SUPPLEMENTAL FIGURES

Figure S1 Use of IGHV mutation status to stratify patient samples. Survival curves on SC→TX for the 17 European patients (A) or for the patient cohort in Friedman et al (2009) (B).

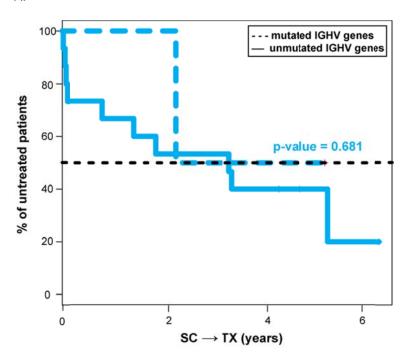
Figure S2 Detection of known disease genes with cancer susceptibility. The enrichment of disease genes is shown for the 38 subnetworks or top 230 genes selected from the 130 patients from UCSD, or for random subnetworks of the same size as the identified 38 subnetworks, but without regard to the expression profiles. Bars chart the percentage of disease genes among all genes covered in the markers. Numbers above the bars are the hypergeometric P-values of enrichment.

Figure S3 Schematic overview of subnetwork identification. Protein interaction networks are used to assign sets of genes to discrete subnetworks. Gene expression profiles of tissue samples are transformed into a "subnetwork activity matrix". For a given subnetwork M_k in the interaction network, the activity is a combined z-score derived from the expression of its individual genes. After overlaying the expression vector of each gene on its corresponding protein in the interaction network, subnetworks with discriminative activities are found via a greedy search. Significant subnetworks are selected based on null distributions estimated from permuted subnetworks. Subnetworks are then used to identify disease genes, and the subnetwork activity matrix is used to train a classifier for prognosis of newly diagnosed patients.

Figure S4 Enriched biological processes in the significantly predictive subnetowrks. The 38 subnetworks are enriched for proteins functioning in a common biological function as annotated by Gene Ontology database (hypergeometric test with a false discovery rate of 5%). Enriched terms from the Biological Process category, are depicted in the top.

Figure S1

Α.



В.

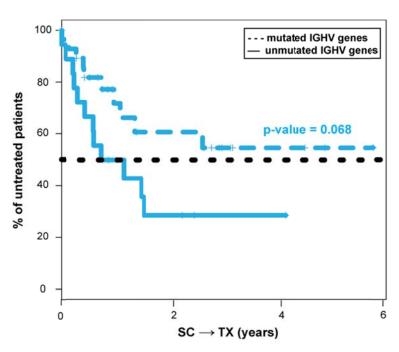


Figure S2

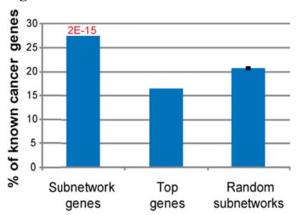
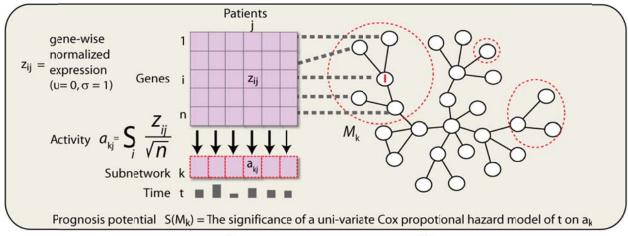


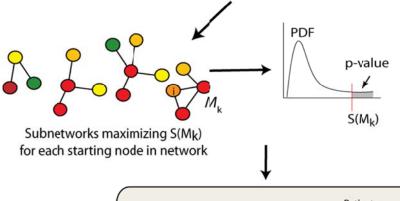
Figure S3

Gene expression profilings using microarrays or sequencing ~20K genes across hundreds patients

- ~50K interactions among ~10K proteins are pooled from 1) protein-protein interactions from
 - a. interaction databases: BIND, REACTOME, HPRD, and BIOGRID
 - b. yeast two-hybrid screening using human proteins: Rual et al., 2005 Stelzl et al., 2005

2) protein-DNA binding from TRANSFAC





n1:

The null distribution of S is estimated by all random subnetworks

p2:

The null distribution of S(M_k) is estimated by random subnetworks seeded at node i

p3:

The null distribution of $S(M_k)$ is estimated by permuting phenotypes

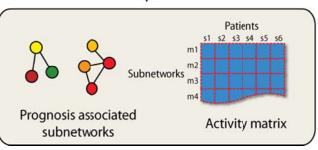
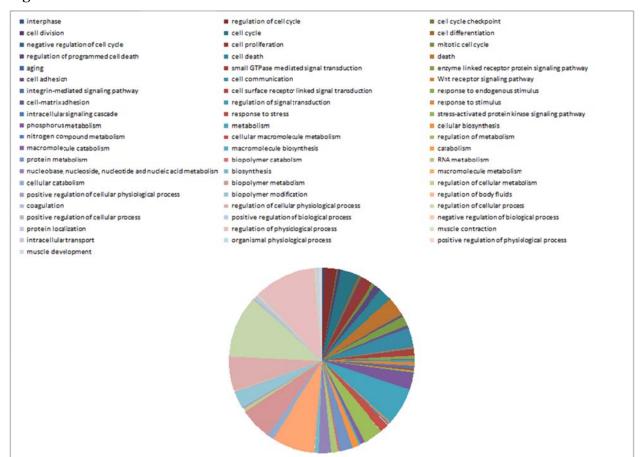


