a. Workflow for tumor-immune infiltrate profiling



b. Investigated immune cell types and gene signatures



* T central and effector memory cells were not gated for CD4 or CD8.

** The cytotoxic cell signature includes genes overexpressed in CD8+ T cells, T $\gamma\delta$ cells, and NK cells.

Figure S1. Workflow and the investigated immune cell types. (a) Workflow for tumor immuneinfiltrate profiling. **(b)** The investigated immune cell types are shown (**bold**) with two hierarchical trees: innate and adaptive immunity cell types (top panel), and distinct T cell subsets (bottom panel). The number of genes in each signature is displayed in parentheses next to the studied cell type.



Figure S2. Number of genes shared between signatures. The number in each box denotes the number of genes in common between the corresponding signatures. 98.4% (501) of these genes were used uniquely in only one signature





Figure S3. Batch effect correction for the three microarray datasets used to derive immune cell gene signatures. PC analysis on the GCRMA-normalized microarray expression data using 501 signature genes revealed batch effects from the three data sources (top panel). Batch effects were corrected using the nonparametric option in ComBat (bottom panel). After batch-effect correction, cell types of similar lineages but from different data sources clustered together. Cell type labels are given in the batch-effect-corrected PC plot in Figure 1a.



Figure S4. PC separation of 14 immune cell types in training data using transcript levels of signature genes. Microarray gene expression data were generated from immune cell types sorted by magnetic or fluorescent activated cell sorting[31-33] and used in Bindea et al to derive the signatures. Other cell types in Bindea et al., such as the ones for which signature genes are based on biological knowledge (such as Tregs and Th17 cells) or the ones that are umbrella terms (such as T helper cells and cytotoxic cells) could not be included in the PC analysis due to absence of microarray data.



After batch effect correction

Figure S5. PC separation of T cell subpopulations using signature genes. Microarray gene expression data generated from sorted immune cell types were normalized with GCRMA and filtered to keep only T cell subpopulation samples and signature genes for these subpopulations. Batch effect correction was then performed with ComBat before running PC analysis on the samples. Signature genes achieve a robust separation of T cell subpopulations.



ABSOLUTE Purity

Methylation-based leuk. fraction





Figure S6. Overall immune infiltration score (IIS) correlations with methylation-based

leukocyte fraction and tumor purity. (Left) The scatter plots of IIS vs. methylation-based leukocyte fraction for 13 tumor types, and (Right) the scatter plots of IIS vs. tumor purity estimates from the ABSOLUTE algorithm. Spearman correlations and the corresponding p-values are shown in each plot. The red lines indicate the regression line for y~x.



Supplementary Figure 5 (continued)



Supplementary Figure 5 (continued)





















Figure S7. T cell infiltration score (TIS) correlations with TCR beta chain abundance. The scatter plots of TIS vs. TCR beta chain abundane for 19 tumor types. Spearman correlations and the corresponding p-values are shown in each plot. The black lines indicate the regression line for y~x.



Figure S8. Pan-cancer analysis of overall immune infiltration score (IIS). Overall immune infiltration score (IIS) (top panel) and the corresponding total number of somatic missense mutations (bottom panel) for 19 tumor types. Each dot represents an individual tumor sample. Tumor types are ordered from left to right according to increasing median IIS (medians indicated by horizontal gray bars). There is little relationship between IIS and the quantity of somatic missense mutations.



Figure S9. T cell subpopulations used in the aggregate TIS score. Pan-cancer comparisons of T cell subpopulation infiltration levels: CD8 T, Th1, Th2, Th17, Treg, Tcm, and Tem cells (Tcm: T central memory, Tem: T effector memory). The order of tumor types is adopted from the TIS order in Figure 3a.



c. Cytolytic index vs Missense mutation count All data



0.0166488

0.0391102

0.0270049

0.3516601

0.6322553

0.1210953

0.0006771

0.2365885

0.0192765

193

126

174

188

258

93

196

312

244

0.057829417

0.078220371

0.069441254

0.436377953

0.669446765

0.181642993

0.006093713

0.327584107

0.057829417

LIHC

LUAD

LUSC

ov

PRAD

SKCM

STAD

THCA

UCEC

-0.172

0.184

0.168

0.068

-0.030

0.162

0.241

-0.067

0.150

Cytolytic index vs Missense mutation count From 5th to 95th percentile



				FDR adjusted
CTYPE	SPERMAN R	P-VALUE	Ν	P-VALUE
BLCA	0.105	0.26194165	115	0.336782117
BRCA	0.114	0.00286943	680	0.025824859
CESC	0.149	0.0527055	170	0.158116486
CRC	0.190	0.00782021	195	0.035190946
GBM	0.104	0.23597264	131	0.326731343
HNSC	0.003	0.96400108	244	0.964001076
KIRC	-0.068	0.20464324	352	0.306964859
KIRP	-0.150	0.07193297	144	0.161849181
LGG	0.201	0.00762423	176	0.035190946
LIHC	-0.117	0.12427578	173	0.203902288
LUAD	0.146	0.12351287	112	0.203902288
LUSC	0.177	0.02732257	156	0.098361238
ov	0.055	0.47687753	169	0.572253034
PRAD	-0.041	0.53808469	232	0.605345273
SKCM	0.170	0.12460695	83	0.203902288
STAD	0.236	0.00159275	177	0.025824859
THCA	-0.032	0.59083449	280	0.625589461
UCEC	0.124	0.0676565	219	0.161849181

