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#### SI Text

1. Microarray Data Analysis. We provide details for the microarray data analysis of the Nederlands Kanker Instituut (NKI) data (1) consisting of 295 tumors, the Breast Cancer Normal (BCN) data (2) consisting of 13 normal breast tissue samples, and the validation data sets Ullevål University Hospital (ULL) (3) consisting of 46 tumors of ductal histological type that had been in the study for longer than 10 mo and *HERSCH* (4) consisting of 188 primary breast tumors.

1.1. Data preprocessing. Data were retrieved, missing values imputed, then data were collapsed by UniGene cluster ID build 219, and genes present in both the tumor cohort and the normal data set were retained.

For NKI, data consisted of 24,479 GeneBank accession IDs on 295 tumor samples, all of which had at least 70% data. Missing data were imputed using a *knn* algorithm (5) with  $k = 10$ . Data were also transformed from the original  $log_{10}$  values to  $log_2$ . Data were then collapsed (mean) by UniGene to the mean. The resulting data set consisted of 18,970 UniGene clusters.

For BCN, data from 13 normal tissue samples (nine nonneoplastic tissue from cancer patients, four reduction mammoplasty tissue) were retrieved with quality filters for each spot:  $(i)$  spot regression correlation  $r > 0.6$ , or (ii) channel 1 mean intensity/ median background intensity  $>1.5$ , or (iii) channel 2 normalized (mean intensity/median background intensity) >1.5. Clones with 70% data were retained: 32,644 clone IDs. Missing data were imputed using a knn algorithm (5) with  $k = 10$ . Data were then collapsed by UniGene to 18,971 UniGene clusters. Of these, 12,237 UniGene IDs were in common with the NKI data set, and 17,441 were in common with the ULL data set (see below).

For ULL, data from 46 tumors were retrieved with quality filters for each spot: (i) spot regression correlation  $r > 0.6$ , or (ii) channel 1 mean intensity/median background intensity  $>1.5$ , or  $(i)$  channel 2 normalized (mean intensity/median background intensity) >1.5. Only clones with 70% good data were retained: 31,667 clone IDs. Missing data were imputed using a *knn* algorithm (5) with  $k = 10$ . Data were then combined with normal tissue data BCN and collapsed by UniGene to 17,441 UniGene clusters.

For HERSCH, data from 188 primary tumors were retrieved with quality filters for each spot:  $(i)$  spot regression correlation  $r > 0.6$ , or  $(ii)$  channel 1 mean intensity/median background intensity > 1.5, or (iii) channel 2 normalized (mean intensity/median background intensity) >1.5. Only clones with 70% good data were retained: 32,644 clone IDs. Missing data were imputed using a knn algorithm (5) with  $k = 10$ . Data were then combined with normal tissue data BCN and collapsed by UniGene to 18,896 UniGene clusters.

1.2. Disease-Specific Genomic Analysis (DSGA). For NKI and BCN, data from tumors and normal tissue were combined along the common 12,237 UniGenes, and columns were normalized to have the magnitude of the mean vector magnitude of 13 normal tissue samples. The Healthy State Model (HSM) was constructed from normal tissue data  $\{N_1, \ldots, N_{13}\}$  as follows: *FLAT* construction (2) is a method to de-sparse the data in high dimensions by (2) is a method to de-sparse the data in high dimensions by substituting for each normal tissue vector  $\vec{N}_i$ , its fit  $\hat{N}_i$  to a linear model in the other normal tissue vectors:

$$
\widehat{N}_i = \sum_{\substack{1 \le j \le 13 \\ j \ne i}} \beta_j \overrightarrow{N}_j.
$$

This was shown to decrease noise in simulated data and help identify a good dimension reduction for Principal Component

Analysis (PCA). We use a method described in ref. 2 to compute the Wold invariant (6) designed to measure a version of signalto-noise ratio:

$$
W(l) = \left(\frac{\lambda_l^2}{\lambda_{l+1}^2 + \ldots + \lambda_{13}^2}\right) \frac{(n-l-1)(13-l)}{(n+13-2l)}.
$$

