The Cancer Genome Atlas

What do we learn from Pan-Cancer Subtyping?

TCGA Symposium

May 12, 2014

Pan-Can Integrated Subtypes AWG

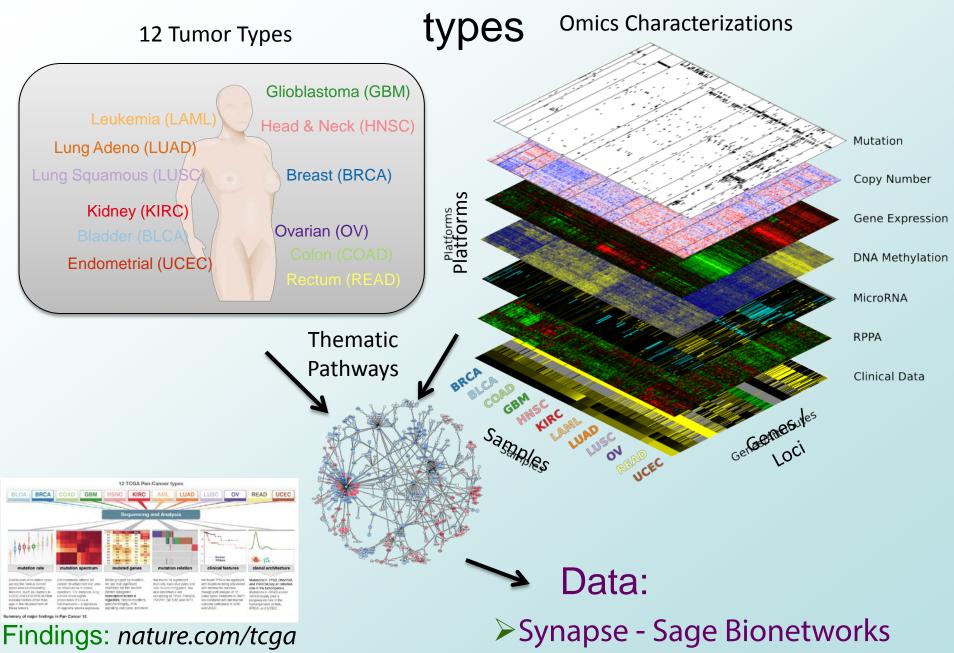
<u>Leads: Josh Stuart</u>, UCSC

Chris Benz, Buck Chuck Perou, UNC

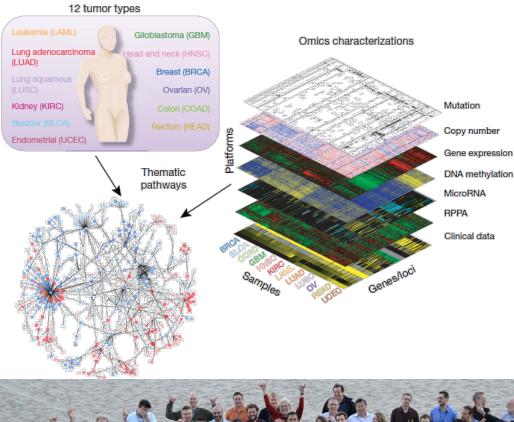




Pan-Cancer: Integrative analysis across tumor



Pan-Cancer-12 Dataset





Defined by Pan-Cancer AWG

~3500 Samples

| Tumor Type | # Somelar | |
|-------------------|--------------|----|
| | Samples | TA |
| AML | 173 | |
| Bladder | 122 | |
| Breast | 845 | |
| Colon | 190 | |
| Endometrial | 370 | |
| GBM | 168 | |
| Head & Neck | 303 | |
| Kidney Clear Cell | 480 | |
| Lung Adeno | 355 | |
| Lung Squamous | 259 | |
| Ovarian Serous | 265 | |
| Rectum | 72 | |

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Need a Map to navigate so much info

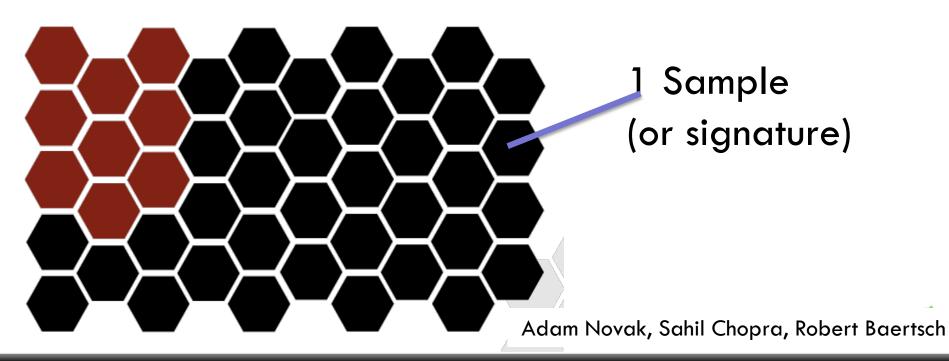
Inspiration: Google Maps

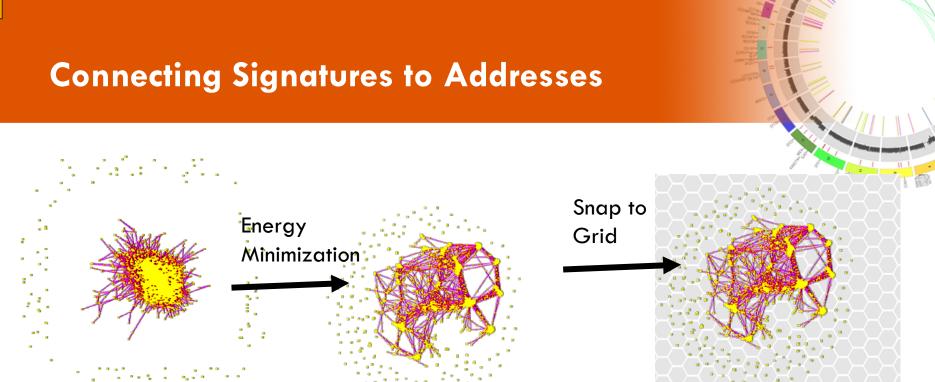
- Fixed, learnable coordinate system
- Natural human intuition
- Overlay stores, places, reviews, photos, video...
- And... Its not a heatmap!



Each sample has its own Address

- Each sample = hexagon (the address)
- Hexagons good packing properties
- Colors display attributes: outcomes, mutations, etc





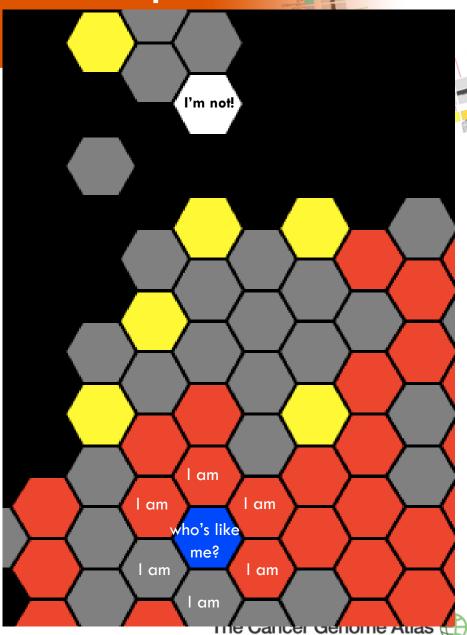
- Spring Layout: Low energy configuration of competing springs
- Snap to grid: Associate one point per hexagon.
- Samples w/ similar signatures \rightarrow same zip code.

Layout Engine: DrL. Sandia National Labs

Adam Novak, Sahil Chopra, Robert Baertsch

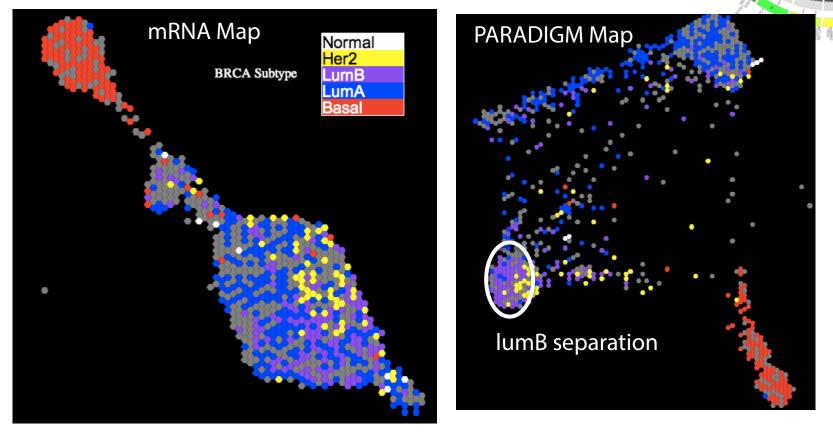
Identify similar samples in the same zip code

- Map address reflects molecular similarity
- "Zip codes" carry information
 - like: Russian Hill,
 Berkeley, Silicon
 Valley, Bethesda, ...



Adam Novak, Sahil Chopra, Robert Baertsch

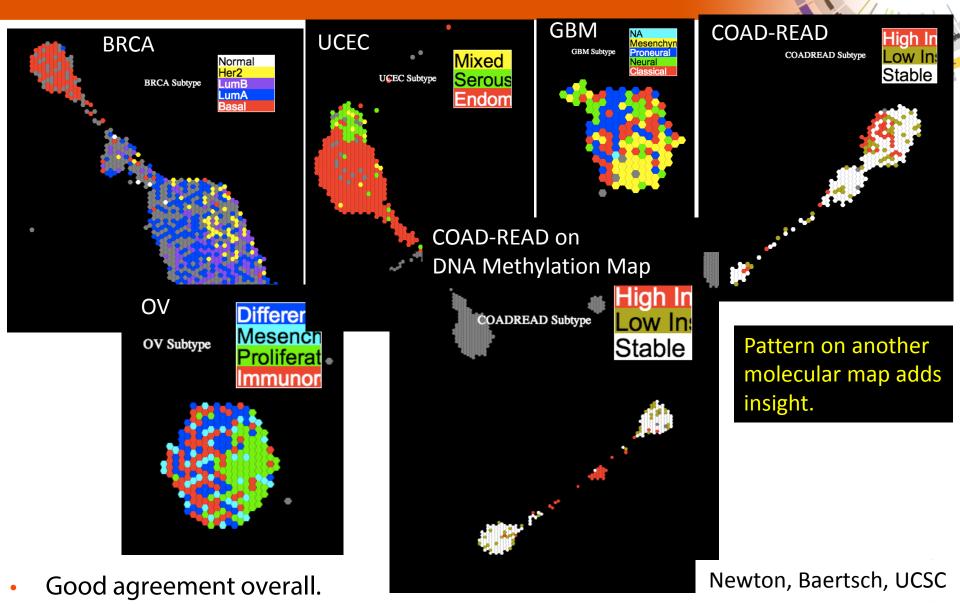
Are disease-specific AWG subtypes recapped in TumorMap?



