SI Appendix

Inter-sample similarity/distance measures

The gene sets used in this paper are given in Supplementary Tables and described in Supplementary Materials. The distance measures used in this paper were:

- 1) **Similarity by SNAs** inner (dot) product of per-gene indicator vectors (1=impacted by nonsynonymous SNA, 0=not impacted).
- 2) **Similarity by CNAs** inner (dot) product of per-gene thresholded GISTIC scores (-2=homozygous loss, -1=single copy loss, +1=single copy gain, +2=multi-copy amplification).
- 3) **Joint similarity by SNAs and CNAs** sum of the *normalized* genome-wide SNA and CNA similarity scores such that the sum of all SNA scores equals the sum of all CNA scores, equals 1.
- 4) **Similarity by expression and CNA combined** inner product of per-gene expression Z-scores & thresholded GISITC scores (as defined in (2) above).
- 5) **G-CIMP DNA methylation probes** In 2010, a TCGA publication by Noushmehr et al (Cancer Cell. 2010 May 18;17(5):510-22) identified 1503 Illumina Infinium 27K array classifier probes that reliably identified hyper-methylated (G-CIMP) samples. We used 1444 of these probes, which had an exact match to the probe names in our Infinium 450K DNA methylation array data.
- 6) **Correlated methylation and expression** We used the Bioconductor package "FDb.InfiniumMethylation.hg19" [\(http://bioconductor.org/packages/release/data/annotation/html/FDb.InfiniumMethylation.hg1](http://bioconductor.org/packages/release/data/annotation/html/FDb.InfiniumMethylation.hg19.html) [9.html\)](http://bioconductor.org/packages/release/data/annotation/html/FDb.InfiniumMethylation.hg19.html) to identify CpG island probes within 2Kbp upstream of the transcription start sites of genes. Among these probes, we selected the top 8000 probes with the greatest Median Absolute Deviation. Probe beta values were averaged on a per gene basis and then used to calculate Spearman's rank correlation as a measure of sample similarity.
- 7) **Expression of stemness marker genes** We used Manhattan distance (p=1 Minkowki distance).
- 8) **Expression of metabolic genes** Sample similarities for the selected genes were visualized using Principle Component Analysis (PCA).
- 9) **Immune gene expression** We performed Single Sample Gene Set Enrichment Analysis (ssGSEA, Bioconductor package [http://www.bioconductor.org/packages/release/bioc/html/GSVA.html\)](http://www.bioconductor.org/packages/release/bioc/html/GSVA.html) using the 1910 gene sets from C7 collection of the MSigDB database [\(http://www.broadinstitute.org/gsea/msigdb/collections.jsp\)](http://www.broadinstitute.org/gsea/msigdb/collections.jsp). The Manhattan distances of the ssGSEA score matrices were used as input to MDS.

Calculation of approximate p-values for detected sample clusters

We performed permutation-based tests to assess if visually identified sample clusters are significantly clustered compared to the rest of the samples. Briefly, for each identified cluster, we compute all pairwise distances within the cluster. Additionally, we compute all pairwise distances for all genes outside of the cluster. Then, we evaluate if these two sets of distances are statistically different from each other by computing a Z-score. Since pairwise distances are correlated, such Z-scores do not have any known statistical properties which can be used to derive a p-value. Hence, 10,000 permutations of the plot data are created under the null hypothesis, and are used to create a distribution of Z-scores.

The observed distance is then compared to null distribution to produce a p-value. For brevity, in Supplementary Materials, we refer to this measure of cluster significance as the "Within Clusters" comparison. Note that the computed p-value is an approximation and quantifies the strength of the visually observed clusters, since creating "clustering patterns by visualization" under the null is nearly impossible.

One potential weakness associated with the above measure is that it may fail to flag a user-selected cluster as significant if the samples outside the selected cluster are also tightly bunched together, resulting in comparable within-cluster distances for the selected cluster and control samples. To address this issue, we introduce a complementary measure: the difference between within-cluster distances for the selected cluster and the distances between every member of the selected cluster and every sample outside of the cluster. For brevity, in Supplementary Materials, we refer to this measure of cluster significance as the "Between Clusters" comparison. Again, we use a permutation strategy to compute an observed Z-score and a Z-score distribution for the null hypothesis.

For all of the eight clusters delineated in Figure 3, the observed Z-scores are well outside of their null distributions, and hence their p-values are below the low bound of the permutation exercise, i.e., 1/10000.

