Supporting Information for "Pathway-based personalized analysis of cancer" by Drier Y, Sheffer M, Domany E.

Principal Curves

The concept of principal curve was first proposed by Hastie and Stuetzle [\(1\)](#page-3-0) as a non-parametric nonlinear extension of the linear Principal Component Analysis. We denote by *f(λ)* a curve in *p-*dimensional space, where *λ* is a single parameter whose variation traces all the points along the curve. A curve *f* is defined to be a principal curve *associated with a distribution P(x)* defined over some space, if and only if it is a smooth, one dimensional non intersecting curve that is *self-consistent*, i.e. each point *y* on the curve is the expected value of all the points *x* whose projection onto the curve is *y.* Let the projection index

 $\lambda_f(x)$ be the λ for which the projection of x on the curve is $f(\lambda): \lambda_f(x) = \sup_{\lambda} \left\{ \lambda : ||x - f(\lambda)|| = \inf_{\mu} ||x - f(\mu)|| \right\}$ The

condition for self-consistency is simply $f(\lambda) = \mathbb{E}(X|\lambda_f(X) = \lambda)$. Since in practice we are given a finite data set *X*, of *n* points in d_P dimensional space $X \in M_{m \times d_P}(\R)$, while the distribution it is sampled from is not known, scatterplot smoothing

is used. Hastie and Stuetzle also offer a two-steps iterative algorithm for finding such a principal curve:

1. Conditional-Expectation step: Fix $\lambda = (\lambda_i)_{i=1}^n$ and minimize $\mathbb{E} \|X - f(\lambda)\|$ by setting $f(\lambda_i)$ to be the local average (of the points projected onto a neighborhood of $f(\lambda_i)$, e.g. the points x_j for which $\lambda_j \cong \lambda_i$).

2. Projection step: Given $f = \{f(\lambda_i)\}_{i=1}^n$ find for each x_i the corresponding value of λ_i = $\lambda_f(x_i)$ assuming f is piecewise linear.

The line along the first linear principal component is used as a starting curve, and the algorithm is iterated until convergence.

Implementation and Availability

The code is implemented in R and uses "princurve 1.1-10" by Andreas Weingessel [\(http://cran.r](http://cran.r-project.org/web/packages/princurve/index.html)[project.org/web/packages/princurve/index.html\)](http://cran.r-project.org/web/packages/princurve/index.html), which is in turn based on the original S/Fortran code princurv by Hastie. The code is available at <http://www.weizmann.ac.il/pathifier/> and on Bioconductor [\(http://www.bioconductor.org/\)](http://www.bioconductor.org/).

Data and preprocessing

GBM mRNA expression data was downloaded from TCGA data portal on April 2011 [\(2\)](#page-3-1). To reduce batch effects of arrays and protocols, we used only Agilent G4502A arrays measured at the UNC medical school, yielding 455 samples, 10 of which were from normal tissue. Additionally, 228 glioblastoma samples and 28 normal brain samples were obtained from REMBRANDT [\(3\)](#page-3-2). Subtypes classification was taken from Verhaak et al. [\(4\)](#page-3-3) Classification of the REMBRANDT data and additional TCGA samples was done using the same genes. Colorectal mRNA data was taken from Sheffer et al. [\(5\)](#page-3-4) which contains 313 samples including normal tissue (52 samples), polyps (49), primary tumors (182) and metastases from the liver (21) and lung (9); Sveen et al. [\(6\)](#page-3-5) containing 13 normals and 76 primary tumors of stages 2,3 (one tumor sample was removed); and Kogo et al. [\(7\)](#page-3-6) containing 9 normal and 132 primary tumors of all stages.

For TCGA data we used level 3 already processed data and for Kogo data we used the downloaded processed data. For all the rest, data was summarized with PLIER and normalized with cyclic LOWESS [\(8\)](#page-3-7), For the Sheffer dataset, batch correction was applied before LOWESS. To eliminate noisy genes only the 5000 most varying genes for each cancer type (sum of variation on all 2 or 3 datasets) were selected for further analysis.