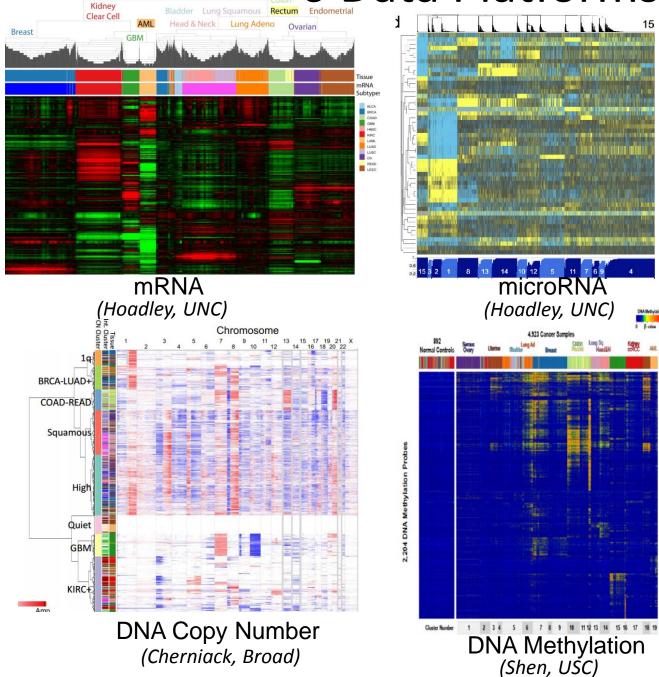
BRCA subtypes resolve clearly on mRNA and PARADIGM maps.



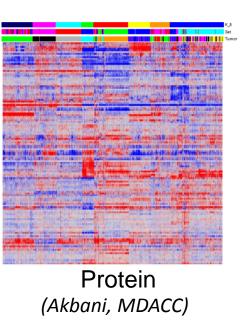
Are disease-specific AWG subtypes recapped in TumorMap?



6 Data Platforms



Breast



15

DNA Methylation β value 1

BLCA

BRCA

COAD

GBN HNSC

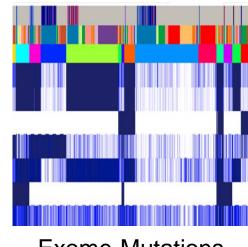
KIRC LANL

LUAD

LUSC OV

READ

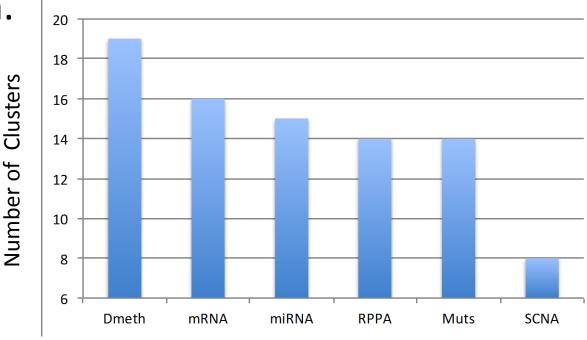
UCEC



Exome-Mutations (not used) (Uzunangelov, UCSC)

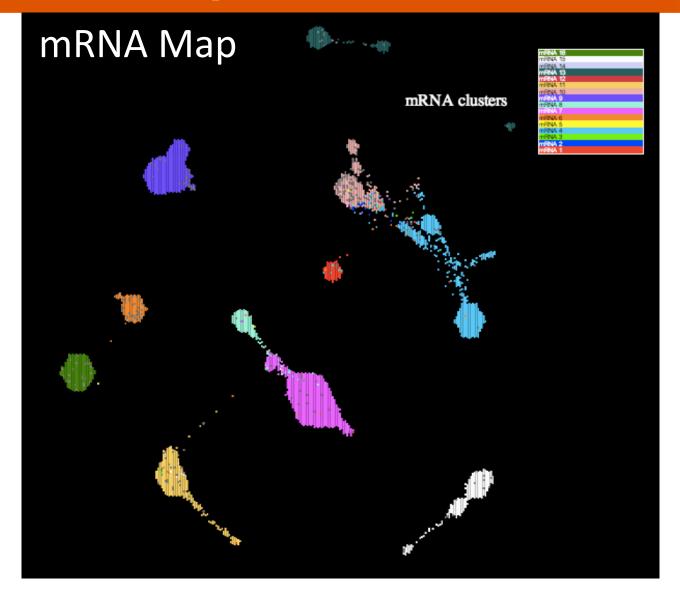
Single Platform Subtypes

- 6 platforms, each produced 8-19 different clusters.
 - DNA Methylation had the most.
- All subtypes show a strong correlation with tissue of origin.



Data Platform

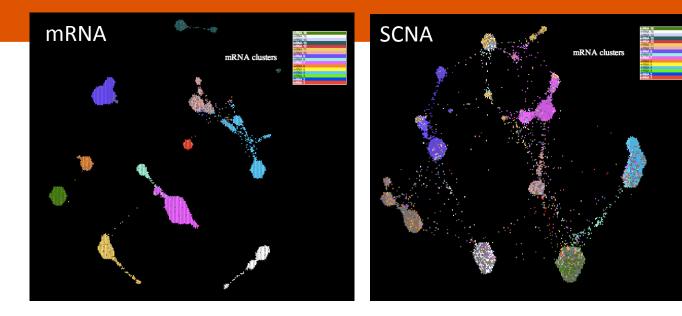
Single Platform Subtypes Recap on TumorMap



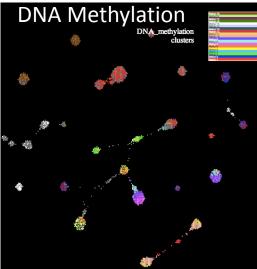
Colors reflect the subtypes obtained using mRNA platform.

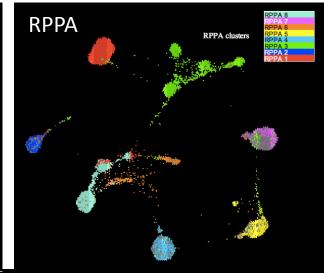
Newton, Baertsch, UCSC

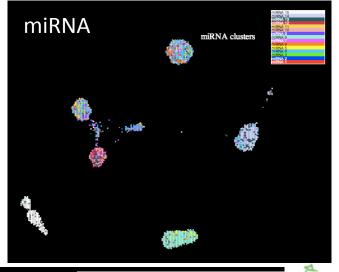
Single Platform Subtypes Recap on TumorN



Colors reflect the subtypes obtained using each different platform.



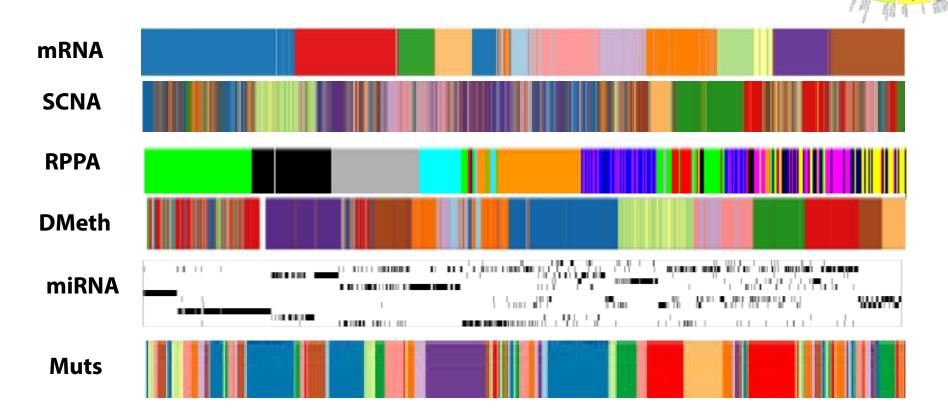




Good agreement w/ most. miRNA still needs work...

Newton, Baertsch, UCSC

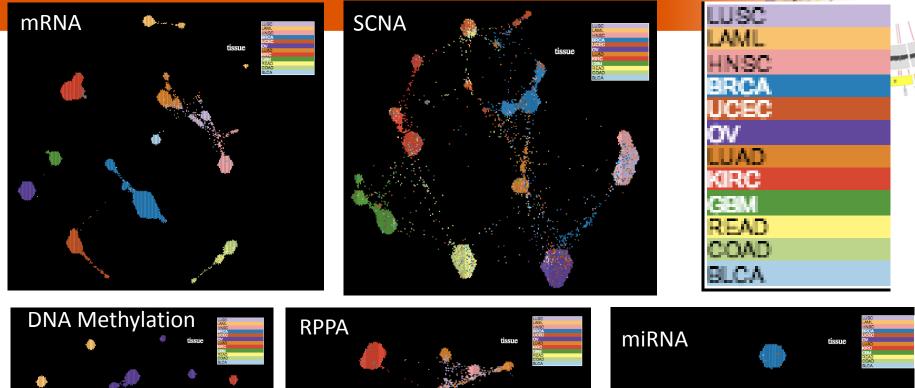
Single Platform Subtypes Correlated with Tissue of Origin

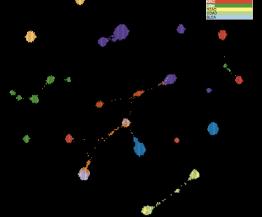


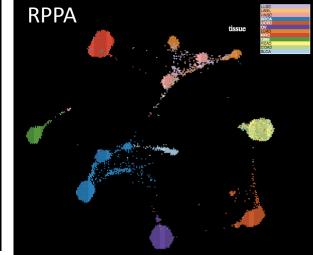
 Exome mutation clusters show least amount of tissue correlation, but still appreciable (~70%, Kandoth et al. *Nature* 2013).

