related to cause of death.

Meningeal cells: M43

We observed that M43 was significantly enriched with genes encoding structural molecules ($P =$ 9.1e–05), cell adhesion molecules (*P* = 3.7e–04), and components of the extracellular matrix (*P* $= 1.5e-06$) (Supplementary Table 8). In the cerebellum, meningeal cells are known to produce many components of the interstitial matrix and basement membrane⁷, including fibronectin, which possessed the strongest membership of any gene for this module (Supplementary Fig. 4bh and Supplementary Table 6). Many other genes with strong membership for M43 are known to be highly expressed in meningeal cells, including *PTGDS*⁸, *VIM*⁹, and *BGN*¹⁰ (Supplementary Table 6). Other genes that encode components of the extracellular matrix and exhibited strong membership for M43 included *DCN*, *MGP*, *COL6A2*, *DSP*, *FBLN1*, *FBLN5*, *COL18A1*, and *COL6A3* (Supplementary Tables 6 and 8). These data suggest that M43 consists of genes that are preferentially expressed in meningeal cells relative to other cell types in cerebellum.

Hypoxia: M12

We observed that many of the genes with the strongest membership for M12A encode transcription factors and immediate early genes, including *FOS*, *JUN*, *JUNB*, *MAFF*, and *FOSB* (Supplementary Table 3). EASE confirmed that the GO category "transcription regulator activity" was significantly over-represented in M12 for both CTX ($P = 5.8e-07$) and CB ($P =$ 4.1e–03) (Supplementary Table 8). In addition, EASE identified a BBID pathway¹¹ related to brain ischemia as significantly over-represented in M12 for CTX ($P = 1.3e-04$) and CB ($P =$ 9.7e–06) (Supplementary Table 8). Like M4 and M5, coexpression in M12 was driven by a small number of individuals (Supplementary Fig. 2l,bi). These observations suggested that coexpression in this module might represent a CNS transcriptional response to hypoxia. To test this hypothesis, we obtained a list of genes with altered expression levels following ischemia and reperfusion in mouse hippocampus¹². M12 was significantly enriched with genes from this list in both CTX ($P = 5.6e-13$) and CB ($P = 2.3e-08$) (Supplementary Table 7). These results provide evidence that coexpression in M12 reflects a response to hypoxia in the human brain.

Gender: M1

We observed that M1 was highly enriched with genes from chromosome Y in CTX ($P = 4.8e-$ 21), CN ($P = 4.8e-16$), and CB ($P = 7.4e-19$) (Supplementary Table 8). Among the genes with the strongest membership for M1 was *XIST*, which is expressed in females and mediates X chromosome inactivation¹³. This gene was negatively correlated with the ME for M1 in all brain regions (Supplementary Tables 3, 5, and 6). These observations suggested that M1 might distinguish genes that are differentially expressed between male and female brains. To test this hypothesis, we correlated the ME for M1 with gender status for all samples from each brain region. Gender status was highly correlated with the ME for M1 in CTX ($r = 0.93$, $P < 2.2e-16$), CN ($r = 0.94$, $P = 2.2e-13$), and CB ($r = 0.98$, $P < 2.2e-16$). These results indicate that coexpression in M1 reflects differences in gene expression between male and female brains. Interestingly, *CD24*, which exhibited extremely strong membership for M13 in CN and CTX, also possessed strong membership for M1 in cerebellum (RMM = 4 , $P = 2.3e-14$; Supplementary Table 6). Expression of this gene in CB was significantly higher in the brains of males compared to females (Supplementary Fig. 2bh). Although most of the genes with the strongest membership for M1 are located on the sex chromosomes, some autosomal genes also revealed strong membership for this module. In CN, these included the glucocorticoid receptor *NR3C1* and the progesterone receptor subunit *PGRMC2* (Supplementary Table 5), both of which were expressed higher in males.