Assembly of pathway associated gene sets

Gene sets were imported from three pathway databases, KEGG [\(9,](#page-3-8) [10\)](#page-3-9), BioCarta [\(11\)](#page-3-10) (both downloaded from MSigDB [\(12\)](#page-3-11)) and the NCI-Nature curated Pathway Interaction Database [\(13\)](#page-3-12). Identity of genes in gene sets was decided according to their official gene symbols. Gene sets with less than 3 genes varying in the data were omitted, leaving 173 KEGG pathways, 188 BioCarta pathways and 197 NCI-Nature PID pathways.

Chromosomal Instability Index

Chromosomal instability index (CIN) was deduced from the normalized gene expression, following reference [\(5\)](#page-3-4). For a given tumor sample, each chromosomal arm was scored as follows. For every gene *i* calculate fc_i the fold change versus the median expression of the gene in the normal samples. The median fold change of the chromosomal arm *a* is defined as $fc_a = median$ fc_i . The total chromosomal instability index is the sum (over all arms) of the squared median fold changes

2 $CIN = \sum f c_a^2$. Spearman correlation between the CIN index and the deregulation score of every pathway was calculated *a*

across each colorectal dataset. We recorded the list of pathways passing 5% FDR for every dataset. We applied Fisher exact test to evaluate the significance of the similarity between every pair of pathway lists.

Pathway deregulation scores that are correlated with necrosis levels of glioblastoma

The PDS of 242 pathways significantly correlate with the necrosis levels of the samples, as quantified by TCGA (Spearman correlation, FDR<1%), see Table S2. Some of these pathways are indeed expected to cause cell death, such as: *SODD* signaling, *FAS* pathway, *NEF* pathway, *BAD* phosphorylation pathway, apoptosis, caspase pathway, Notch signaling, Induction of apoptosis through DR3 and DR4/5 Death Receptors, p75(NTR)-mediated signaling, oxidative stress induced gene expression via *NRF2* and *ERK5* in neuronal survival. Many of the other pathways are growth factor pathways, such as: *NGF*, *ERBBs*, *PDGFRB*, IGF, and Trk receptor pathways. A few hypoxia and angiogenesis related pathways are also correlated with necrosis (*VEGF* pathways, HIF pathways, angiopoietin receptor pathway, lymphangiogenesis pathway, Hypoxia and p53 in the Cardiovascular system).

Pathway clusters in the TCGA GBM dataset

Pathway cluster TgP1 consists of cell cycle arrest and cell death pathways; TgP2 contains cell cycle pathways and many of KEGG's "cancer" pathways (including glioma) which capture cancer progression and signaling; TgP3 contains mainly cell death and DNA repair pathways and is deregulated mostly on the Neural and Proneural samples; The pathways of cluster TgP4 correspond to the EGF activated pathways mentioned above; Cluster TgP5 contains pathways that are deregulated mostly on the Classical samples. Some of them are indeed suspected to be specific to this subtype, such as hedgehog-GLI signaling [\(4\)](#page-3-3) and GPCR/CXCR4 signaling [\(14\)](#page-3-13) while the deregulation of some others in this subtype is a new prediction: such as PAR1(*F2R*) mediated thrombin signaling, axon guidance, etc.; Half of the TgP6 pathways involve alpha synuclein amyloids; All TgP7 pathways involve phospholipase C; the pathways that comprise clusters TgP8-TgP10, TgP12-TgP15 belong to the 242 pathways that were correlated with necrosis that were mentioned above, and are also highly expressed on many Mesenchymal samples. As mentioned, many of these pathways (and specifically the pathways of TgP8-TgP10, TgP13 and TgP15) are related to hypoxia and angiogenesis, and we find, in agreement with previous knowledge, that they score higher in Mesenchymal glioblastoma [\(15\)](#page-3-14). Clusters TgP8 and TgP12 contain several Epithelial-Mesenchymal Transition (EMT) related pathways (such as N-cadherin signaling, epithelial tight junctions, Rho/Rac/CDC42 signaling, regulation of actin cytoskeleton, ECM-receptor, Focal adhesion) obviously related to Mesenchymal tumors; 7 of the 8 pathways of TgP11 are key signaling pathways involving caveolin; TgP12 contains many of the pathways correlated with NF1 mutation (P3 in Fig. 2C); TgP14 contains mostly cell death pathways; TgP15 pathways all involve phospholipase A2; TgP16 contains many immune pathways. The full details of the pathways in each cluster can be found in Dataset S1.