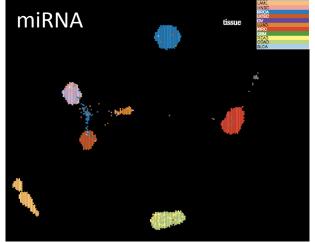
The Cancer Genome Atlas

Single platform maps are tissue driven







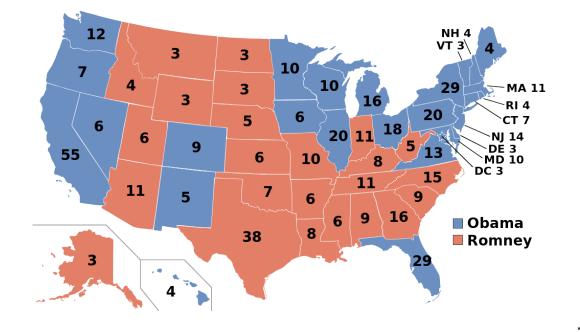


• Each layout driven by a different data platform.

Newton, Baertsch, UCSC

Cluster of Cluster Assignments - COCA

- Question: How do get one cluster solution from many?
- Answer: Democracy!
 - But like the electoral college system:
 - Every Platform Gets a Vote for Each of its Clusters



Katherine Hoadley, UNC

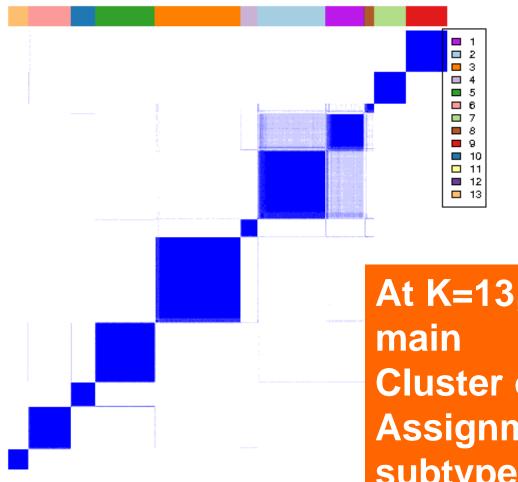
The Cancer Genome Atlas 🕀

Cluster Of Cluster Assignments (COCA subtypes

| | 127 | • G | Jx 1 | | | | | | | | | | | | | Ŷ |
|---|-----------------|----------|----------|-----------|----------|-----------|-----------|----------|----------|-----------|----------|----------|-----------|----------|-------------|-------|
| | А | В | С | D | E | F | G | Н | I. | J | К | L | М | N | 0 | Ρ 🛓 |
| 1 | NAME | TCGA-BH- | TCGA-B6- | TCGA-E2-A | TCGA-BH- | TCGA-A2-A | TCGA-E2-A | TCGA-AN- | TCGA-AN- | TCGA-B6-A | TCGA-B6- | TCGA-BH- | TCGA-E2-A | TCGA-BH- | TCGA-B6-/ T | CGA- |
| 2 | CN.1 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | |
| 3 | CN.2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | |
| 4 | CN.3 | 1 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| 5 | CN.4 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 1 | 1 | 0 | |
| 6 | CN.5 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| 7 | Methy.1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | |
| 8 | Methy.2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | |
| 9 | Methy.3 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | Methy.4 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | |
| | Methy.5 | 0 | 0 | 1 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | |
| 12 | miRNA.1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| 13 | miRNA.2 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | |
| 14 | miRNA.3 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | |
| 15 | miRNA.4 | 1 | 1 | 1 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | |
| 16 | miRNA.5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| 17 | miRNA.6 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| 18 | miRNA.7 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| 19 | PAM50.Basal | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | |
| 20 | PAM50.HER2 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| 21 | PAM50.LumA | 0 | 0 | 0 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | |
| 22 | PAM50.LumB | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| 23 | PAM50.Normal | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| 24 | RPPA.Basal | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| 25 | RPPA.Her2 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| 26 | RPPA.X | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | |
| 27 | RPPA.LumA | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | |
| 28 | RPPA.LumB | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| 29 | RPPA.ReactiveII | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | |
| 30 | RPPA.Reactivel | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | |
| _31 | | | | | | | | | | | | | | | | |
| K ← → H Subtypes.Matrix.5platforms.2012 / □ | | | | | | | | | | 4000 | | | | | | |
| Rea | ау | | | | | | | | | | | | | 100% | | + .:: |