[Fig. S1](http://www.pnas.org/lookup/suppl/doi:10.1073/pnas.1102826108/-/DCSupplemental/pnas.201102826SI.pdf?targetid=nameddest=SF1) plots  $W(l)$  vs. the dimension l and shows a jump at  $l = 10$ , indicating that signal-to-noise ratio is higher at dimension 10, thereby justifying PCA dimension reduction of the FLAT normal data to 10. This produced the 10 dimensional HSM. Linear models are then used to compute the fitted tumor data matrix to the HSM (normal component Nc.mat) and the residuals (disease component *Dc.mat*). Along with tumor data, a leave-one-out procedure gives an estimate of the deviation of normal tissue data from the model of the healthy state HSM. Details of this procedure are found in ref. 2.

The validation data sets ULL and HERSCH were similarly transformed using the same normal data set BCN.

For gene thresholding, the 12,237 genes in the disease component matrix *Dc.mat* of tumors were reduced to 262 through the following method of testing for significance in deviation from the null hypothesis space. For each gene we computed the 5th and 95th percentiles of values in the disease components of the 295 tumors, and we recorded the larger of the two in absolute value and denoted the collection of these gene-by-gene deviations from normal by MaxAbs595. A histogram of these values is seen in [Fig. S2.](http://www.pnas.org/lookup/suppl/doi:10.1073/pnas.1102826108/-/DCSupplemental/pnas.201102826SI.pdf?targetid=nameddest=SF2) We then computed the 85th and 98th percentiles of MaxAbs595 and denoted these as relaxed threshold and stringent threshold, respectively. A total of 1,836 genes exceeded the relaxed threshold, and 245 genes exceeded the stringent threshold. Genes were retained for further analysis if they passed the relaxed threshold and if they were also highly correlated  $(r > 0.6)$ to at least three genes that passed the stringent threshold. A total of 262 genes satisfied the condition. This method ensures that genes are retained in the analysis if they not only  $(i)$  deviate significantly from the null hypothesis space  $HSM$  but  $(ii)$  do so in groups of highly correlated genes. We denote the reduced matrix of disease component of NKI data: nkiDc.mat. The result of clustering the nkiDc.mat array and gene mean-centered can be found in supplementary folder Dataset S1: nkiDc.AGmc.cdt. It can be explored with TreeView (7), and all of the known clusters of genes can be observed, but because this is not germane to our present study we forgo any in-depth analysis of this clustering.

We did not follow the same thresholding procedure for the validation data sets ULL and HERSCH; rather, we found that of the 262 genes retained in the NKI data set, 255 genes were present in the ULL data and 221 in the HERSCH data.

1.3. Progression Analysis of Disease (PAD) on NKI. We give details of PAD on the reduced and DSGA-transformed NKI data matrix: nkiDc.mat of 295 tumors and 262 genes. First, this was combined with the leave-one-out matrix that estimates normal tissue: bcnL1.mat. The Mapper filter function was computed on each column vector, as explained in the main text (Eq. 2). The image space was then fragmented into 15 intervals, with 80% overlap. Two outputs of mapper were obtained: the first, which included all of the bins, can be found in Fig. 3 (main text). The second provides the tighter streamlined subset of Mapper output, by excluding all bins with only one data point in them. The two outputs appear side by side in [Fig. S3.](http://www.pnas.org/lookup/suppl/doi:10.1073/pnas.1102826108/-/DCSupplemental/pnas.201102826SI.pdf?targetid=nameddest=SF3)

1.4. Comparison with clustering. Although Mapper incorporates clustering at the local level, the final output captures a wide

range of characteristics that are obfuscated by the standard methods of clustering the entire data. We provide in [Fig. S4](http://www.pnas.org/lookup/suppl/doi:10.1073/pnas.1102826108/-/DCSupplemental/pnas.201102826SI.pdf?targetid=nameddest=SF4) an expanded version of the comparison presented in Fig. 4 (main text) between clustering and PAD analysis, complete with heat maps and progressions of bins. It is important to note that the comparison is performed after both Mapper and clustering were applied to exactly the same data matrix. Thus, whatever transformations one might perform on the data, for example DSGA, and however genes are thresholded to provide a reduced number of genes used in the analysis, the final step of clustering vs. Mapper generates very different outputs. Because both clustering and Mapper are methods that identify the shape of the data, this comparison highlights the fact that shape characteristics identified by Mapper can be lost by clustering. Note as well that clustering has scattered the  $c$ - $MYB$ <sup>+</sup> tumor group among several clusters. This is a common problem known to clustering: data points will be segregated into separate clusters, and sometimes data points that are fairly close to one another will be torn apart and scattered into separate clusters. This is precisely what has happened with the  $c$ - $\overline{M}YB$ <sup>+</sup> group. Despite how similar the  $c-MYB<sup>+</sup>$  tumors are to one another, clustering has not kept them together.