Differential expression/ methylation analysis

Differential expression analysis was performed with the Bioconductor package 'limma' [\(http://bioconductor.org/packages/release/bioc/html/limma.html\)](http://bioconductor.org/packages/release/bioc/html/limma.html) using the batch-effect corrected RNA-seq data. Differential methylation analysis was performed with the Bioconducto package 'DMRcate' ([http://www.bioconductor.org/packages/release/bioc/html/DMRcate.html\)](http://www.bioconductor.org/packages/release/bioc/html/DMRcate.html) using batcheffect corrected probe values. We found 1,808 differentially expressed genes and 620 differentially methylated regions containing 11,127 probes across 658 genes.

Supplementary Materials

Motivation for sample similarity plots

The millions of molecular data points (per patient) that are generated with high-throughput sequencing, array platforms, and proteomics, make brute-force, statistical, machine-learning, and other commonlyused 'unbiased' methods for discovering patient groups extremely inefficient. This limitation is fundamental. With only two dimensions (measurements), unsupervised clustering algorithms can identify distinct patient groups fairly reliably. But the efficiency of unsupervised clustering drops precipitously as the number of measurements grows, for the following reasons:

(1) Improvements in resolution when we measure multiple genes per patient only grow as the square root of the number of measurements. For example, measuring the expression level of 10,000 genes (instead of one) can increase the straight-line distance among samples in a scatter plot at most 100-fold. The figures below visually demonstrate this property for 1, 2 and 3 dimensions (measured values).

A remarkable consequence of this effect is that the distance difference between the nearest and farthest neighbors in a scatter plot shrinks as the number of dimensions (biomarkers) increases, thus making unambiguous assignment of points to clusters difficult and error prone.

Expert-guided Visual Exploration (EVE) addresses this challenge by relying on human visual pattern recognition capabilities, both when detecting sample clusters in 2 or 3D plots, and in selecting parameters for automated sample clustering.

- (2) Clustering relies on calculating similarity distances among samples. The efficiency of computing distances falls with the number of measurements made. Measuring sample distances across millions of dimensions – as is the case for genomic medicine – becomes prohibitive for $>0(1000)$ patients.
- (3) As the number of measurements (N) increases, a larger fraction of the possible biomarker values for any given sample will be "tucked away" in the corners of an N-dimensional scatter plot. In other words, high-dimensional data is inherently fragmented. This fragmentation makes it difficult to identify subsets of biomarker groups that cluster patients in biologically meaningful ways.

The above effect is illustrated in the figures below. With only two measurements (left panel), the area of the largest circle inside the 2D box of all possible biomarker values covers more than 78% of the total area of the box. Thus, if all measured values were distributed uniformly across

samples, more than 78% of the patients would fall inside this 'central' circle. With three biomarkers, the area of the largest sphere contained in the 3D cube of all possible biomarker combinations is only ~52% of the volume of the cube (right panel). For 10 biomarkers, this fraction becomes less than 2.5% of the measurement space. Thus when millions of molecular species are measured, there are virtually no 'average' patients; everybody is 'special' in some way (dimension), which makes clustering difficult.

EVE circumvents this challenge by relying on the domain-knowledge of expert users to nominate candidate gene/probes sets for delineation of specific sample subtypes.

(4) The common approach of combining measurements of different biomolecular entities (e.g. gene mutations and DNA-methylation probe β -values) into a single measure of similarity/distance among samples is problematic because in biology we do not currently have 'laws' governing the relationships among different measurable quantities (cf. volume and pressure, or energy, mass, and displacement in physics). To overcome this issue, clustering of biomarkers is often performed for one data type at a time, but then integration across multiple measurements is performed in arbitrary ways.

Because EVE allows users to select from among multiple methods, measures, and parameters, users can interactively explore the relative merits of different approaches to combining data types.

(5) Automated (statistical/algorithmic) clustering methods come in many flavors, each with its own limitations, such as sensitivity to outliers, inability to detect concave clusters, or using approximations that may not hold in some cases.

EVE provides a flexible framework in which users can explore the effect of changes in cluster methods, distance measures, etc.

Supplementary Figures

Supplementary Figure 1. Multiple subsets of genome-wide methylation probes unambiguously divide TCGA glioma samples into CIMP and non-CIMP groups. (a) Using the published 1503 CIMP classifier probes, the samples divide sharply into two groups: CIMP (red) and non-CIMP (blue). (b) Sample similarity using all probes located in gene bodies. Samples are colored according to panel (a). (c) Sample similarity using all probes located in promoters (defined as within 1000bp of transcription start sites). Samples are colored according to panel (a). (d) Sample similarity using only the 80000 most variable probes across all samples. Samples are colored according to panel (a).