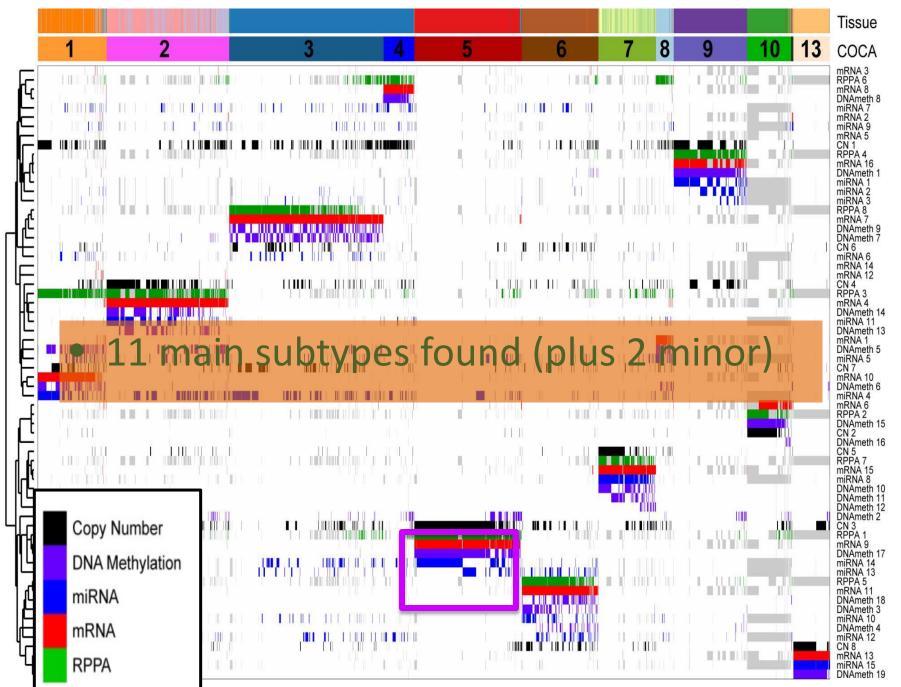
Katherine Hoadley, UNC

Consensus Clustering defines number of groups

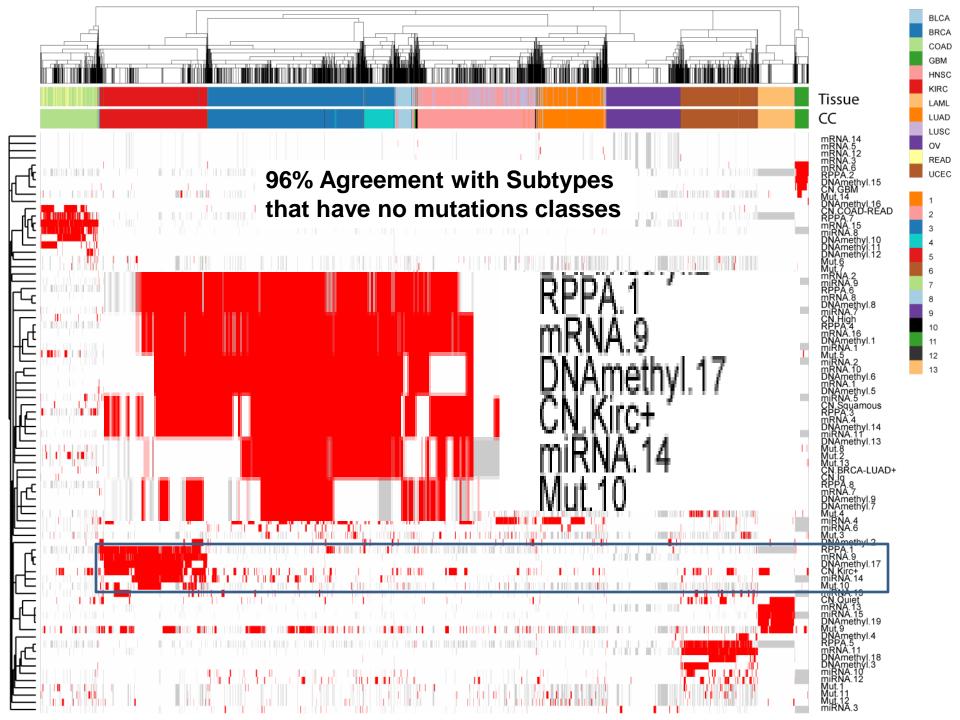


At K=13, we have 11 main Cluster of Cluster Assignment (COCA) subtypes

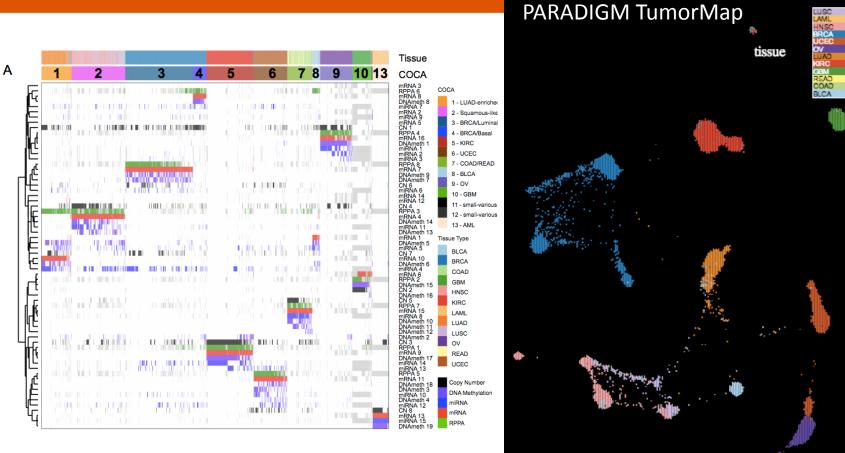
^T Katherine Hoadley, UNC



Katherine Hoadley, UNC



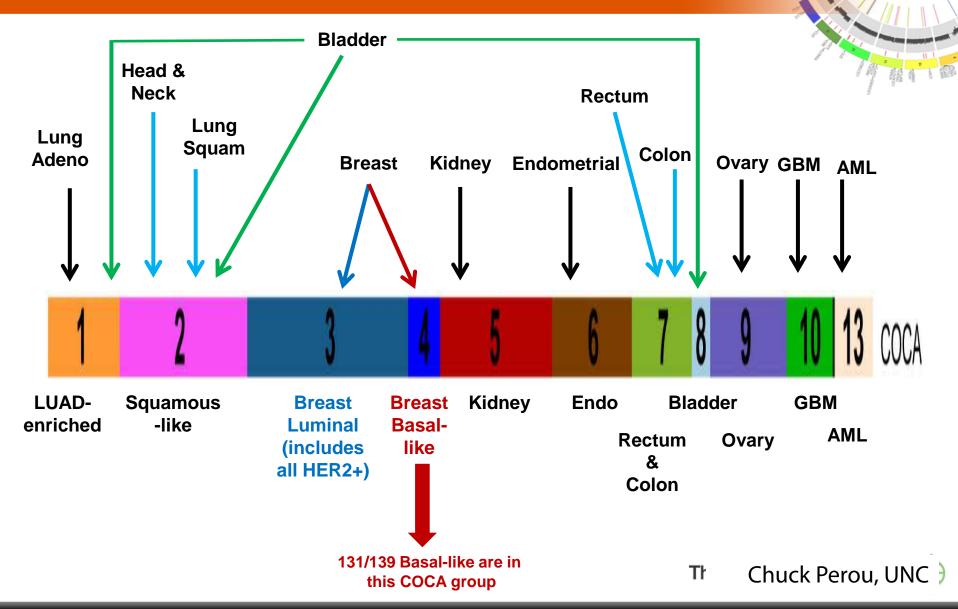
11 main COCA Subtypes



- 11 main subtypes found (plus 2 minor)
- ~90% of samples cluster with their tissue
- PARADIGM TumorMap corresponds well to COCA

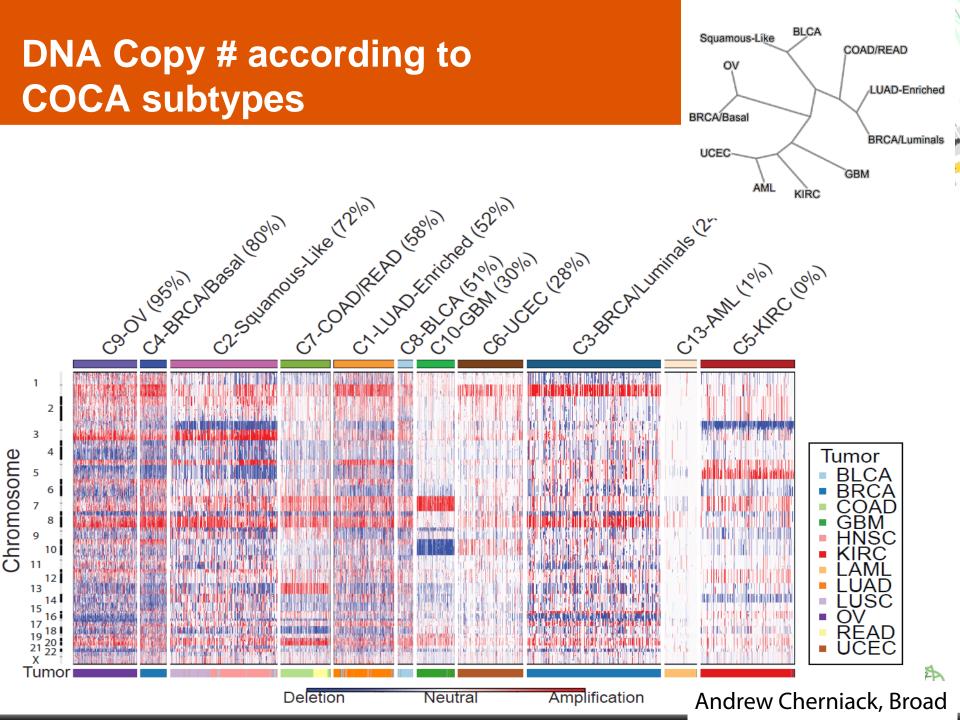


12 Tissue of Origin Sites Translate into 11 COCA Subtypes

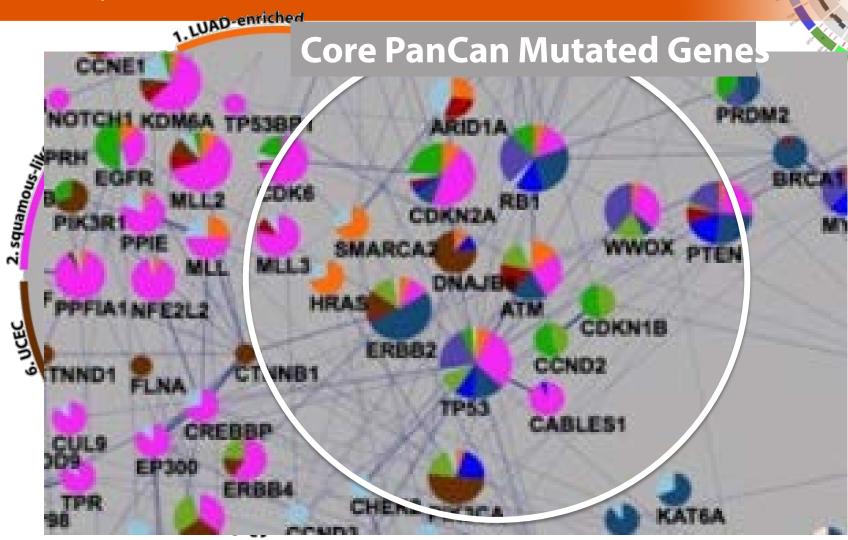


Mutations according to COCA subtypes

| | | | | | | | | | | - | | | |
|-------------|----------|----------|---------|---------|------|--------------|--------|-------------------|--------|-------------------|-----------------|-------|-------------|
| | 1- | | | | | | | | | 4 | | | - |
| | Adeno- | 2- | 3- BRCA | 4- BRCA | | | 7-COAD | 8- | | | | | |
| Gene | enriched | Squamous | Luminal | Basal | | UCEC | TEA | Bladder | 9-0V | 10-GBM | <u>13- AM</u> I | Total | David State |
| TP53 | 52% | 72% | 24% | 80% | | 21 | 58% | | | <u></u> 3% | 9% | 41% | |
| PIK3CA | 7% | 19% | 40% | 4% | 3% | 51% | 18% | 17% | 1% | 9% | 0% | 20% | |
| PTEN | 3% | 4% | 4% | 3% | 4,0 | % . 1 | re | | | % | 0% | 10% | |
| APC | 6% | 4% | 0% | 2% | 2% | 5% | 82% | 5% | 2% | 1% | 0% | 0 /0 | |
| MLL3 | 18% | 11% | 7% | 5% | 4% | 5% | 3% | 25% | 2% | 4% | 1% | 8% | |
| VHL | 0% | 0% | 0% | 0% | 52% | 1% | 0% | 0% | 0% | 0% | 0% | 7% | |
| | | | | | | | | | | | | | |
| KRAS | 24% | 0% | 1% | 0% | 0% | 20% | 46% | 2.% | 1% | 1% | 4% | 7% | |
| MLL2 | 10% | 20% | 2% | (%) | roma | | emo | | ers, a | 536 | 1% | 7% | |
| ARID1A | 8% | 5% | 2% | - cla | SS%a | CĈÕU | ntefa |) ^{ko} m | añv_ | 2% | 1% | 7% | |
| PPPI | 001 | 00/ | 00/ | | _ | | | | | 40/ | 00/ | 001 | |
| PBRM1 | 2% | 3% | 0% | 2% | 32% | 2% | 0% | 5% | 0% | 1% | 0% | 6% | |
| NAV3 | 20% | 11% | 1% | 2% | 1% | 5% | 2% | 5% | 2% | 1% | 0% | 5% | |
| PIK3R1 | 2% | 2% | 3% | 1% | 0% | 31% | 2% | 0% | 0% | 15% | 0% | 5% | |
| NF1 | 12% | 5% | 2% | 3% | 2% | 4% | 1% | 11% | 3% | 8% | 1% | 5% | |
| SETD2 | 7% | 3% | 1% | 1% | 12% | 3% | 3% | 8% | 2% | 2% | 1% | 5% | |
| ATM | 7% | 4% | 2% | 2% | 3% | 6% | 6% | 8% | 1% | 2% | 0% | 4% | |
| EGFR | 11% | 4% | 1% | 0% | 2% | 1% | 2% | 0% | 1% | 25% | 1% | 4% | |
| FBXW7 | 1% | 6% | 0% | 2% | 0% | 12% | 12% | 6% | 1% | | | | |
| | | 20/ | | | | 10/ | | =0/ | | Beifang Niu, Wash | | | |



Interconnected mutated networks reveal subtype and tissue preferential

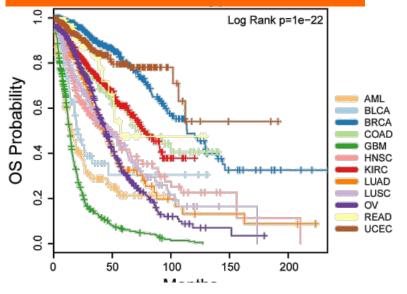


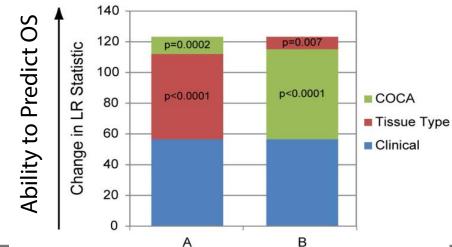
HotNet2 mutated subnetworks spanning all tumor types.

The Max Leiserson, Brown

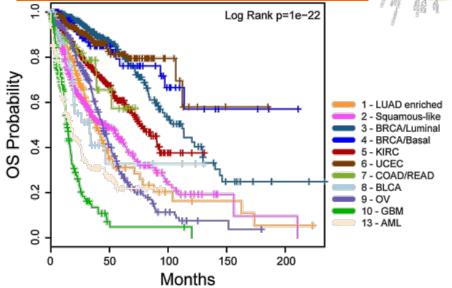
Do Integrated Subtypes Provide New Prognostic Information?