Synaptic function: M10, M14

We observed that M10A was highly enriched with genes encoding synaptic proteins ($P = 5.3e-$ 18 and $P = 6.9e-12$), neuronal markers ($P = 9.8e-06$), and genes up-regulated in glutamatergic cortical neurons ($p = 1.1e-06$) (Supplementary Table 7). A similar pattern was observed for M10B and M10D, including enrichment of genes encoding synaptic proteins (M10B and M10D) and genes up-regulated in glutamatergic cortical neurons (M10B) (Supplementary Table 7). Consistent with these observations, EASE identified numerous over-represented categories in M10 related to synaptic function, including "synaptic vesicle" ($P = 2.4e-07$), "synapse" ($P =$ 1.9e–05), and "transmission of nerve impulse" $(P = 1.7e-03)$ (Supplementary Table 8). These results support the conclusion that gene coexpression in M10 is related to glutamatergic synaptic function. Interestingly, *DICER1* exhibited very strong membership for M10A, but was negatively correlated with the ME for this module (Supplementary Table 3 and Supplementary Fig. 4j), suggesting a link between RNA interference¹⁴ and glutamatergic synaptic function in cerebral cortex.

Analysis of M14A also revealed enrichment for genes encoding synaptic proteins ($P =$ 1.6e–20 and $P = 1.1e-13$, neuronal markers ($P = 2.2e-08$), and genes up-regulated in glutamatergic cortical neurons ($P = 1.1e-09$), while M14D also exhibited significant enrichment for synaptic proteins $(P = 1.2e-03)$ (Supplementary Table 7). EASE identified enrichment in M14 for numerous categories related to synaptic function, including "transmission of nerve impulse" ($P = 4.4e-12$), "synaptic transmission" ($P = 2.0e-11$), and "synaptic vesicle" ($P = 1.9e-$

05) (Supplementary Table 8). These results support the conclusion that gene coexpression in M14 is also related to glutamatergic synaptic function. Although M10 and M14 possessed similar characteristics, some functional distinctions between these modules were evident. For example, M10, but not M14, contained numerous over-represented EASE categories related to calcium channel activity, while M14 was enriched with many more EASE categories pertaining to signal transduction than M10 (Supplementary Table 8).

Organellar composition and function: M7, M2

We observed that M7 was highly enriched with genes comprising the GO cellular compartment "mitochondrion" for both CTX ($P = 2.0e-16$) and CB ($P = 4.4e-07$) (Supplementary Table 8). Other over-represented categories identified by EASE for M7 included "hydrogen ion transporter activity" ($P = 2.2e-20$ [CTX] and $P = 2.7e-11$ [CB]), "electron transport chain" ($P = 5.5e-17$ [CTX] and $P = 7.2e-10$ [CB]), "oxidative phosphorylation" ($P = 9.8e-16$ [CTX] and $P = 2.3e-16$ 09 [CB]), and "energy metabolism" ($P = 4.7e-11$ [CTX] and $P = 5.0e-07$ [CB]) (Supplementary Table 8). Genes with strong membership for M7A included many components of the electron transport chain, including *NDUFA2*, *COX6B1*, *NDUFA13*, *COX5B*, *NDUFS8*, *ATP5H*, *NDUFB2*, *ATP5G1*, and *NDUFA7* (Supplementary Tables 3 and 8). These results provide evidence that gene coexpression in M7 is related to mitochondrial function in the human brain. Interestingly, *AQP4*, which encodes a water-specific channel important for the regulation of cell volume¹⁵, was strongly negatively correlated with the ME for M7A (Supplementary Table 3 and Supplementary Fig. 4g), providing a previously unrecognized link between osmoregulation and energy metabolism in cerebral cortex.

EASE results indicated that another module, M2, was highly enriched with genes encoding ribosomal subunits (*P* = 2.3e–64) and elements of the KEGG pathway "translation" (*P* $= 7.6e-48$) (Supplementary Table 8). Although most of the genes with the strongest membership for this module encode known structural constituents of the ribosome, for some (e.g. *C6orf49* and *C10orf116*; Supplementary Table 3), association with this structure has not been previously described. The strong coexpression of these genes with so many components of the ribosome suggests that they are likely to be intimately involved with the function of this macromolecular complex and the process of translation.

Genomic clustering of coexpressed genes

EASE analysis revealed that for both CTX and CTX_95, the most significant over-represented category for M10, which was highly enriched with genes involved in glutamatergic synaptic function (see above), was chromosome 19 ($P = 3.2e-18$ [CTX] and $P = 1.2e-14$ [CTX_95]; Supplementary Table 8). Significant enrichment was also observed for M10 on chromosome 16 $(P = 4.2e-07$ [CTX] and $P = 3.0e-03$ [CTX_95]) and chromosome 22 ($P = 1.1e-04$ [CTX] and P $= 1.2e-02$ [CTX_95]) (Supplementary Table 8). Another module that was highly enriched with genes involved in glutamatergic synaptic function (M14A; see above) also showed significant enrichment for genes found on the same chromosomes (chromosome 16: $P = 3.2e-04$; chromosome 22: $P = 3.3e-03$; chromosome 19: $P = 7.2e-03$; Supplementary Table 8). These data provide evidence for genomic clustering of coexpressed genes related to glutamatergic synaptic function in human cerebral cortex.