Matching between REMBRANDT and TCGA GBM pathway clusters

Cluster ReP1 matches TgP1, ReP2 matches TgP2, ReP3 matches TgP15, ReP4 matches TgP16, ReP7 matches TgP3, ReP8 matches TgP14, ReP9 includes parts of TgP10-TgP13 (most strongly related to TgP12), and ReP10 includes parts of TgP4-TgP9 (most strongly related to TgP5 and TgP9). Under this mapping, similar characteristics of the deregulation profiles of sample types emerge (Fig. 2B). Some of the Neurals/Proneurals are mostly not deregulated (ReS1/ReS2 vs. TgS7/TgS15/TgS13) and some are deregulated on TgP1/TgP2/TgP3 or the matching ReP1/ReP2/ReP7. Classical tumors are deregulated on TgP4/TgP5 and possibly TgP6/TgP7 as well as on the matching ReP10 (and unmatched ReP6/ReP7). Pathways of clusters TgP8-TgP16 as well as the matching ReP10/ReP9/ReP8/ReP3/ReP4 (and unmatchable ReP5) are highly deregulated in the Mesenchymal samples. The Classical-Mesenchymal cluster TgS4 matches ReS8, and indeed the corresponding samples are deregulated on TgP4-TgP5/TgP10-TgP12/TgP14-TgP15 and, respectively, on the matching ReP10/ReP9/ReP8/ReP3 (as well as on the unmatchable ReP5).

Deregulation scores of many pathways are correlated with survival of GBM patients

35 pathways were found to be related to survival in both GBM datasets (see Table S3), many of them make biological sense: Agrin deregulation may temper the blood-brain barrier in glioblastoma [\(16\)](#page-3-15); Growth hormone (GH) plays a crucial role in stimulating and controlling the growth, metabolism and differentiation of many mammalian cells, and hence clearly relevant for cancer aggressiveness [\(17\)](#page-3-16); The hematopoiesis pathway contains cytokines and it is suspected to be related to cancer progression and drug resistance by interactions with the immune system [\(18-20\)](#page-3-17); Linolenic acids and their products were suggested to prolong cancer patient survival [\(21\)](#page-3-18); FcεRI may protect against cancer by IgE antitumor immunity [\(22\)](#page-3-19); Cell-matrix adhesions are clearly related to invasion and metastasis [\(23\)](#page-4-0); *GnRH* is a neurohormone that may drive proliferation in glioblastoma and other cancers, and therefore is also a suggested drug target [\(24-29\)](#page-4-1); Phosphatidyl-inositol 3- and 4-kinases, key ingredients of the inositol phosphate pathway, are known to have important roles in glioblastoma and cancer in general, and hence are possible drug targets [\(30-32\)](#page-4-2); Surprisingly, cholera toxin was also found related to glioblastoma; WNT signaling has a key role in brain and other cancers, and is related to cancer stem-like cells and poor prognosis [\(33-35\)](#page-4-3); Alterations in Ecadherin mediated cell-cell adhesion are associated with an increase in carcinoma cell motility, invasiveness and metastasis [\(36\)](#page-4-4); Glypican-1 is crucial for efficient growth, metastasis, and angiogenesis of cancer, and lack of it slows down pancreatic tumor progression [\(37\)](#page-4-5); Fas and TNF-alpha are key players in apoptosis whose deregulation is a clear hallmark of cancer [\(38,](#page-4-6) [39\)](#page-4-7); α4β1 integrin is related to angiogenesis [\(40\)](#page-4-8), and is involved the survival and chemoresistance of several types of cancer [\(41\)](#page-4-9); β2 integrins are known to predict poor survival in blood cancers [\(42,](#page-4-10) [43\)](#page-4-11), and may cause fibrinolysis via uPA/uPAR; α6