Tissue → Overall Surviva





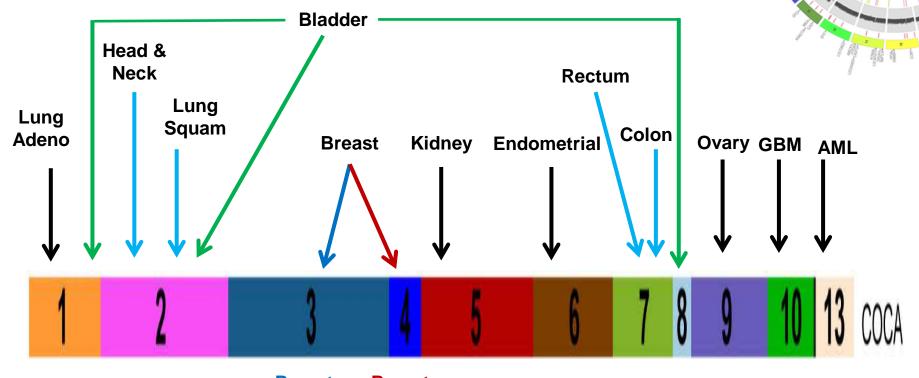




Improvement w/ integrated subtypes over clinical *and tissue*

^T Katherine Hoadley, UNC

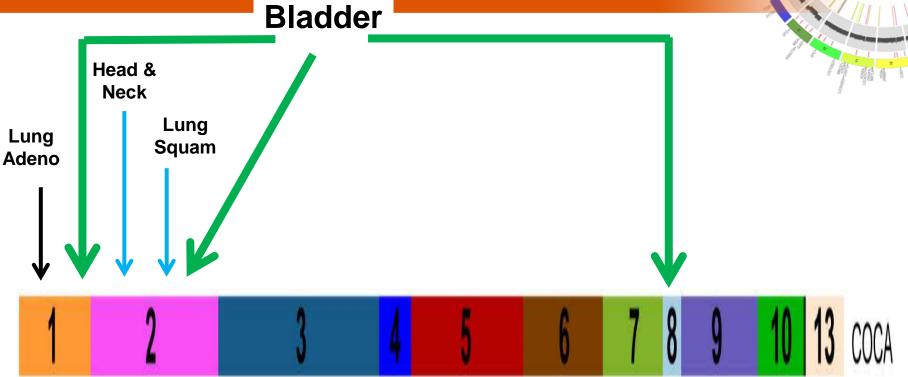
12 Tissue of Origin Sites Translate into 11 COCA Subtypes



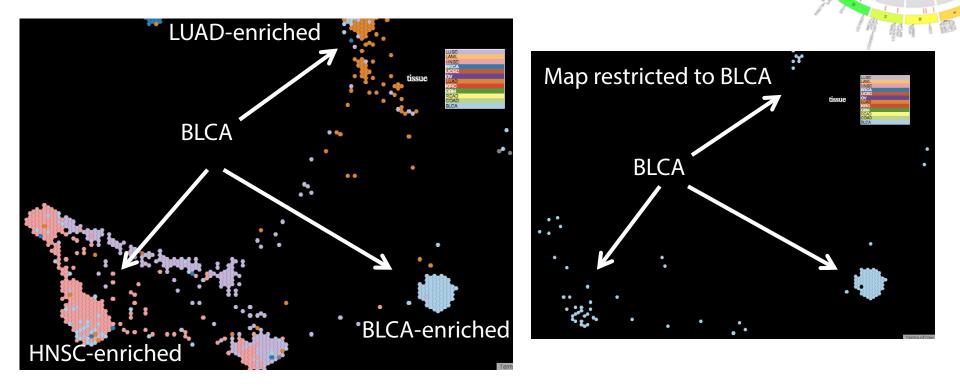
Breast Breast Luminal Basal-(includes like all HER2+) 131/139 Basal-like are in this COCA group

Th Chuck Perou, UNC

BLCA samples diverge into 3 integrated subtypes



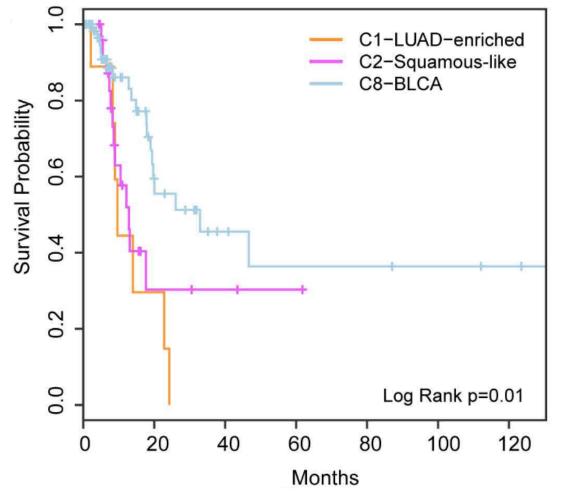
BLCA divergence in Pan-Can-12



 BLCA diverge into bladder-enriched, squamous, and LUADenriched islands

The Cancer Genome Atlas

Integrated subtyping of BLCA distinguishes patient outcomes

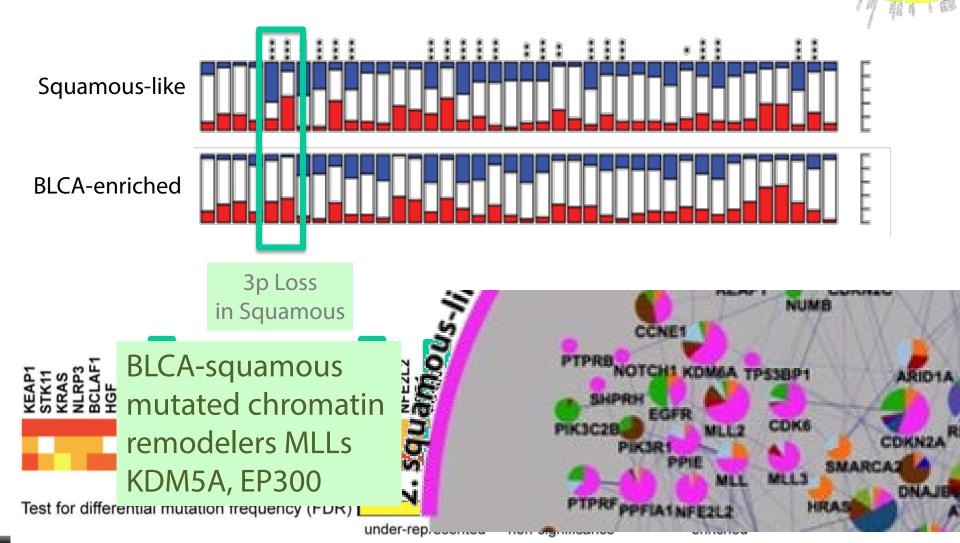


COCA clusters distinguish different survival classes for BLCA

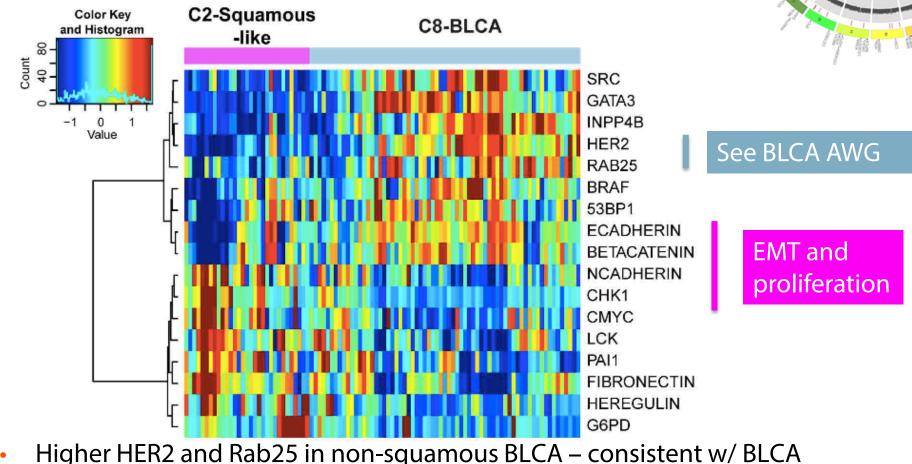
The Cancer Genome Atlas 💮

Expression determinants of BLCA divergence

Squamous-like BLCA show significant genomic differences



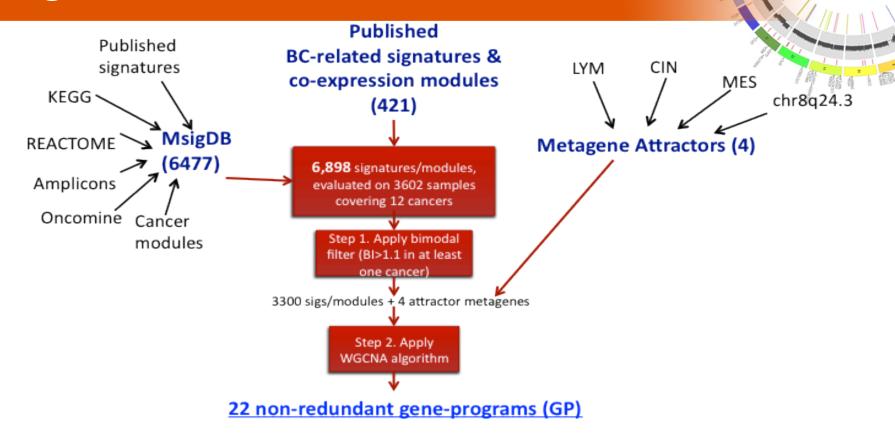
Expression determinants of BLCA divergence



- Higher HER2 and Rab25 in non-squamous BLCA consistent w/ BLCA AWG
- Markers of EMT expressed in squamous BLCA cases

Th Rehan Akbani, MDACC

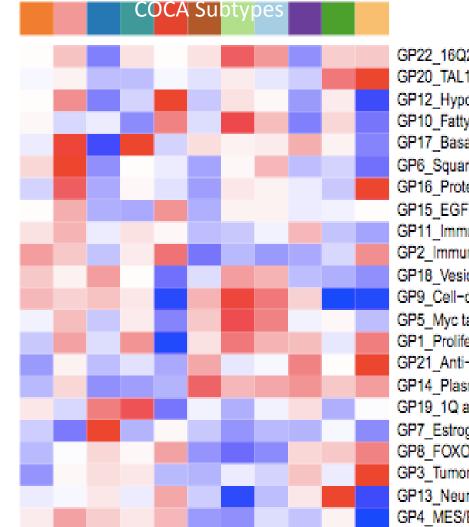
Gene Programs – functionally coupled gen coregulated across PanCan-12



- Identified 22 sets of functionally-related genes coregulated in PanCan-12.
- Gene Programs can recapitulate the integrated subtypes