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2. Genes of Interest Analysis. We isolated a subgroup of tumors,  $c-MYB^+$ , through the use of PAD. We provide Prediction Analysis of Microarrays (PAM) (8) analysis outputs for comparison of this group to the normal tissue group. We provide Significance of the Analysis of Microarrays (SAM) (9) analysis for genes most significantly distinct between the  $c$ - $MYB$ <sup>+</sup> group and the normal tissue group, as well as genes most significantly distinct between the  $c$ - $MYB$ <sup>+</sup> group and the most adjacent tumors to the  $c$ - $MYB$ <sup>+</sup> group in the PAD output, namely the tumors in the  $ER^+$  arm that are not part of the  $c-MYB$ <sup>+</sup> group.

2.1. PAM. PAM finds a small set of predictor genes for distinguishing between two groups of tumors. [Fig. S5](http://www.pnas.org/lookup/suppl/doi:10.1073/pnas.1102826108/-/DCSupplemental/pnas.201102826SI.pdf?targetid=nameddest=SF5) shows PAM output for comparing the  $c\text{-}MYB^+$  group to the normal tissue group.

2.2. SAM. SAM finds a large number of significant genes that behave differently between two groups of tumors. [Table S1](http://www.pnas.org/lookup/suppl/doi:10.1073/pnas.1102826108/-/DCSupplemental/pnas.201102826SI.pdf?targetid=nameddest=ST1) shows SAM output genes significantly distinct between the  $c$ -MYB<sup>+</sup> group and the rest of the  $ER^+$  arm of PAD output. [Table S2](http://www.pnas.org/lookup/suppl/doi:10.1073/pnas.1102826108/-/DCSupplemental/pnas.201102826SI.pdf?targetid=nameddest=ST2) shows SAM output genes significantly distinct between the  $c-MYB$ <sup>+</sup> group and the normal tissue group.

2.3. c-MYB signature. Genes that are believed to be downstream from  $c-MYB$  (10) were tested in the  $c-MYB^+$  group vs. normal tissue using a one-sided Student  $t$  test. Results are listed in [Table S3.](http://www.pnas.org/lookup/suppl/doi:10.1073/pnas.1102826108/-/DCSupplemental/pnas.201102826SI.pdf?targetid=nameddest=ST3)

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Fig. S1. The wold invariant is plotted as a function of the dimension reduction K. As the wold invariant is a measure of signal to noise, a local maximum in this plot indicates a good place to perform dimension reduction. In this case  $K = 10$  is a good choice.

#### **Histogram of larger absolute value of**

#### **5***th* **and 95***th* **percentiles for each gene**





larger absolute value of 5th and 95th percentiles computed for each gene

Fig. S2. For each gene, the 95th and 5th percentiles of expression levels in the disease component is computed. The larger of the two in absolute value denoted as  $Q_{gene}$  gives an estimate of the extent of deviation from normal for the gene. This deviation can be positive, indicating overexpression relative to normal levels, or negative, indicating underexpression relative to normal levels. The figure shows a histogram of the collection  $Q_{gene}$  of deviations from normal for the set of all genes. There are 1,836 genes for which this value exceeds the 85th percentile (lax-threshold genes) and 245 genes for which it exceeds the 95th percentile (stringent-threshold genes).