integrin regulated stemness and invasiveness in glioblastoma [\(44,](#page-4-12) [45\)](#page-4-13), and has a prognostic value in breast cancer [\(46\)](#page-4-14); P53 is a key player in glioblastoma and cancer in general; *PTPN1* (aka PTP1B) may promote apoptosis in cancer and is a possible drug target for gliomas [\(47\)](#page-4-15); Reelin is a secreted glycoprotein guiding migratory neurons, it is downregulated in neuroblastoma, which may contribute to metastasis [\(48,](#page-4-16) [49\)](#page-4-17); Syndecans induce proliferation and invasion [\(50-52\)](#page-4-18), and may serve as a prognostic predictor [\(53,](#page-5-0) [54\)](#page-5-1).

Deregulation scores of many pathways are correlated with CIN in colorectal tumors

84 pathways were found to have significant positive correlation with the estimated CIN level in the tumors. To check that this correlation does not reflect only the differences between the MSI-high (most with low CIN) and MSS (most with high CIN) subtypes, we re-calculated the correlations for the subset of MSS and MSI-low tumors of the Sheffer and Sveen datasets. 71 pathways were significant (p<0.046, for every dataset pair, Fisher exact test), with an overlap of 55 with the previously found 84 pathways, suggesting that the correlations between CIN and deregulation of tumorigenic pathways is not only due to the differences between MSS and MSI-high tumors.

Deregulation scores in MSS colorectal tumors compared with MSI-high

In the Sheffer dataset, 325 pathways are differentially deregulated between MSS and MSI-high tumors (Mann–Whitney, 10% FDR, Supplementary Tables S6 and S7). 120 pathways are more deregulated on MSI-high tumors: They include Mismatch repair, nucleotide excision repair, ATM pathway, ATR pathway, cell cycle, MCM, DNA replication, RB1 pathway, oxidative stress, chemokines and cytokines signaling, and different interleukin pathways. This differential deregulation is in agreement with the fact that DNA mismatch repair is deregulated in MSI tumors [\(55\)](#page-5-2), which are usually characterized by higher levels of inflammation and tumor infiltrating lymphocytes [\(56\)](#page-5-3). A significant part of these pathways was also deregulated in the MSIhigh tumors in the Sveen dataset (p=1.92×10⁵ for MSS deregulated pathways, p=0.022 for MSI-high, Fisher exact test, Supplementary Tables S6 and S7)**.** It is reassuring that the mismatch repair pathway is deregulated in MSI-high tumors, in both datasets. Almost all pathways that are deregulated in MSS in the Sheffer dataset (200/205, 98%) also show significant positive correlation with the CIN index. Interestingly, in the MSS tumors, where p53 mutation is frequent, pathways downstream of p53 are highly deregulated (KEGG's p53 signaling pathway and PID's direct p53 effectors, which focus of the downstream effects of p53, as well as many death pathways), while in the MSI tumors, where p53 is often functional, many pathways upstream of p53 are deregulated (i.e. DNA damage and cell cycle). Indeed, we found that 123 out of 140 pathways that are differentially deregulated between wild type and mutant p53 (Mann–Whitney, 5% FDR) were shared with the group of 325 pathways deregulated in either MSI-high or MSS.