Supplementary Figure 2(a). Approximately computed P-values for cluster 1 of Figure 3.

Within Clusters (p<1E-4)

Supplementary Figure 2(b). Approximately computed P-values for cluster 2 of Figure 3.

Supplementary Figure 2(c). Approximately computed P-values for cluster 3 of Figure 3.

Supplementary Figure 2(d). Approximately computed P-values for cluster 4 of Figure 3.

Within Clusters (p<1E-4)

Supplementary Figure 2(e). Approximately computed P-values for cluster 5 of Figure 3.

Supplementary Figure 2(f). Approximately computed P-values for cluster 6 of Figure 3.

Within Clusters (p<1E-4)

Supplementary Figure 2(g). Approximately computed P-values for cluster 7 of Figure 3.

Within Clusters (p<1E-4)

Supplementary Figure 2(h). Approximately computed P-values for cluster 8 of Figure 3.

Within Clusters (p<1E-4)

Supplementary Figure 3, The TCGA GBM expression subtypes are not regionally distributed in our genomic sample-similarity plot. The units of the horizontal and vertical axes are arbitrary.

Supplementary Figure 4. The distribution of tumor grades in the SNA/CNA sample similarity plot. The units of the horizontal and vertical axes are arbitrary.

Supplementary Figure 5. The proliferation markers MKI67 and PCNA are not regionally distributed in the SNA.CNA sample similarity plot, in contrast to similarity by stemness marker gene expression. Expression levels were divided into 3 quatiles and colored differentially for ease of visualization.

Supplementary Figure 6. Sample placement on the sample similarity plot is robust and offers an intuitive approach to classifying new patients given a large number of 'training set' samples (e.g. TCGA data). To explore the ability of EVE to correctly classify new samples (generalization), we performed leave-one-out (LOO) validation. In each LOO iteration, one sample is left out of the 'training set' used to generate the SNA.CNA sample similarity plot. This sample is then super-imposed onto the plot by triangulation, and its position is compared to its position in the equivalent plots without any sample removal.

MDS projection of high dimensional data preserves inter-sample distances, not the locations of the samples in different plots. To accommodate this characteristic when comparing before and after sample coordinates, in the panel below left the coordinates of each plot point are calculated as the centroid of the three nearest neighbors in full dimensional space. We first estimated the location of each sample by the centroid of its three nearest neighbors using the full data. The result is shown in blue. We then removed one sample at a time from the plot, re-calculated the MDS projection of the resulting intersample distances, and then re-estimated the location of the missing sample from its previously marked three nearest neighbors. The resulting sample centroid locations are plotted in red (empty circles mark sample locations given full data). Overall, >96% of samples have identical actual and predicted nearest neighbors across all LOO runs. Even including outlier samples (for which neighbor-centroid calculations are inappropriate), the LOO and actual nearest neighbors are the same for >96% of all samples.

Sample locations vs. centroid of 3 nearest neighbors

Supplementary Figure 7. 1000 DNA methylation probes are sufficient to perfectly distinguish the two subtypes of CIMP LGGs. Colors are the same as in Figure 2f.

Supplementary Figure 8. The three major clusters detected by genomic data have distinct methylation expression profiles. (A) Methylation levels of 4,500 probes re-capitulate the three genomic clusters. Inset: 1000 probes are sufficient to segregate the Astro and Oligo CIMP LGG clusters. (B) REST/NRSF methylation levels are lower in the Astro cluster compared to the Oligo cluster. (C) Consistent with (B), REST/NRSF mRNA expression levels are higher in the Astro cluster compared to the Oligo cluster. (D) Consistent with (B) and (C), the NRSF co-repressor HDAC1 is expressed at significantly lower levels in the Oligo cluster (Benjamini and Hochberg FDR adjusted p-value = 0.03).