The C: Denise Wolf, UCSF

Gene Programs: Surrogates of Integrated Subtypes

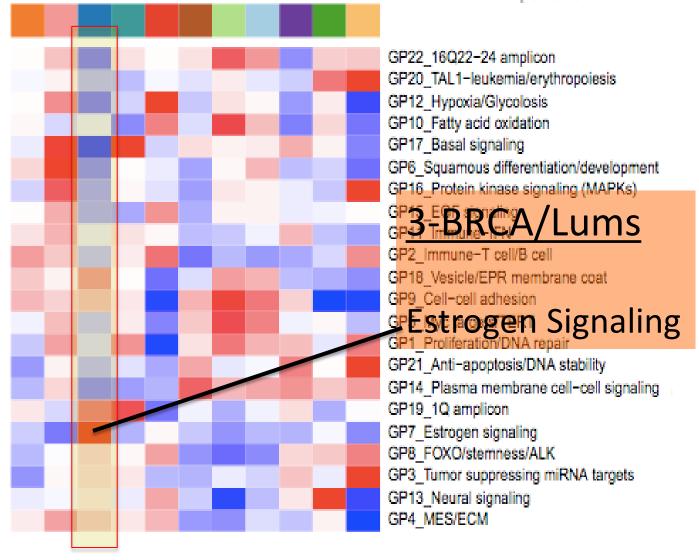


• 90% classification accuracy (LDA)

GP22 16Q22-24 amplicon GP20 TAL1-leukemia/erythropoiesis GP12 Hypoxia/Glycolosis GP10 Fatty acid oxidation GP17 Basal signaling GP6 Squamous differentiation/development GP16 Protein kinase signaling (MAPKs) GP15 EGF signaling GP11 Immune-IFN GP2 Immune-T cell/B cell GP18 Vesicle/EPR membrane coat GP9 Cell-cell adhesion GP5 Myc targets/TERT GP1 Proliferation/DNA repair GP21 Anti-apoptosis/DNA stability GP14 Plasma membrane cell-cell signaling GP19_1Q amplicon GP7 Estrogen signaling GP8 FOXO/stemness/ALK GP3 Tumor suppressing miRNA targets GP13 Neural signaling GP4 MES/ECM

Denise Wolf, UCSF

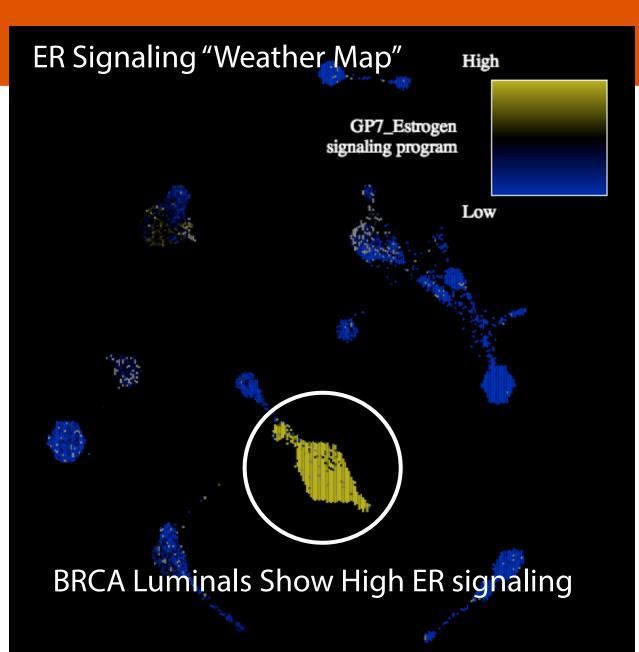
Gene Programs: Surrogates of Integrated Subtypes



90% classification accuracy (LDA)

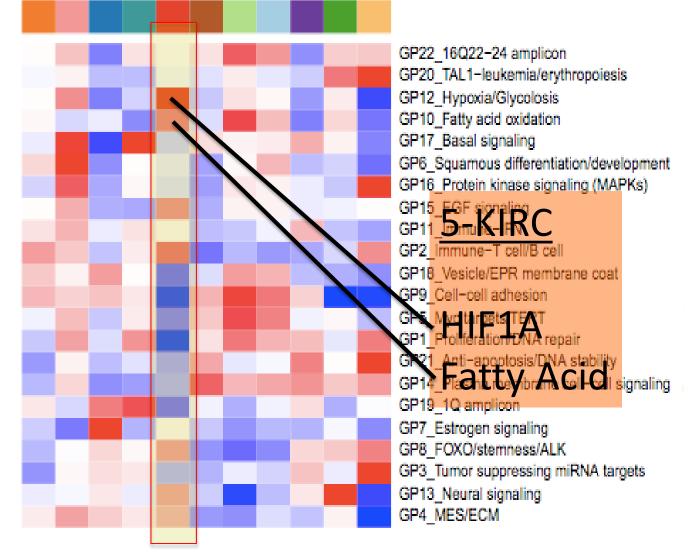
Denise Wolf, UCSF

Viewing Gene Programs on the TumorMap



The C Denise Wolf, UCSF

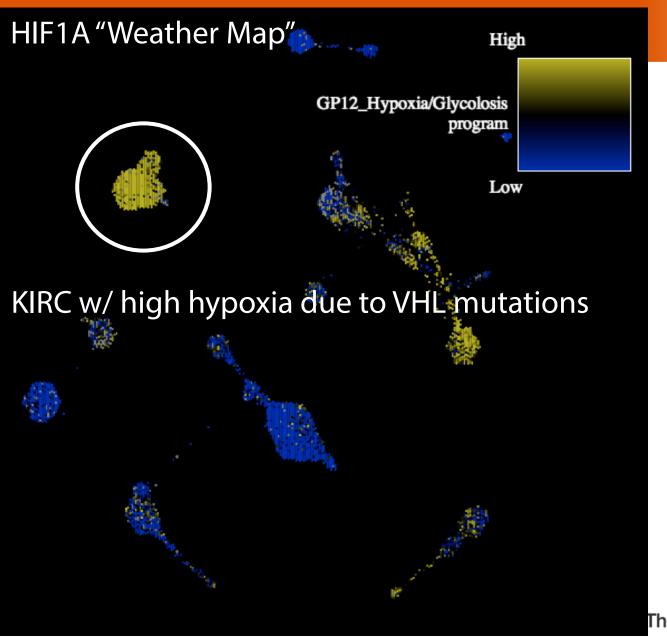
Gene Programs: Surrogates of Integrated Subtypes



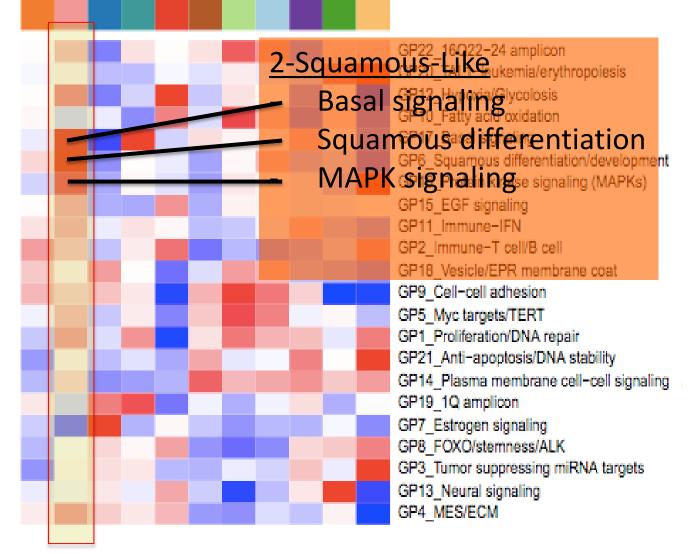
90% classification accuracy (LDA)

Denise Wolf, UCSF

Viewing Gene Programs on the TumorMap



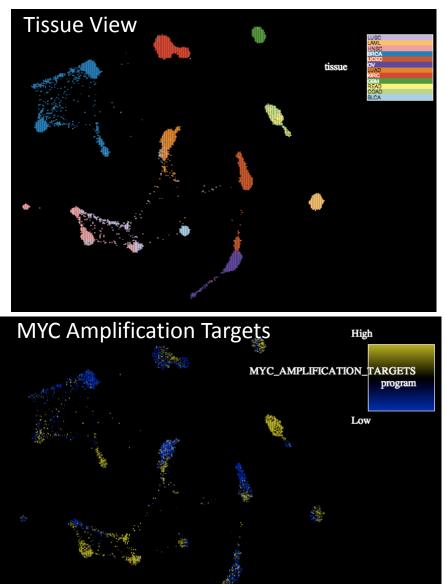
Gene Programs: Surrogates of Integrated Subtypes

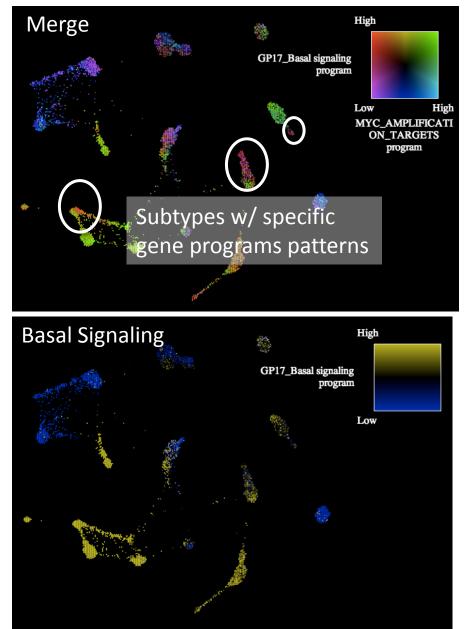


90% classification accuracy (LDA)