Pathway clusters in the Sheffer colorectal dataset

ShP1 includes B-cell receptor and T-cell receptor pathways, and ShP2 includes antigen processing and presentation, T-cell differentiation, T helper cell surface molecules, T cytotoxic cell surface molecules, Graft-versus-host disease, Autoimmune thyroid disease etc. Clusters ShP4 and ShP5 include ECM pathways, focal adhesion, syndecan pathways, integrin pathways such as α9/β1 that induce adhesion and migration of endothelial and cancer cells [\(57\)](#page-5-4); interleukines that mediate inflammation and angiogenesis [\(58\)](#page-5-5); toll like receptors, that are involved in innate immune response and HIF2, a transcription factor that induces the hypoxia response. Other pathways are related to metabolism, such as glycolysis and drug metabolism. Cluster ShP7 includes regulation of actin cytoskeleton, cell adhesion, JAK/STAT signaling, MAPK signaling and complement and coagulation cascades pathway. Interestingly, this cluster is also deregulated in the polyps (cluster ShS2), although polyps show low level of CIN. Cluster ShP8 includes various cAMP-dependent signaling pathways, triggered by receptor binding to GPCRs involving the G-Protein such as insulin and BAD phosphrylation. Other pathways include metabolism of different amino acids and TGF-beta signaling. Cluster ShP9 includes a number of death associated pathways such as apoptosis, T-cell apoptosis, p53 downstream signaling, lysosome and *FAS* signaling. In addition, it includes also fatty acid metabolism, VEGF, mTOR, and notch signaling. Cluster ShP10 includes mitochondrial metabolic pathways such as pyruvate metabolism, TCA cycle, metabolism of sugars and oxidative phosphorylation. Cluster ShP11 includes cell cycle related pathways such as G1/S check point, aurora pathway, p53 upstream regulation, E2F, RB1, MCM, DNA replication, mismatch repair, purine metabolism, and more.

72 pathways out of the 106 that exhibited increase of PDS with progression of the disease (see above) belong to clusters ShP8, ShP9 and ShP10 (p <10⁻³ for all three clusters, Fisher exact test). This group of pathways consists of cell death, cAMP-dependent signaling and mitochondrial metabolism pathways, along with p53 pathways.

Comparison to PARADIGM

PARADIGM is useful for integrating many types of data, but it does not handle well complex pathways when information is missing. The reason is that PARADIGM is based on full knowledge and understanding of all the interactions in the pathway; in complex pathways, however, much of these interactions depend on protein-level information, such as abundance, activity, location and structure (e.g. whether it is phosphorylated or not). When all this information is available, we believe informative and reliable results are produced by PARADIGM. However, in most cases, when much of the necessary information is missing, it is very hard to deduce the behavior of the pathway by following all the details of the interactions within the pathway.

Pathifier implicitly assumes that when all or most of the genes in the pathway are taken into account, a lot of the information on the pathway's activity status is coded in their readily available mRNA abundances. The details are context depended and cannot be fully deduced, but a data based analysis, specific for the pathway and the type of cancer, is likely to reveal the differences between the samples. Clearly, the validity of this assumption cannot be generally proven, but testing the results obtained for different cancers and different datasets of the same cancer types does support it strongly.

Despite the differences in approach and philosophy we compared the results of PARADIGM and Pathifier, to assess what highlevel findings are in agreement between the methods, and what additional information can be uncovered by Pathifier. We repeated the analyses described above using the scores derived obtained by PARADIGM. EGFR gene and EGFR complexes were indeed found to be correlated to EGFR mutations as expected (FDR<1%). However, no pathways were found to be correlated to the EGFR mutations. Not much more could be inferred by the analysis based on PARADIGM scores (Supplementary Figure S10). As reported in [\(59\)](#page-5-6), some stratification of glioblastoma is possible by PARADIGM IPA's, but it does not match strongly the known subtypes. Though it successfully detected a relevant cluster of *HIF1A* low and E2F high tumors, PARADIGM missed many of the observations we mention above. Moreover, none of the IPA's is found to be related to survival with FDR<19%. Therefore we conclude that while PARADIGM is a very useful method to integrate different types of data and deduce simple complexes and downstream activations (such as EGF receptor activation), Pathifier provides additional clinically relevant and easy to interpret information about the deregulation of complex pathways.