We observed that modules related to ribosomal and mitochondrial function (M2 and M7) were also enriched with genes encoding synaptic proteins $(P = 5.5e-12 \text{ [M2]}$ and $P = 2.8e-12$ [M7A]; Supplementary Table 7). Like M10, these modules also showed significant enrichment for genes found on chromosome 19 ($P = 4.3e-09$ [M2] and $P = 4.3e-12$ [M7A]) and chromosome 16 ($P = 8.9e-07$ [M7A]) (Supplementary Table 8). These results provide evidence for the existence of coordinated transcriptional programs in human cerebral cortex underlying synaptic function, energy metabolism, and protein synthesis. Furthermore, our data indicate that this coordination may have resulted in part from genomic clustering of functionally related genes on chromosomes 16 and 19.

Generation of novel functional hypotheses regarding human disease genes on the basis of module membership

The characterization of gene coexpression modules provides an opportunity to generate novel functional hypotheses for thousands of genes expressed in the human brain, including genes involved in neurological or neuropsychiatric disease, through the principle of "guilt-byassociation". For example, in CTX, *FMR1* exhibited extremely strong membership for M17A (RMM = 11, *P* = 1.3e–10; Supplementary Table 3), a module with characteristics of *PVALB+* interneurons. This observation predicts that disruption of this gene, which results in fragile X mental retardation syndrome¹⁶, should preferentially affect the function of this neuronal subtype in the adult human brain. Interestingly, a recent study identified major deficits in neocortical GABAergic inhibitory circuits in a mouse model of fragile X syndrome¹⁷. Specifically, this study found a 20% reduction in the density of *PVALB*+ interneurons in somatosensory cortex of mutant mice relative to wild-type mice¹⁷. Similarly, *SCN1B*, which encodes an auxiliary subunit of voltage-gated sodium channels and has been linked to generalized epilepsy with febrile seizures¹⁸, exhibited extremely strong membership in CTX for M6A (RMM = 4, $P < 2.2e-16$; Supplementary Table 3), another module with characteristics of *PVALB*+ interneurons. The protein encoded by this gene interacts with pore-forming subunits of voltage-gated sodium channels such as SCN1A, which has also been linked to generalized epilepsy with febrile seizures¹⁸. Recently, expression of *SCN1A* was localized to the axon initial segments of $PVALB$ + interneurons in mouse neocortex¹⁹. Like *SCN1B*, *SCN1A* also exhibited strong membership for M6A (RMM = 67 , $P = 9.3e-06$; Supplementary Table 3). Collectively, these observations predict that the epileptic phenotype associated with disruption of *SCN1B* may be mediated by altered neurotransmission in *PVALB*+ interneurons. These examples illustrate how gene coexpression patterns within tissues can be used to generate novel functional hypotheses related to human disease genes.

Sources of sample variation in cell quantity

It is interesting to speculate on the potential sources of variation that may influence the quantities of specific cell types in different samples of brain tissue. This variation may be influenced by technical factors. For example, although samples analyzed in this study were extracted from gray matter, it is easy to imagine how different dissections might inadvertently introduce varying amounts of white matter "contamination". A sample with relatively more white matter should exhibit a spike in the expression of oligodendrocyte-related genes, perhaps similar to that seen in individual H74 in M9D (Supplementary Fig. 2ca). Because this spike applies to only a small subset of genes on the microarray, this sample was not identified as an outlier when considering all expressed genes. However, in an analysis of differential expression between two groups, asymmetric representation of such samples might erroneously suggest functional differences where none exist. Biological factors are also likely to contribute to differences in cell quantity between samples. For example, the relative densities of certain cell types in the brain may differ between individuals^{20,21}. In CTX_95 (the only dataset that included multiple samples from the same individual), expression of genes in M15B was relatively constant in cortical areas from the same individual when compared to cortical areas from different individuals (Supplementary Fig. 2ae). This observation is consistent with a role for biological factors in determining the number of astrocytes that are present in cortical samples.

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