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**B.** Only bins with at least 2 data points are included in output

Fig. S3. (A) Complete output of the analysis. Each colored disk represents a bin containing several data points or patients. Thus, individual patients (data points) are not visible, and we only see bins containing collections of very similar points. This step provides a simplification of the original set of data points, because instead of showing a multitude of individual points, it shows a much smaller collection of bins, each bin containing a collection of very similar points. The size of bins relates to the number of data points contained in them. Thus, bins containing many data points appear as large discs, whereas bins with few points are drawn much smaller. When two bins have patients in common, an edge connects them. Thus, the bins provide a granularity to the overall set of data points, and the connections between bins, the edges that connect them, capture a rough shape of the data. Each data point has assigned to it a value of the Mapper xtit filter function, and the bins are colored by the average value of this function for the points in the bin. The legend with assigned colors is seen at the top. In this particular example, each data point is a tumor sample, its gene expression transformed by DSGA to measure deviation from the HSM. The filter function is the overall amount of deviation from the HSM. Thus, red bins contain patients whose overall molecular profiles deviate a lot from normal, whereas blue bins contain patients whose profile is very close to normal. Sometimes data points are quite sparse, and this sparseness is visible in the output as well. When the data points become some what sparse, we see the graph fan out in a slight web-like feature. When data becomes really sparse, pieces of the graph become completely disconnected. Areas of local data sparseness are indicated in the figure. Finally, some bins are very small, containing only a few data points. To get a more streamlined, simplified picture, we can choose to ignore bins that are very small. This is similar to ignoring outliers. (B) Same output, but with bins containing single points not shown. Notice that this more streamlined version loses some of the sparseness information (for example that the long ER+ arm no longer exhibits the sparseness at the halfway point) and accentuates some sparseness areas by causing breaks in some places (for example the Basal arm now appears in two pieces).



Fig. S4. Comparison between cluster analysis and PAD. Specifically, PAD consists of two major steps: the first step, DSGA, defines a transformation of the original data to detect extent of deviation from normal. It also provides a means to threshold genes so that only genes that deviate significantly from normal are retained. The second step, Mapper, involves detecting the shape of the data points in space. Cluster analysis is a different method to detect the shape of the data in space. This figure shows the difference between using cluster analysis as opposed to using Mapper to detect the shape of the same data matrix. We took the matrix whose columns are the disease components of the DSGA-transformed data, with only the 262 genes obtained by thresholding genes according to deviation from normal. This matrix was analyzed to detect its shape in space in two distinct ways: (i) it was clustered with associated heatmap and dendrograms shown, and (ii) it was processed with Mapper, with the output shown. The ER<sup>+</sup> arm is magnified, and the position of each tumor in each consecutive bin is shown relative to its placement in the clustering dendrogram. It is easily visible that whereas the  $c$ -MYB<sup>+</sup> group of tumors are close to one another in the PAD output, they are scattered throughout the ER<sup>+</sup> portion of the clustering diagrams. It is important to note that the same matrix was fed into the Mapper and the cluster analysis. The figure shows these outputs to be very distinct. The figure does not and cannot identify which output is identifying features that deserve to be noticed: cluster analysis did not identify the c-MYB<sup>+</sup> group, but it is not clear, simply on the basis of this figure, that the group is a real feature rather than an artifact of Mapper. It is through subsequent analysis methods that we see that the c-MYB<sup>+</sup> group is indeed both mathematically and biologically distinct. Thus, the PAM analysis shows the group to be mathematically coherent and easily distinct, and functional exploration of the genes identified by SAM analysis, along with survival analysis of the group, show it to be a biologically coherent and meaningful group of tumors. This figure shows that the shape analysis provided by clustering is different from that provided by Mapper.



#### PAM analysis c-MYB+ group vs. Normal

Fig. S5. Output of PAM analysis on the c-MYB<sup>+</sup> group vs. Normal data. Two genes provide class prediction with error rate = 0: TRH,TSH-releasing hormone, and PCSK1, proprotein convertase subtilisin kexin type 1. The centroids, cross-validation probabilities, and misclassification error plots are shown.

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## Table S1. Genes significantly up-regulated and down-regulated in  $MYB+vs.$  the rest of  $ER<sup>+</sup>$  sequence



# Table S1. Cont.

PNAS PNAS

MYB level vs. rest of



## Table S2. Genes significantly up-regulated and down-regulated in MYB+ vs. Normal tissue



## Table S2. Cont.



# Table S2. Cont.



## Table S3. Testing the MYB signature genes