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Supplementary Figure S1 - Histograms of the Pathifier PDS's variance in each dataset. The variance over the normal samples (red) and over the tumor samples (blue) was calculated for each pathway, showing much lower variance over the normal samples. The mean variance for these two groups is indicated for GBM (**A.** TCGA **B.** REMBRANDT) and colorectal cancer (**C.** Sheffer **D.** Sveen **E.** Kogo) datasets.

Supplementary Figure S2 - Expression of genes shared between pathways in the immune clusters. A. Cluster ShP2 of the Sheffer dataset. The upper panel shows the PDS of cluster ShP2. As the PDS of the normal samples is around zero (green-blue), highly positive PDS (dark red) and highly negative PDS (dark blue) correspond to pathway deregulation, but in different directions. The lower panel shows the expression of genes that participate in at least five of the pathways in ShP2: each row represent a gene, blue corresponds to low expressions and red to high expressions. The color bars at the bottom correspond to the tissue type of the tumor (normal, polyp, tumor and metastasis) and the CIN index (equally distributed into 10 bins). These genes are related to lymphocytes, and may represent TILs (tumor infiltrating lymphocytes). Note that positive PDS co-occur with low expression (mostly in metastatic samples and in some of the polyps), while negative PDS correlate with high expression (mostly found among the tumors with low CIN). **The Cluster SvP4 (Sveen dataset) and the Cluster KoP1 (Kogo dataset) are shown in B, C** in a similar manner. Note that in SvP4 positive PDS co-occur with high expression and in KoP1 positive PDS co-occur with low expression, which is explained by the fact that the direction of the curve is chosen according to the normal samples. The association between high expression and low CIN is reconstructed in both SvP4 and in KoP1.

Supplementary Figure S3 - A. Clustering analysis of all the PDS in the Sveen dataset. Each row corresponds to a pathway and each column to a sample. Pathways and samples are clustered according to PDS. For most pathways the PDS of the normal samples are minimal (dark blue), and hence the higher the PDS are the more deregulated the pathway is. For a few pathways (mostly in SvP4) the PDS of normal samples are around zero (green-blue), and hence highly positive PDS (dark red) and highly negative PDS (dark blue) both correspond to pathway deregulation, but in different directions. The color bars at the bottom correspond to the MSI status of the tumor (normal, low high, MSS and unknown) and the CIN index (equally distributed into 20 bins). **B. Oxidative phosphorylation pathway is associated with survival**. Kaplan-Meier plots for the deregulation scores of oxidative phosphorylation in the Sveen dataset. The primary tumor samples were divided into three equal groups, based on their level of deregulation (high, medium and low). Low deregulation scores are associated with better prognosis. **C. CXCR3 pathway is associated with survival**. High deregulation scores are associated with better prognosis.

Supplementary Figure S4 - Clustering analysis of all the PDS in the Kogo dataset. Each row corresponds to a pathway and each column – to a sample. Pathways and samples are clustered according to PDS. For most pathways the PDS of the normal samples are minimal (dark blue), and hence the higher the PDS are the more deregulated the pathway is. For a few pathways (mostly in KoP1) the PDS of normal samples is around zero (green-blue), and hence highly positive PDS (dark red) and highly negative PDS (dark blue) both correspond to pathway deregulation, but in different directions. The color bars at the bottom correspond to the tissue type of the tumor (normal, tumors) and the CIN index (equally distributed into 20 bins).

Supplementary Figure S5 - Summary of recurrent clusters in the colorectal datasets (A. Sheffer, B. Sveen, C. Kogo). Each row corresponds to a pathway cluster and each column to a sample cluster, displaying the median value of deregulation for each pair of clusters. These four pathway clusters were reproduced in all three datasets. In the first row are pathway clusters for which the PDS of the normal samples are minimal around zero (cyan), and hence highly positive PDS (dark red) and highly negative PDS (dark blue) both correspond to pathway deregulation, but in different directions. For all other clusters the PDS of the normal samples are minimal (dark blue), and hence the higher the PDS are the more deregulated the pathway is. Arrows connect between pathway clusters that match (that is, the pathways in the clusters significantly overlap).