Supplementary Tables

Supplementary Table 1. A set of 396 stemness marker genes were constructed by combining gene sets from Wong et al. Cell Stem Cell. 2008 Apr 10; 2(4): 333–344, and

[http://www.sabiosciences.com/rt_pcr_product/HTML/PAHS-404A.html.](http://www.sabiosciences.com/rt_pcr_product/HTML/PAHS-404A.html)

C11orf48 C2orf47 CBX3 CCNA2 CCNB2 **CCNC** CCND1 CCND2 CCNF CCT5 CDC20 CDC34 CDC6 CDC7 CDCA3 CDCA5 CDCA7 CDCA8 CDK4 CDK5R1 CDK5RAP1 CDK5RAP2 CDK5RAP3 CDKN1C CDKN3 CHAF1A CHEK1 CHEK2 CHRM2 CKAP2 CKS1B CKS2 CLPP COQ3 COX4NB COX5B CRABP2 CSE1L CSRP2 CTNNA1 **CTSC** CXCL1 **CYCS**

DAP3 DARS2 DBF4 DDX18 DEK DHX9 DLAT DLG4 DLL1 DNMT1 DPP3 DRD1 DRD2 DTL DTYMK DVL3 E2F3 EBNA1BP2 ECHS1 EEF1E1 EEF2 EFNB1 EGF EIF2S2 EIF2S3 EIF4A1 EIF4B EIF4EBP1 ELOVL6 ENO1 EP300 ERBB2 ERCC6L ERP29 ETFA EXO1 EXOSC7 FAM136A FAM60A FARSA FBL FDPS FEZ1

KIF22 KIF23 KIF4A KPNA2 KPNA6 KRAS LMNB1 LSM10 LSM2 LSM4 LSM5 LYPLA1 MAD2L1 MAPK13 MCM2 MCM3 MCM4 MCM5 MCM7 MDK MEF2C MID1IP1 MKI67IP MLL MRPL11 MRPL12 MRPL13 MRPL15 MRPL16 MRPL37 MRPL39 MRPL4 MRPS17 MRPS18B MRPS2 MRPS28 MRPS30 MRPS36 MRTO4 MSH2 MTF2 MTHFD2 MYBL2

MYC NAP1L1 NASP NCAPD2 NCAPH NCBP2 NCL NCOA6 NDC80 NDN NDP NDUFA11 NDUFA9 NDUFAB1 NDUFB10 NDUFB7 NDUFB8 NDUFS2 NEK2 NEUROD1 NIP7 NIPSNAP1 NLN NME2 NME4 NOG NONO NOTCH2 NPTX1 NRCAM NRG1 NRP1 NRP2 NT5DC2 NTHL1 NTN1 NUDCD2 NUP107 NUSAP1 ODZ1 ORC1L OTX2 PA2G4

Supplementary Table 2. Human metabolic genes were downloaded from the Kyoto Encyclopedia of Genes and Genomes [\(http://www.genome.jp/dbget-bin/www_bget?pathway+hsa01100.](http://www.genome.jp/dbget-bin/www_bget?pathway+hsa01100) For our glioma analyses, to avoid confounding effects, we removed from this list genes associated with specific GBM expression subtypes (1157 genes remained).

A4GALT AADAT AANAT AASS ABAT ABO ACAA1 ACAA2 ACACA ACACB ACAD8 ACADL ACADM ACADS ACADSB ACADVL ACAT1 ACAT2 ACER1 ACER2 ACLY ACMSD ACO1 ACO2 ACOT1 ACOT2 ACOT4 ACOT8 ACOX1 ACOX2 ACOX3 ACSBG1 ACSBG2 ACSL1 ACSL3 ACSL4 ACSL5 ACSL6

ACSM1 ACSM2A ACSM2B ACSM3 ACSM4 ACSM5 ACSS1 ACSS2 ACSS3 ACY1 ADA ADAM29 adenylate ADH1A ADH1B ADH1C ADH4 ADH5 ADH6 ADH7 ADI1 ADK ADO ADPGK ADSL ADSS ADSSL1 AFMID AGK AGL AGMAT AGPAT1 AGPAT2 AGPAT3 AGPAT4 AGPAT5 AGPAT6 AGPAT9 AGPS AGXT AGXT2 AHCY AHCYL1

AHCYL2 AK1 AK2 AK4 AK5 AK6 AK7 AK8 AK9 AKR1A1 AKR1B1 AKR1B10 AKR1C3 AKR1C4 AKR1D1 ALAD ALAS1 ALAS2 ALDH18A1 ALDH1A1 ALDH1A2 ALDH1A3 ALDH1B1 ALDH2 ALDH3A1 ALDH3A2 ALDH3B1 ALDH3B2 ALDH4A1 ALDH5A1 ALDH6A1 ALDH7A1 ALDH9A1 ALDOA ALDOB ALDOC ALG1 ALG10 ALG10B ALG11 ALG12 ALG13 ALG14