Denise Wolf, UCSF

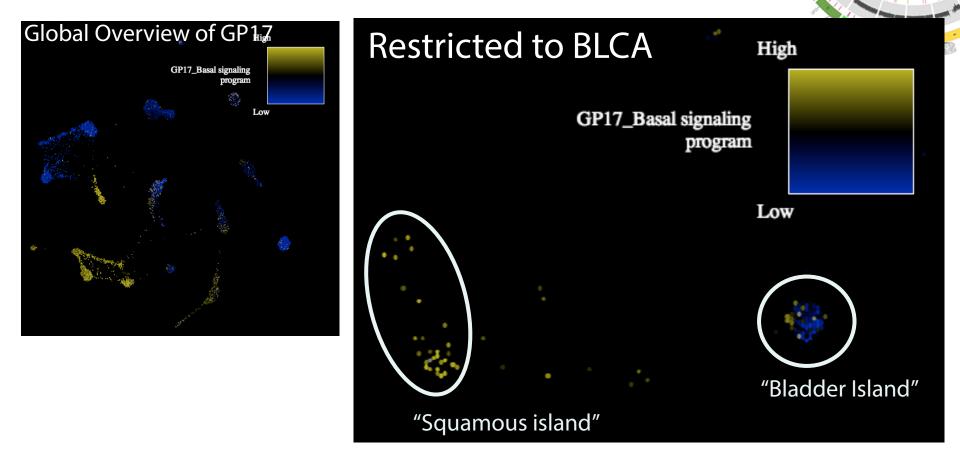
Viewing Gene Programs on the TumorMap





Denise Wolf, UCSF

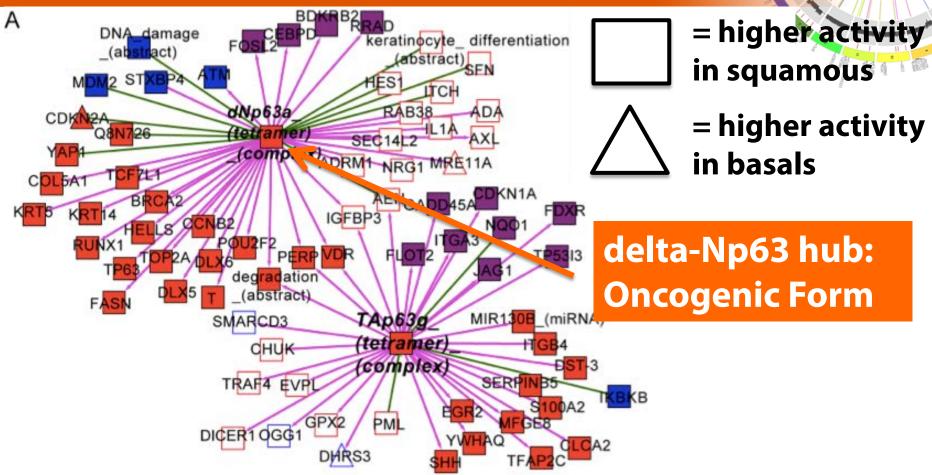
Gene Program markers of BLCA divergence



• Squamous BLCA cases show higher GP17



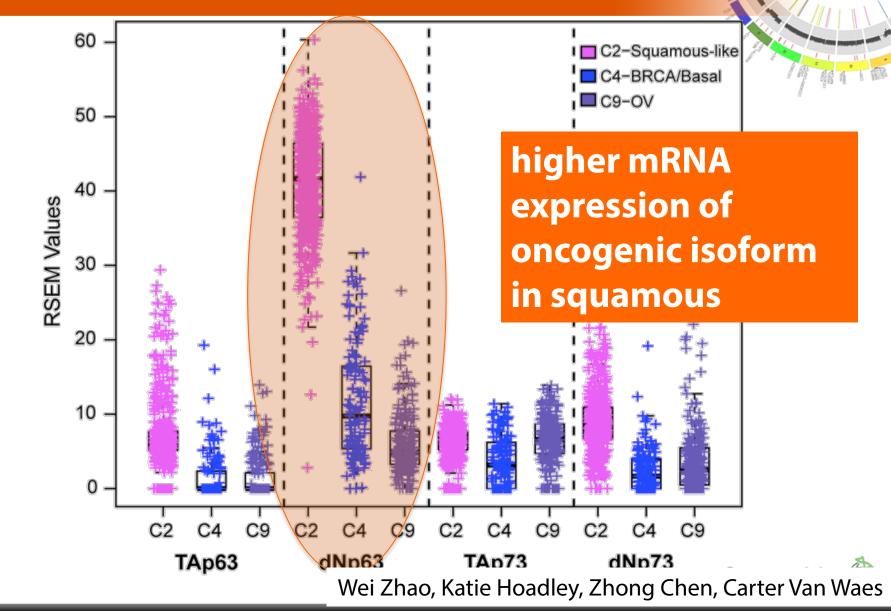
Oncogenic Tp63 forms are more active in Squamo vs BRCA/Basal (or OV) TP53 mutants



 Most targets in network higher activity in Squmaous (more "squares in diagram")

The Ca Christina Yau, Buck

Oncogenic Tp63 forms are more active in Squamou vs BRCA/Basal (or OV) TP53 mutants



Published as a Resource

Synapse contribute to the cure

Multi-platform integration of 12 cancer types reveals cell-of-o classes with distinct molecular signatures *

Synapse ID: syn2468297

Wiki Files Single Platform derived Clustering Source Description RNA mRNA expression clustering of 12 Pan-Cancer tumor types miRNA Unsupervised clustering of miRNA-seq data. (1) Schematic of an miRNA primary transcript (pri), the trimmed pre-miRNA (pre), reference miRBase 5p an representation used. (2) From the NMF rank survey the profile of average silhouette width suggests a 15-group solution (gray triangle). (3) Consensus m clusters consistently over 200 iterations. (4) NMF consensus clustering. Top to bottom: normalized abundance heatmap for 51 discriminatory miRNAs, s table of group number (c), number of samples (n) and average silhouette width (w) for each group, and for the overall set of 4229 tumor samples SCNA Clustering of SCNAs across all tumors. SCNAs in tumors (vertical axis) are plotted by chromosomal location (horizontal axis). Tumors are clustered base 2.0 analyis of the entire set. The heatmap shows the presence of amplifications (red) and deletions (blue) throughout the genome. Colorstrips on the side Methylation DNA methylation subtypes. Shown in the heatmap are DNA methylation beta values for 4.923 tumors (columns) of twelve tumor types at 2.204 CpG loci (

- Datasets and subtypes provide pivot for further analyses
- All datasets hosted on a Synapse project page
 - Links to all relevant PanCan-12 datasets

To appear in *Cell*



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Zhong Chen

Hoadley and Zhu

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Summary

- Analysis of 12 tumor types w/ 6 platforms display tissue-of-origin as dominant
- Integrated analysis reveals 11 major groups, with some tumor types merging together (HNSCC, Lung Squamous, some Bladder) and others separating (breast luminal vs. Basal-like)
- 1:10 re-classified cases based on the map.
 - Rate similar to EGFR mutations in NSCLC cancers
 - Convergences and Divergences of tissues
- Intriguing subtype-specific differences in TP53 pathway activity between OV, BRCA-Basals, and the Squamous tumors
- Classification adds prognostic information independent of tissue and stage.
 - E.g. COCA clusters define clear prognostic groups for BLCA
- Clearly more investigation will be beneficial; especially those that subtract away tissue-of-origin signals (see Verhaak paper)



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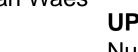




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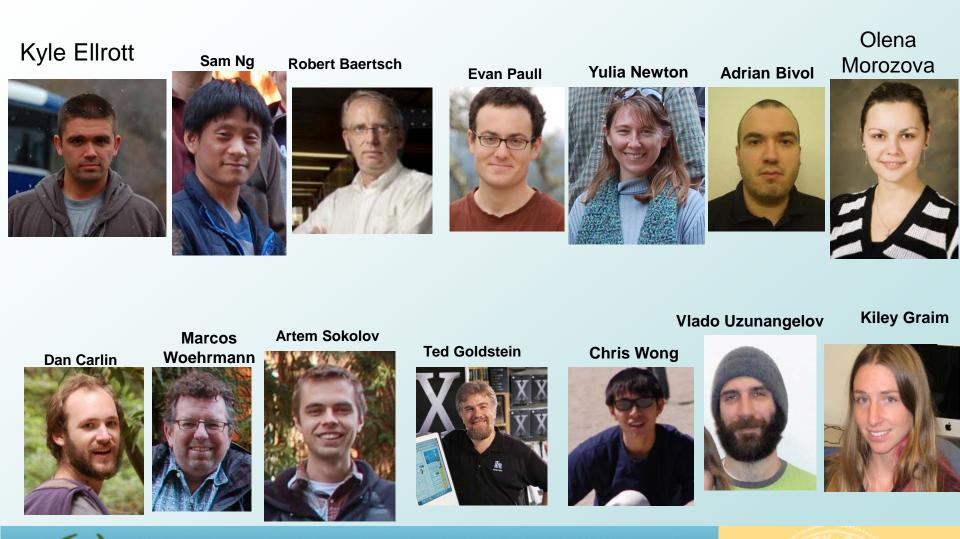
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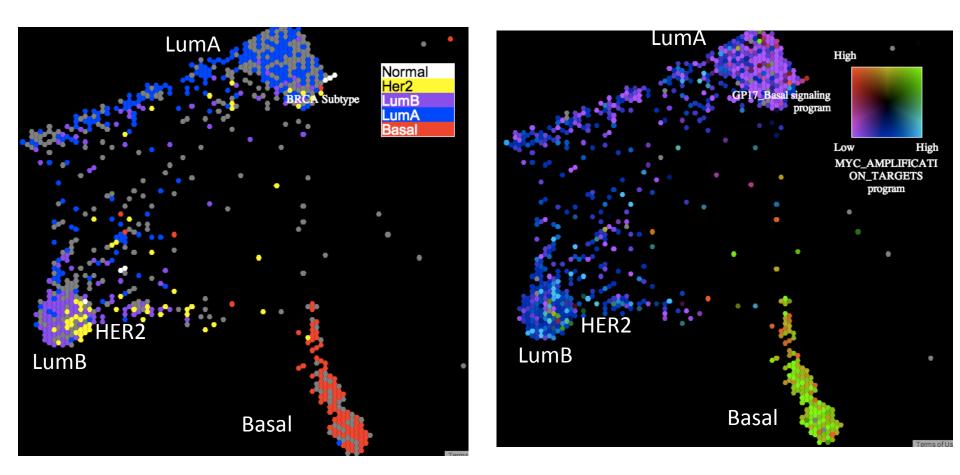
- Li Ding, WashU
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- Joe Gray, OHSU
- Laura Heiser, OHSU
- Nuria Lopez-Bigas, UPF
- Abel Gonzalez, UPF
- Adam Margolin, Sage
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The Cancer Genome Atlas



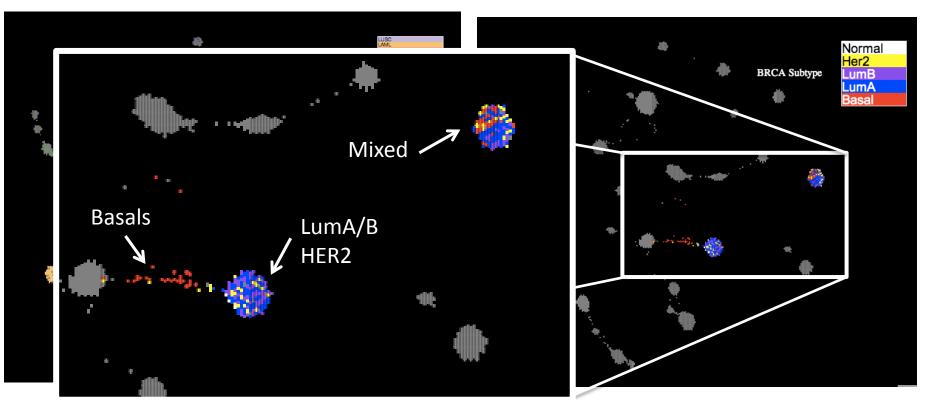
Supplemental

LumB's w/ Different Gene Program Expression



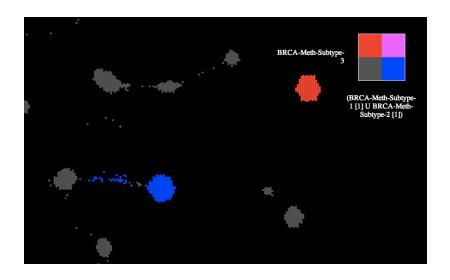
 LumB BRCA (and HER2's) have high MYC but low basal signaling.