Figure S10. Local regression curves and correlations between cytolytic activity index (CYT) and mutation counts. (a-b) Local regression curves and correlations between CYT and total mutation count (a) when the entire range of the mutation data is used (b) when only the 9th to 95th percentile of the mutation data is used as implemented in [13]. (c-d) Local regression curves and correlations between CYT and number of somatic missense mutations (c) when the entire range of the mutation data is used (d) when only the 9th to 95th percentile of the mutation data is used (d) when only the 9th to 95th percentile of the mutation data is used. Cancer types where the correlations is significantly different from zero at 0.05 alpha level after multiple hypothesis correction are highlighted in green. CYT and total mutation data were obtained from [13], and missense mutation data were obtained from the Feb 4, 2015 output of Firehose.



Figure S11. Pan-cancer tumor-normal differences for APM. APM scores for cancer types are shown with boxplots adjacent to the relevant normal tissue. Tumor-normal differences are compared with Mann-Whitney tests, and p-values are corrected for multiple hypothesis testing with the Benjamini & Hochberg method. TCGA RNA-seq data are used for the analysis.

a. APM expresssion vs. tumor grade



b. APM expresssion vs. tumor stage

Figure S12. Grade– and stage–specific APM expression. We investigated the association of antigen presentation machinery gene expression with (a) tumor grade and (b) tumor stage. Even though the grade and stage groups showed significant differences at α =0.1 (p = 0.07 and 0.004 respectively, ANOVA), a linear trend between APM and these variables does not exist. A positive association could suggest that APM expression increases with necrosis.









Neutrophils



Low Group



Figure S13. The signatures where ccRCC is among the highest or lowest across 19 cancer

types. Analysis of immune cell and angiogenesis levels across 19 human cancers. ccRCC tumors stand out from others by having elevated levels of angiogenesis, several T cell signatures (T cells, *CD*8⁺ T cells) along with pDCs, cytotoxic cells and neutrophils. ccRCC tumors are relatively poorly infiltrated by Tregs and Th2 cells.

a. Random forest prediction of immune infiltration class for Sato et al. patients



Figure S14. Validation of ccRCC immune infiltration classes with the SATO dataset. (a) A random forest classifier trained on the TCGA ccRCC cohort was used to predict the immune infiltration class for 101 patients in the SATO cohort. As was observed in TCGA ccRCC tumors (Figure 5a), T cell enriched tumors show higher expression of antigen presentation machinery genes, granyzme B and interferon gamma. The order of samples in each class from left to right is by increasing immune infiltration score (IIS). The order along the y-axis is adopted from the TCGA ccRCC heatmap in Figure 5a. (b) Heatmap of genes overexpressed in each immune infiltration class (p-value threshold 0.01). The order along the y-axis is obtained by hierarchical clustering with Euclidean distance and Ward linkage. DAVID gene set enrichment analysis reveals that T cell enriched tumors have overexpression of immune response genes while non-infiltrated tumors have overexpression of mitochondrial genes. These results validate the findings in the TCGA ccRCC cohort.

a. Subclustering within the T cell enriched cohort



b. Network analysis for overexpressed genes in TCa and TCb



c. Kaplan-Meier curves for cancer-specific survival in TCa and TCb



Figure S15. Subclustering within the T cell enriched cohort demonstrates gene expression and survival differences. (a) Hierarchical clustering within the T cell enriched cohort revealed two distinct subclusters, here termed TCa and TCb, that had differences in immune cell levels such as macrophages as well as in grade, stage, and stromal score (top panel). Hierarchical clustering was performed with Euclidean distance and Ward linkage. Differential gene expression analysis was performed with Mann-Whitney tests (bottom panel). Only genes that are significantly overexpressed in one cluster at a q-value cutoff of $5x10^{-5}$ are shown. Pathway analysis using DAVID[44] reveals that the genes overexpressed in TCa and TCb (N = 328 and 501 respectively) are enriched in 1) metabolic and mitochondrial processes; and 2) extracellular matrix (ECM), cell cycle and cell proliferation respectively. (b) Network analysis with ClueGO[50] highlights the upregulation of metabolic processes in TCa, and the upregulation of ECM, cell cycle, cell proliferation in TCb. (c) Kaplan-Meier curves for cancer-specific survival in the TCa and TCb patients. Patients in the TCa subcluster have significantly better survival (log-rank test p-value = 0.016)



Figure S16. The correlation between the macrophage and ESTIMATE stromal scores in ccRCC. We investigated the association between the macrophage scores in ccRCC and the stromal scores calculated with the gene signature in ESTIMATE. These scores were positively correlated across the entire TCGA ccRCC cohort (Spearman r = 0.561, p < 2x10-16).