ASS1 ATIC ATP5A1 ATP5B ATP5C1 ATP5D ATP5E ATP5F1 ATP5G1 ATP5G2 ATP5G3 ATP5H ATP5I ATP5J ATP5J2 ATP5L ATP5O ATP6 ATP6AP1 ATP6V0A1 ATP6V0A2 ATP6V0A4 ATP6V0B ATP6V0C ATP6V0D1 ATP6V0D2 ATP6V0E1 ATP6V0E2 ATP6V1A ATP6V1B1 ATP6V1B2 ATP6V1C1 ATP6V1C2 ATP6V1D ATP6V1E1 ATP6V1E2 ATP6V1F ATP6V1G1 ATP6V1G2 ATP6V1G3 ATP6V1H ATP8 AUH

CDA CDIPT CDO1 CDS1 CDS2 CEL CEPT1 CERS1 CERS2 CERS3 CERS4 CERS5 CERS6 CES1 CHDH **CHKA** CHKB CHPF CHPF2 CHPT1 CHSY1 CHSY3 CKB CKM CKMT1A CKMT1B CKMT2 CMAS CMBL CMPK1 CMPK2 CNDP1 CNDP2 COASY COMT COQ2 COQ3 COQ5 COQ6 COQ7 COX1 COX10 COX11

COX15 COX17 COX2 COX3 COX4I1 COX4I2 COX5A COX5B COX6A1 COX6A2 COX6B1 COX6B2 COX6C COX7B COX7B2 COX7C COX8A COX8C CPOX CPS1 CRLS1 CRYL1 CS CSAD CSGALNACT1 CSGALNACT2 CTH CTPS1 CTPS2 CYC1 **CYCS** CYP11A1 CYP11B1 CYP11B2 CYP17A1 CYP19A1 CYP1A1 CYP1A2 CYP21A2 CYP24A1 CYP26A1 CYP26B1 CYP26C1

DGKE DGKG DGKH DGKI DGKQ DGKZ DGUOK DHCR24 DHCR7 DHFR DHFRL1 DHODH DHRS3 DHRS4 DHRS4L1 DHRS4L2 DHRS9 DLAT DLD DLST DMGDH DNMT1 DNMT3A DNMT3B DOLK DPAGT1 DPM1 DPM2 DPM3 DPYD DPYS DSE DTYMK DUT EARS2 EBP ECHS1 EHHADH ENO1 ENO2 ENO3 ENOPH1 ENPP1

GAA GAD1 GAD2 GADL1 GAL3ST1 GALC GALE GALK1 GALM GALNS GALNT1 GALNT10 GALNT11 GALNT12 GALNT13 GALNT14 GALNT15 GALNT16 GALNT18 GALNT2 GALNT3 GALNT4 GALNT5 GALNT6 GALNT7 GALNT8 GALNT9 GALNTL5 GALNTL6 GALT GAMT GANAB GANC GAPDH GAPDHS GART GATB **GATC** GATM GBA GBA2 GBA3 GBE1

GPT GPT2 GRHPR GSS GSTZ1 GUK1 GUSB H6PD HAAO HADH HADHA HADHB HAL HAO1 HAO2 HDC HEXA HEXB HGD HGSNAT HIBADH HIBCH HK1 H_{K2} HK3 HKDC1 **HLCS** HMBS HMGCL HMGCLL1 HMGCR HMGCS1 HMGCS2 HOGA1 HPD HPGDS HPRT1 HPSE HPSE2 HSD11B1 HSD17B1 HSD17B10 HSD17B12

MAOA MAOB MAT1A MAT2A MAT2B MBOAT1 MBOAT2 MCAT MCCC1 MCCC2 MCEE MDH1 MDH2 ME1 ME3 MECR MGAM MGAT1 MGAT2 MGAT3 MGAT4A MGAT4B MGAT4C MGAT4D MGAT5 MGAT5B MGLL MINPP1 MLYCD MMAB MOCS1 MOCS2 MOGAT3 MOGS MPI MPST MRI1 MSMO1 MTAP MTHFD1 MTHFD1L MTHFD2 MTHFD2L **MTHFR MTHFS** MTM1 MTR MUT MVD MVK NADK NADSYN1 NAGLU NAGS NAMPT NANP NANS NAPRT NAT1 NAT2 NAT8L ND1 ND2 ND3 ND4 ND4L ND5 ND6 NDST1 NDST2 NDST3 NDST4 NDUFA1 NDUFA10 NDUFA11 NDUFA12 NDUFA13 NDUFA2 NDUFA3 NDUFA4 NDUFA4L2 NDUFA5 NDUFA6 NDUFA7 NDUFA8 NDUFA9

