Additional file 1: Development of an \textit{n}\text{-}gene signature of prostate cancer aggressiveness by cross-study examination of gene expression profiling data.

\textit{Datasets and processing}

To investigate multigene signatures of prostate cancer (PCa) aggressiveness we evaluated gene expression profiling data from three independent PCa studies comparing tumor and normal prostate tissue. In our analysis we considered only primary tumor specimens from each study which had sufficient follow-up PSA data available.

A. Singh \textit{et al} [1]: RNA microarray dataset containing 12,625 genes (Human Genome U95Av2 array; Affymetrix, Santa Clara, CA) was obtained from the Broad Institute database. Specimens included 21 primary prostate adenocarcinomas and were classified as aggressive (\(n=8; 38.1\%\)) if the patient experienced two successive PSA values of 0.2 ng/mL or higher post-prostatectomy.

B. Yu \textit{et al} [2]: RNA microarray dataset containing 12,625 genes (Human Genome U95A array; Affymetrix) was obtained from NCBI GEO DataSets (accession GSE6606). Specimens included 58 primary prostate adenocarcinomas and were classified as aggressive (\(n=26; 44.8\%\)) if the patient experienced increased PSA value post-prostatectomy, local tumor invasion, and/or distant metastasis.

C. Lapointe \textit{et al} [3]: cDNA microarray dataset containing 26,260 genes (custom cDNA spotted array; Stanford University) was obtained from NCBI GEO DataSets (accession GSE3933) and used as a validation dataset. Specimens included 28 primary prostate adenocarcinomas and were classified as aggressive (\(n=7; 25.0\%\)) if the patient experienced >0.07 ng/mL rise in PSA post-prostatectomy and/or distant metastasis.
Raw RNA expression data were normalized within each dataset by applying the Robust Multichip Average (RMA) algorithm using Affymetrix Expression Console. A maximum threshold was set at the 99th percentile to mitigate the effects of extreme outliers. To correct for differences in differential intensity profiles between arrays within a dataset, arrays were least squares normalized by multiplying each array by 1/slope of an array constructed from the median expression value of each gene across all samples as described [4]. To provide a relative measure of fold-change which is more generalizable for cross-study analysis, arrays were adjusted by dividing each array was by its median expression value.

Raw cDNA expression data from Lapointe et al was not compatible with Affymetrix Expression Console software so our normalization technique for the Lapointe dataset was meant to approximate RMA for a two channel non-Affymetrix chipset using four steps: background correction, normalization, log correction, and linear modeling as described [5]. A procedure for the quantile normalization step is outlined by Bolstad et al [6]. The linear modeling step was omitted since cDNA expression data does not need probe set summarization normally required for RNA microarrays.

**Gene filtering**

Datasets from Singh et al [1] and Yu et al [2] were used as training datasets for building a supervised prediction model. To compare expression data from individual genes with tumor aggressiveness or non-aggressiveness we calculated the signal-to-noise ratio ($S_x$) for each gene:

$$S_x = \frac{\mu_{NA} - \mu_A}{\sigma_{NA} + \sigma_A}$$

where, $\mu$ is the mean expression value and $\sigma$ is the standard deviation of the expression values for a given gene $x$ across all non-aggressive (NA) or aggressive (A) specimens in a single dataset as described [4, 7]. The 500 genes with the most positive $S_x$ ("non-
aggressiveness genes”) and 500 genes with the most negative $S_x$ (“aggressiveness genes”) were selected from each dataset to create a group of the 1000 most informative genes in each dataset. The top 1000 genes ranked by informational content (decreasing absolute value of $S_x$) in each training dataset are listed in Additional file 2: Table S1 (Singh et al) and Additional file 3: Table S2 (Yu et al). UniGene names were then mapped from Affymetrix probe set identifiers using GeneSifter (Geospiza, Seattle, WA). A total of 110 genes were shared between both top 1000 lists although complement component genes C2 and C7 were excluded (due to their ubiquitous presence in blood/tissues and unlikely specificity for PCa) resulting in 108 shared genes retained within each dataset for further analysis. Expression values for genes with multiple probe set identifiers were averaged. Signal-to-noise ratios for this selected gene set were averaged and weighted to account for difference in sample size between datasets. The list of genes was truncated at 50 as we aimed to validate these markers by immunohistochemistry; an additional 4 genes (UGT2B11, ITPR1, DNM2, and RFPL3) were subsequently excluded because they were not represented by cDNA probes in the Lapointe et al validation dataset. This final ordered list of 46 genes was ranked by decreasing informational content (absolute value of weighted average $S_x$) (Additional file 4: Table S3) and used in weighted voting analyses.