Figure S17. Significant associations between immune cell infiltration levels and tumor stage. Tumor stage is positively associated with Treg cell infiltration (left panel) and negatively associated with Th17 cells (right panel) in the TCGA ccRCC cohort. Adjusted p (i.e. q) values are shown here as all 24 immune cell types were tested against stage.

a. TCGA



b. SATO

APM, **p** = 0.116 High purity Low purity samples 0.50 ssGSEA score 0.48 0.46 0.44 2 2 3 5 1 3 4 Number of SNV clusters

Cytotoxic cells, p = 0.07



ED8 T cells, p = 0.18 High purity samples Low purity samples OUSPENDENT OF THE SAMPLES Service of the samples of the sample

TIS, p = 0.122



Figure S18. Immune cell score differences in gene expression-based ccRCC subtypes ccA (N=205) and ccB (N=175). Association of immune cell scores with previously defined molecular ccRCC subtypes (ccA and ccB). ccA exhibits significantly higher Th17 and $CD8^+$ T cell infiltration levels, but lower scores for Treg and Th2 cells. The former two cell types are associated with improved survival, and the latter two with poor survival (Figure 6b). These findings are consistent with reports that showed ccA has better prognosis compared with ccB[56]. Adjusted p (*i.e.* q) values are shown here as all 24 immune cell types were tested against molecular subtype.



Figure S19. SciClone clonality analysis for SATO samples. The x axis shows the number of single nucleotide variant (SNV) clusters for each tumor where 1 corresponds to clonal tumors and higher number of clusters indicate subclonal architecture. The y axis shows the ssGSEA scores for immune signatures APM, CD8 T cells, cytotoxic cells, and TIS. A trend for an inverse association between immune infiltration and subclonal architecture is observed, although p-values do not reach significance (One-sided p-value = 0.12, 0.18, 0.07, 0.12 respectively). The fraction of samples for each SNV cluster number is 45.8% for 1 cluster (N=44), 26.0% for 2 clusters (N=25), 19.8% for 3 clusters (N=19), 7.3% for 4 clusters (N=7), 1.0% for 5 clusters (N=1).

a. TCGA



b. SATO

APM, **p** = 0.116 High purity Low purity samples 0.50 ssGSEA score 0.48 0.46 0.44 2 2 3 5 1 3 4 Number of SNV clusters

Cytotoxic cells, p = 0.07





TIS, p = 0.122



Figure S20. Purity-adjusted clonality analysis for TCGA and SATO samples.

Immune scores are adjusted for purity by regressing immune scores on purity estimates on obtaining the residuals. The association between purity-adjusted immune scores and clonality is investigated with a trend test, and p-values are shown in the subfigure titles. Each subfigure contains two groups of boxplots, one for high purity and and for low purity samples. The axes are the same as in **Figure S19**. (a) TCGA dataset, (b) SATO dataset.

a. Recurrent driver mutations





Figure S21. Association of ccRCC immune infiltration classes with recurrent driver mutations and copy number variants

Between the three ccRCC groups, we observed no significant differences in the frequency of recurrent (a) driver mutations or (b) copy number variants.



Figure S22. Association of ccRCC immune infiltration classes with neoantigenicity

There were no significant differences between the three ccRCC immune infiltration classes in **(a)** the count of mutations that code for at least one neo-antigen predicted to bind to MHC-I (IC50 < 500nM), or **(b)** the overall quality of neo-antigens. We assessed the overall quality of the neo-antigens found in each cluster by selecting the highest affinity pMHC for each mutation and taking the median of these IC50s (IC50 is inversely related to binding affinity).

Noiseless mixture



Noisy mixtures



Figure S23. Empirical null distributions for the Spearman correlations between simulated and inferred immune cell levels

ssGSEA was run 1000 times on all *in silico* noiseless and noisy mixture datasets generated for **Figure 2a** top panel, each time with a different set of four random signatures that emulated the signatures for NK cells, macrophages, $CD4^+$ and $CD8^+$ T cells. Each run inferred the four types of scores for 200 samples, and then a Spearman correlation was computed for each cell type between the inferred scores and the simulated mixing proportions. At each noise level, 1000 correlation values from random bootstrap signatures formed an empirical null distribution (shown with density curves here) for the observed correlation from the actual signature. Bootstrap p-values are computed by using these empirical null distributions.



Figure S24. The correlation between the APM signature score and each infiltrating immune cell in **TCGA samples.** In cancer types with low TIS-APM correlations (GBM, LGG, KICH, ACC), APM is most strongly correlated with macrophages or dendritic cell subpopulations (DC, iDC, aDC).



Figure S25. Correlation of angiogenesis and pDC scores across 19 cancer types.

The 1-gene pDC signature score is highly correlated with the 40-gene angiogenesis signature score across different cancer types.