DNA Methylation View of BRCA Subtypes

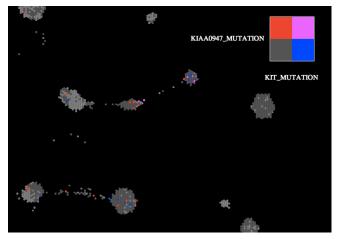


- 3 distinct DNA methylation subtypes revealed:
 - One all BRCA-basals, one all luminals and HER2, and one mixed

BRCA DNA Methylation Subtypes



Slightly more TP53 in BM3 (P<0.04)



- Created a contrast between BRCA methylation subtypes {1,2} vs {3}.
- SCNA in {1,2}: deletions in CNTN5 (11q22.1) RB1 (13q14.2), ITM2B (13q14.3)
- SCNA in {3}: chr3-12484849-12485147 amplification
- Slightly more TP53 in BRCA-Methylation subtype 3 (BM3) (P<0.04).
- More mutations in ORF KIAA0947 in BM1 and BM2.
 - ORF interacts with transcriptional elongation proteins ELL, ELL2, EAF1, MED26 (mediator). Cell 2011 – Takahashi et al.

BRCA Methylation Subtypes (indep of transcriptional subtypes)

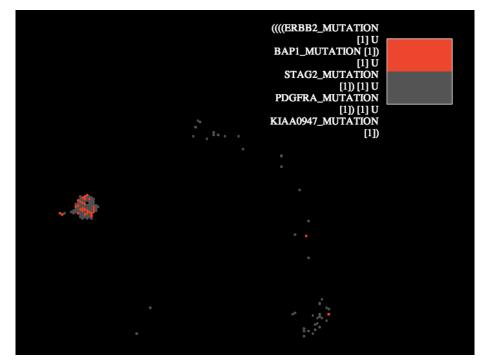


- Correcting for Subtype.
- Restrict only to the luminals. Enriched in BRCA-Meth-2 vs 3: RB1 deletions (P < 0.0076)
- Restric to basals. Only found one amplicon on 6p21 (POLR1C, POLH, KLK2, CUL9, ...)
- POLH could be *very* interesting as it copies past thymidine dimers and causes hypermutation rates. Do the subset of patients have higher mutation rates?

BLCA Subtypes

- Bladder cancers are split into two subtypes on the map.
- One set tightly associated with squamous cancers of HNSC and LUSC
- The other with the rest of the BLCA

BLCA non-squamous genomic determinants

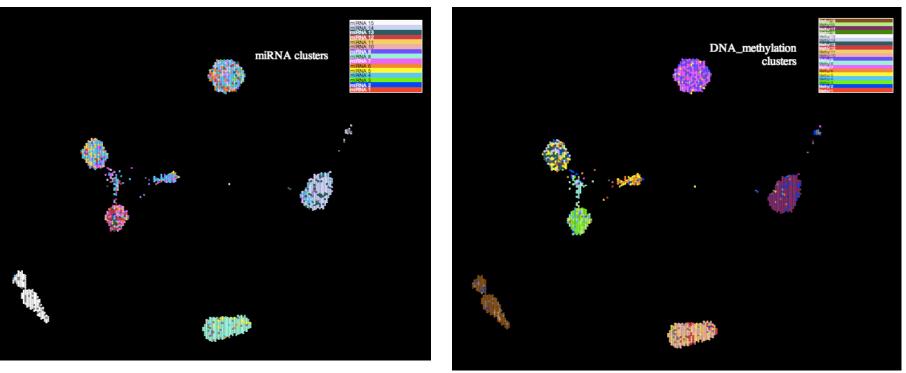


 The non-squamous BLCA tumors are characterized by mutations in several genes including ERBB2, BAP1, STAG2, PDGFRA, and the ORF KIAA0947.

Closer Look at miRNA subtypes

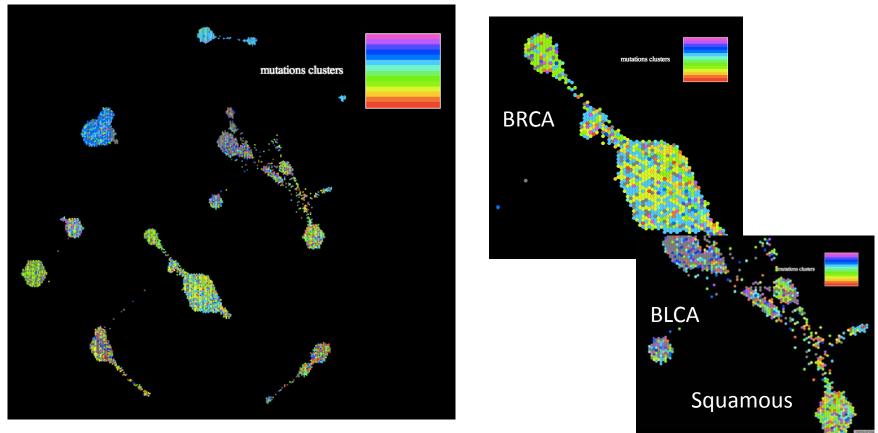
miRNA subtypes on miRNA map

DNA methylation subtypes on miRNA map



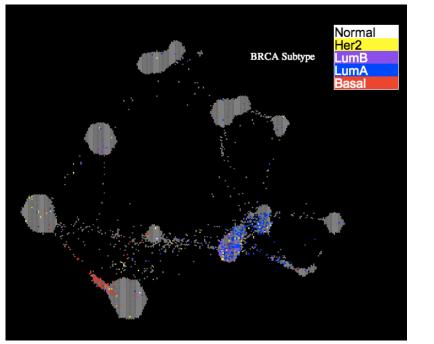
 The DNA methylation pancan subtypes correspond better to the TumorMap miRNA clusters than the miRNA pancan subtypes!

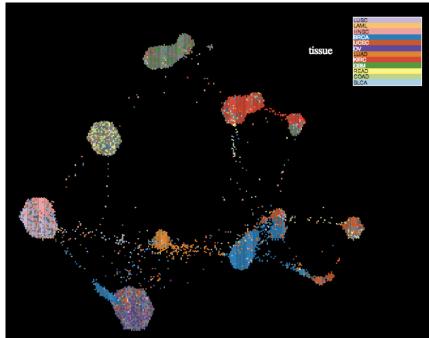
Mutation Clusters: To Be Continued



- Clustering by mutations gives more tissueorthogonal clustering.
- But mutation clustering is difficult
- This solution used prior pathway knowledge to help unify evidence.

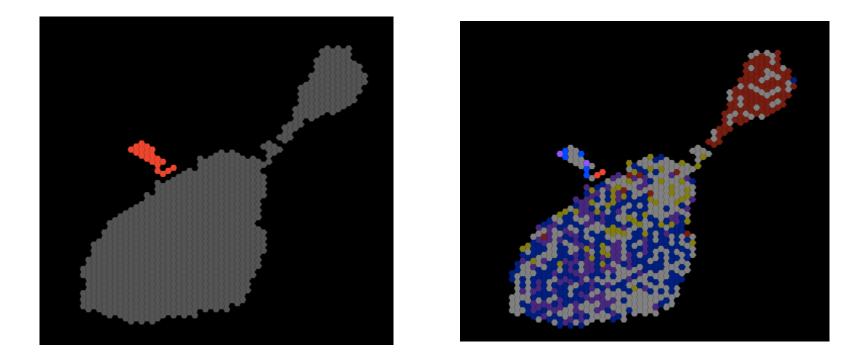
Copy Number View of BRCA Subtypes





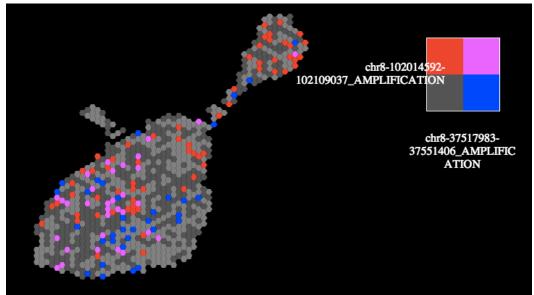
- BRCA transcriptional subtypes also reflected in the somatic copy number data.
- BRCA basals similar to OV.
 - And to a lesser extent, the Squamous group (HNSC/LUSC)
- BRCA luminals similar to UCEC and LUAD

Interesting minor BRCA subtype



- A luminal area distinct from the major luminal BRCA area.
- What distinguishes this subtype?

Minor BRCA subtype



- Absence of amplifications
 - chr8p11 amplifications absent in the subtype
 - Genes: LETM2 (8p11.23), WHSC1L1 and POLB (8p11.2)
 - chr11q14 amps absent
 - Genes: ALG8 (11q14.1), KCTD14 (11q14.1)
- Absence of mutations
 - GATA3, MLL3, MAP2K4, PTEN, NCOR1, SYNE1, DMD, PIK3R1, NF1, SPEN, BRCA2, CTCF, TBX3,