PCYT2 PDHA1 PDHA2 PDHB PDHX PDXK PDXP PEMT PFAS PFKL PFKM PFKP PGAM1 PGAM2 PGAM4 PGAP1 PGD PGK1 PGK2 PGLS PGM1 PGM2 PGP PGS1 PHGDH PHOSPHO1 PHOSPHO2 PHYKPL PI4K2A PI4K2B PI4KA PI4KB PIGA PIGB PIGC PIGF PIGH PIGK PIGL PIGM PIGN PIGO PIGP

PIGQ PIGS PIGT PIGU PIGV PIGW PIGX PIGY PIK3C2A PIK3C2B PIK3C2G PIK3C3 PIP5K1A PIP5K1B PIP5K1C PIP5KL1 PIPOX PISD PKLR PKM PLA2G10 PLA2G12A PLA2G12B PLA2G16 PLA2G1B PLA2G2A PLA2G2C PLA2G2D PLA2G2E PLA2G2F PLA2G3 PLA2G4A PLA2G4B PLA2G4C PLA2G4D PLA2G4E PLA2G4F PLA2G5 PLA2G6 PLA2G7 PLB1 PLCB1 PLCB2

PLCB3 PLCB4 PLCD1 PLCD3 PLCD4 PLCE1 PLCG1 PLCG2 PLCH1 PLCH2 PLCZ1 PLD1 PLD2 PLD3 PLD4 PMM1 PMM2 PMVK PNLIP PNLIPRP1 PNLIPRP2 PNLIPRP3 PNMT PNP PNPLA2 PNPLA3 PNPO POC1B-GALNT4 POLA1 POLA2 POLD1 POLD2 POLD3 POLD4 POLE POLE2 POLE3 POLE4 POLG POLG2 POLR1A POLR1B POLR1C

POLR1D POLR1E POLR2A POLR2B POLR2C POLR2D POLR2E POLR2F POLR2G POLR2H POLR2I POLR2J POLR2J2 POLR2J3 POLR2K POLR2L POLR3A POLR3B POLR3C POLR3D POLR3F POLR3G POLR3GL POLR3H POLR3K PON1 PON2 PON3 PPAP2A PPAP2B PPAP2C PPAT PPCDC PPCS PPOX PPT1 PPT2 PRDX6 PRIM1 PRIM2 PRODH PRODH2 proline

SARDH SAT1 SAT2 SC5D **SCLY** SCP2 SDHA SDHB SDHC SDHD SDS SDSL SEPHS1 SEPHS2 SGMS1 SGMS2 SGPL1 SGSH SHMT1 SHMT2 SI SLC27A5 SLC33A1 SMPD1 SMPD2 SMPD3 SMPD4 SMS SORD SPAM1 SPHK1 SPHK2 SPR SPTLC1 SPTLC2 SPTLC3 SQLE SRM ST20-MTHFS ST3GAL1 ST3GAL2 ST3GAL3 ST3GAL4

Supplementary Table 3. A list of the 45 genes with the highest impact on the layout of the SNA.CNA sample similarity plot.

ImpactScore was calculated as the change in the sum of all inter-sample distances in similarity plots obtained before and after removing the named gene. 45 genes with the highest impact scores are listed below.

Supplementary Table 4. Genes that are both differentially expressed and differentially methylated between the two CIMP-LGG groups.

HCN4 HCRTR1 HIST1H2AG HLA-DMA HOXA13 HOXC4 HOXD8 HTR6 IKZF1 IRX1 IRX2 IRX5 KCNB2 KCNS2 LEKR1 LHX1 LHX5 LHX9 LMX1A LOC91149 LRRC10B LRRC33 MAP3K9 MESP2 **MKX** MLXIPL NKX2-4 NOS1 OSR2 PCDH20 PDE8A PHACTR1 PIK3R5 PITX3 PLD5 POU4F1 POU4F2 PRCD PRDM13 PRLHR PYDC1 **REST** RIBC2

RNF182 RNF32 RNF39 SALL3 SCGBL SELV SIX2 SLC35D3 SLC35F1 SLC6A3 SLC7A14 SMC1B SPRY4 ST8SIA2 SYCE2 SYT9 TAS1R1 TFAP2E TLR5 TLX1 TMC8 TRIM67 TSPAN32 USP44 WNT9B YBX2 ZIC5 ZNF662 ZNF876P

Supplementary Table 5. 22 genes associated with GPCR signaling. 22 GPCR genes.