Supplementary Figure S6 - Normal samples sensitivity test. Histograms for the Pearson correlation coefficient between the Pathifier PDS scores using the full set of normal samples against ten different runs using 80% of randomly chosen normal samples. The correlation was measured for pathways (blue) and for samples (red), using the set of tumor samples. The average and standard deviation of the ten runs are shown, for each bin. Results are shown for **A.** TCGA GBM, **B.** Rembrant and **C.** Sheffer datasets.

Supplementary Figure S7 - Histograms of Pearson correlations between Pathifier scores and alternative methods for GBM datasets- A. TCGA. **B.** REMBRANDT. The correlations between the three methods and Pathifier were calculated using the set of tumor samples, for pathways (upper) and for samples (lower). The correlations to Segal et al. and to GenMAPP are low.

Supplementary Figure S8 - Histograms of Pearson correlations between Pathifier scores and alternative methods for colorectal cancer datasets- A. Sheffer et al. **B.** Sveen et al. **C.** Kogo et al. The correlations between the three methods and Pathifier were calculated using the set of tumor samples, for pathways (upper) and for samples (lower). Note that the correlations to Segal et al. and to GenMAPP are low.

Supplementary Figure S9 - Clustered normalized pathways score of TCGA GBM using other methods (A. Segal et al. B. linear pathifter, scoring by Euclidean distance C. Adjusted GenMAPP/MAPPFinder score). Each row corresponds to a pathway and each column to a sample. Pathways and samples are clustered according to pathway scores. Blue color represents low score ("no deregulation"), and red high. The bottom bar represents the glioblastoma subtype. Segal et al. do not score most samples and most pathways are not scored (in green), due to strict significance requirements.

Supplementary Figure S10 - **A. PARADIGM's IPAs for the TCGA GBM dataset.** Each row corresponds to a PARADIGM "entity" and each column to a sample. Entities (pathways, interactions, complexes etc.) and samples are clustered according to the IPAs. Blue color represents low activity, and red high activity. The bottom bar displays the subtype. **B. PARADIGM's IPAs correlated with mutations.** The bottom bars display the mutation status for the corresponding gene.

Supplementary Table 1 - **Pathways whose deregulation corresponds to point mutation of selected genes (TCGA GBM data).** Pathways are ordered and numbered as in Figure 2C.

Supplementary Table 2 - **Pathways whose deregulation correlates with necrosis levels (TCGA GBM data).** With significance measures, and Spearman correlation coefficient (denoted by ρ).

Supplementary Table 3 - **Pathways predicting survival in both glioblastoma datasets**. We found significant agreement between the pathways that predict survival. Pathways were identified by logrank p-value, with FDR < 10% for each dataset.

Supplementary Table 4 - **Pathways whose deregulation scores significantly differentiate between all subsequent stages of progression (normal->polyp->primary tumor->metastasis) in the Sheffer dataset.**

Supplementary Table 5 - **Pathways whose deregulation scores have significant positive correlation with the CIN index, in all three colorectal datasets (Sheffer, Sveen and Kogo).** Listing the Spearman correlation coefficient (ρ), p-value, and Benjamini-Hochberg false discovery rate (FDR) of each.

Supplementary Table 6 - **List of pathways that are more deregulated in microsatellite stable (MSS) tumors than in MSI-high tumors in the Sheffer et al. dataset**. Additionally, for those pathways that are significantly differentially deregulated in Sveen the p-value of the significance is listed.

Supplementary Table 7 - **List of pathways that are more deregulated in MSI-high than in MSS in the Sheffer et al. dataset**. Additionally, for those pathways that are significantly differentially deregulated in Sveen the p-value of the significance is listed