Figure S4



SUPPLEMENTAL METHODS

Selecting significant subnetworks. To assess the significance of the identified subnetworks, Ms, three tests of significance are performed. For the first test, we perform the same search procedure over 100 random trials in which the expression vectors of individual genes are randomly permuted on the network. Such permutation disrupts the correlation between expression and interaction. The score S(M), $-\log p$ -value of a χ^2 test on a Cox proportional hazard model on T, of each real subnetwork is indexed on the 'global' null distribution of all random subnetwork scores. The second test indexes each real subnetwork score on a 'local' null distribution, estimated from the S(M) scores of 100 random subnetworks initialized from the same seed protein as the real subnetwork. Third, we test whether S(M) of a Cox proportional hazard model on real T is stronger than that obtained with random assignments of T to patients. For the random model, these assignments are permuted in 20,000 trials, yielding a null distribution of mutual information scores for each trial; the real score of each subnetwork is indexed on this null distribution. In this study, significant subnetworks are selected that satisfy all three tests with $P_1 < 0.05$, $P_2 < 0.05$, and $P_3 < 0.00005$, according to the three different null distributions of S(M).

DNA primers for Real time PCR in serial gene expression experiments

1. TCEB3		
Forward 5'-	TTTGCCAGGGACCTAGTGG	-3'
Reverse 5'-	CGCTTTCGGGAATTGCTCT	-3'
2. MED9		
Forward 5'-	CCTTTGGTTCACAACATCATCAA	-3′
Reverse 5'-	CTGGAACTTGCTTTTGAGGG	-3′
3. CEBPA		
Forward 5'-	CCACGCCTGTCCTTAGAAAG	-3′
Reverse 5'-	CCCTCCACCTTCATGTAGAAC	-3'
4 (5500		
4. CEBPB Forward 5'-	GGCCCTGAGTAATCGCTTAAAG	-3'
rorward 5 -	GGCCTGAGTAATCGCTTAAAG	-3
Reverse 5'-	TCCCAAAATATACAGACGCCTC	-3'
5. CSPG6	CCCACCAACCATTTCAAAAC	2/
Forward 5'-	CCCCAGGAAGCATTTGAAAAG	-3′
Reverse 5'-	CTGCTCGGAGAAATTTACAAACTG	-3'
6. PFTK1		
Forward 5'-	TGGCCTGGAGTTCATTCTTTAC	-3'
Reverse 5'-	AACATTGTAGGAGCTTGGAGG	-3'

7. ACVR1 Forward 5'-GAAGATATGAGGAAGGTAGTCTGTG -3' -3' Reverse 5'- AGTGCTGTGAGTCTTGCG 8. FKBP4 Forward 5'-CAATATGTTTGAGAGGCTGGC Reverse 5'- CTATGCTTCTGTCTCCACCTG 9. DYNLL1 Forward 5'- ACATAGAGAAGGACATTGCGG Reverse 5'- GCCCAGGTAGAAGTAGATGAAG 10. SMAD2 Forward 5'--3' GCCGTCTATCAGCTAACTAGAATG Reverse 5'- TTTGTCCAACCACTGTAGAGG -3' 11. IRAK2 Forward 5'- AAGCGAGTGGACATCTTCAG -3' Reverse 5'- CTGCTTGGAATATCACTGAGGA 12. SUPT3H Forward 5'- ATTTCGAGACTGGTTGGACTG Reverse 5'- GGTTACCATGTCTTGCCTCAC 13. CSNK2A1 -3' Forward 5'-TTCAGTGCCAACCCCTTC Reverse 5'- AGGCATCAGGAGACAGATAGG

14. SKP2		
Forward 5'-	CCAACACCTATCACTCAGTCG	-3'
Reverse 5'-	TCTGTATGTTTGAGGGCATCC	-3'
15. CDC26		
Forward 5'-	GACGGAAACCAACACGCCTA	-3'
Reverse 5'-	GCCTCCTACAACTTCCACATC	-3'
16. TNFRS	E7	
Forward 5'-	GCTCCGATTTTATTCGCATCC	-3'
Reverse 5'-	TGTAACGACAAGGCTCTGC	-3'
17. MCP		
Forward 5'-	CCTCCATCTAGTACAAAACCTCC	-3'
Reverse 5'-	CACAGCAATGACCCAAACATC	-3'
40 545		
18. DMD		
Forward 5'-	AGAAATACCCCTGGAAAGCC	-3'
Reverse 5'-	TTCTGCTCCTTCTTCATCTGTC	-3′
19. CCT4		
Forward 5'-	CAGAACTAAGAAACCGGCATG	-3'
Reverse 5'-	TCAGTTGCAAGAGTCAGAGC	-3'
20 CCT7		
20. CCT7 Forward 5'-	ATGCCCACACCAGTTATCCTA	-3'
rui wai u 5 -	ATUCCACACCAGTTATCCTA	-3
Reverse 5'-	CAGGGTAGTTCTTACAGCCTCA	-3′

21. CREB3

Forward 5'-	CCTTGTACCTGCTATGTACTCC	-3′
Reverse 5'-	TCTTTCGGCACTTCTGACTG	-3′