Supervised prediction using a weighted voting process

To examine the prognostic value of $n$-gene signatures derived from our ranked list of 46 genes, we utilized a weighted voting and class prediction process described by Ramaswamy et al [4] and originally developed by Golub et al [7]. Gene expression data and signal-to-noise ratios described above from Singh et al [1] and Yu et al [2] were used as inputs for training the
weighted voting algorithm to recognize aggressive from non-aggressive PCa. The independent cDNA expression dataset from Lapointe et al [3] was used for validation testing.

Aggressiveness or non-aggressiveness of a specimen \( y \) was predicted by the summation of weighted votes \( (V) \) from the \( n \) highest quality genes included in the model (consecutively added from the ranked set of top 46 genes in Additional file 4: Table S3). First, a vote \( (v_x) \) towards aggressive or non-aggressive was defined as \( v_x = S_x \left( g_x^y - b_x \right) \) and assigned to each ranked gene based on the signal-to-noise quality factor \( (S_x) \) and proximity of a given specimen’s gene expression level \( (g_x^y) \) to the gene’s average expression level among non-aggressive \( (\mu_{NA}) \) or aggressive specimens \( (\mu_A) \) using its midpoint boundary \( (b_x = (\mu_{NA} + \mu_A) / 2) \). Weighted voting calculations are shown in Additional file 5: Table S4 (Singh et al) and Additional file 6: Table S5 (Yu et al). A final decision towards aggressiveness or non-aggressiveness was formulated by the summation of weighted votes \( (V) \) for \( n \) genes included in the model: \( V = \Sigma_x v_x \) where the summation \( (V) \) is positive (non-aggressive) or negative (aggressive). Genes were consecutively added to the \( n \)-gene model by decreasing weighted average \( S_x \) beginning with the single highest quality gene from the ranked set of top 46 genes in Additional file 4: Table S3 (e.g., 1-gene model = CASR; 2-gene model = CASR+ACPP; 3-gene model = CASR+ACPP+GADD45B, etc.). Final \( n \)-gene voting predictions and statistical results for each model are shown in Additional file 7: Table S6 (Singh et al) and Additional file 8: Table S7 (Yu et al). Negative predictive values (NPV) and positive predictive values (PPV) were calculated under the assumption that a positive test result was defined by a prediction of aggressiveness and a negative test result was defined by a prediction of non-aggressiveness. Maximum NPVs occurred at 8 genes (100.0%; Singh et al) and 11 genes (72.7%; Yu et al).
Validation of n-gene models

Using the ranked set of top 46 genes (and weighted average $S_x$ quality factors) generated from the Singh et al and Yu et al training datasets, we tested $n$-gene models using normalized cDNA expression data from a third independent validation dataset (Lapointe et al [3]) (Additional file 9: Table S8). Weighted voting was performed as described above using normalized cDNA gene expression data from the Lapointe et al validation dataset and weighted average $S_x$ values derived from the training datasets (Additional file 10: Table S9). Final $n$-gene voting predictions and statistical results for each model using the Lapointe validation dataset are shown in Additional file 11: Table S10. Maximum NPV (94.7%) of a test for non-aggressiveness (optimized to identify aggressive tumors, even at the risk of scoring non-aggressive disease as “aggressive”) occurred with an 11 gene model (Additional file 12: Table S11).

In the Singh et al dataset, this 11-gene model successfully identified 7 of 8 aggressive tumors and 10 of 11 non-aggressive tumors, resulting in 87.5% sensitivity and 90.1% specificity. In the Yu et al dataset, the 11-gene model successfully identified 17 of 24 aggressive tumors and 24 of 31 non-aggressive tumors, resulting in 70.8% sensitivity and 77.4% specificity. In the Lapointe et al dataset, the 11-gene model successfully identified 6 of 7 aggressive tumors and 15 of 16 non-aggressive tumors, resulting in 85.7% sensitivity and 93.8% specificity. Prediction of aggressiveness using the 11-gene model was significantly associated with actual prognosis in the Lapointe et al validation dataset using Fisher’s Exact test ($p=0.001$).

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