

# **Informatics links between histological features and genetics in cancer**

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The Ohio State University Wexner Medical Center**

**Department of Medicine  
Precision Health Initiative – Data Science Program  
Indiana University School of Medicine**



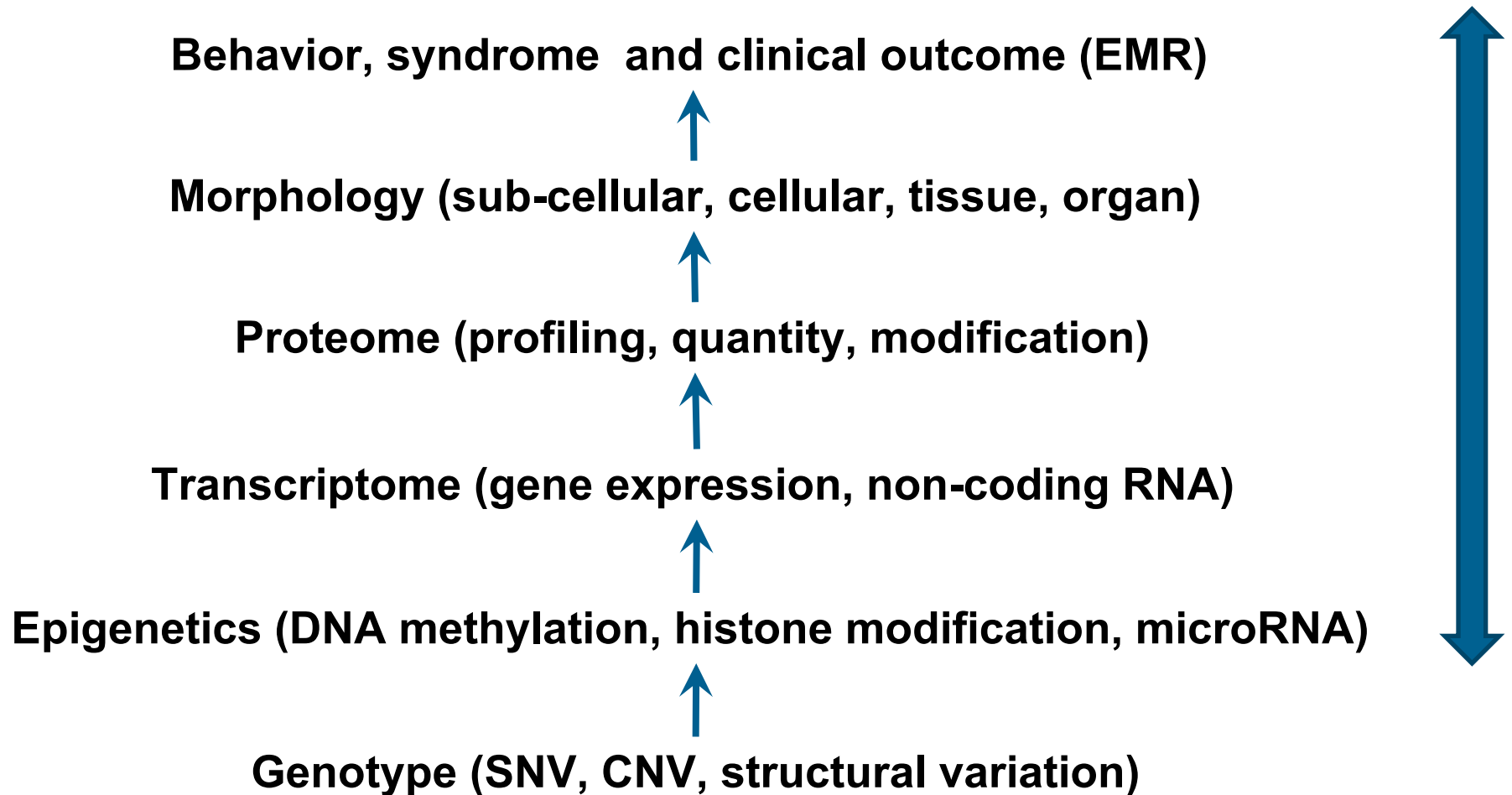
**INDIANA UNIVERSITY**  
SCHOOL OF MEDICINE



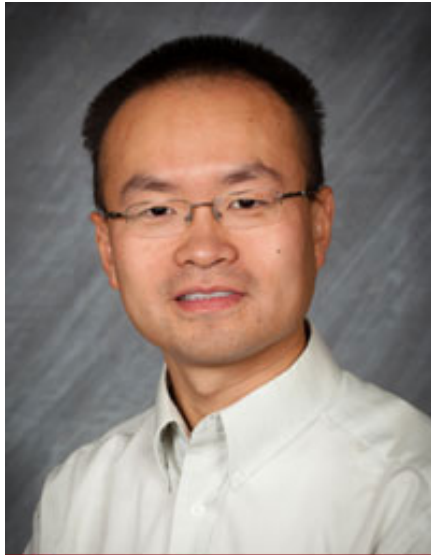
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# Data Integration

- **Integrative genomics / trans-omics approach**



# Team



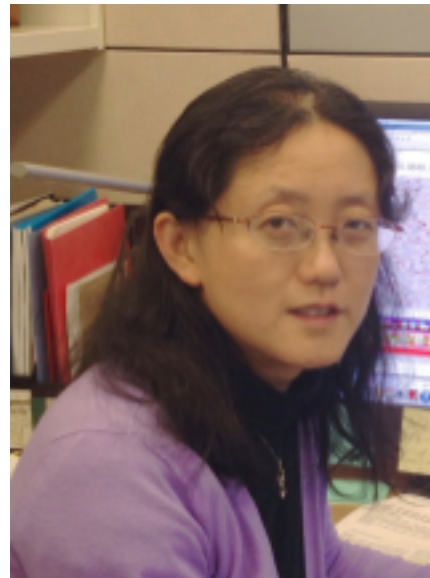
*Huang*



*Machiraju*



*Jeff Baumes, Kitware*



*Jie Zhang*



*Omar Padron,  
Kitware*

# Leveraging

- NCI CPTAC Contract
  - Integrate proteomics data from CPTAC project
  - High performance computing (GPU and cluster)



**HPC**



**Proteomics**



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# Trainees

- Chaitanya Kulkarni (OSU CSE)
- Arunima Srivastava (OSU CSE)
- Xusheng Wang (OSU ECE)
- Jun Cheng (SMU, China)
- Yatong Han (HEU, China)
- Tongxin Wang (OSU ECE)
- Dr. Hao Ding (OSU CSE, Walmart Lab)
- Dr. Chao Wang (OSU ECE, Thermo Fisher)
- Dr. Xing Tang (OSUCCC, St. Jude Children's Hospital)
- Sanaya Shroff (Cornell U)
- Kelly Pan (Brown U)
- Duong Au (OSUMC)



# Tasks

**Aim 1** – Develop software libraries for integrative genomics in cancer research, specifically for ***integrating genomic, histological images and clinical data for cancer biomarker discovery and subtyping.***

**Aim 2** – Develop an integrative and expandable open source platform for ***managing, analyzing, and integrating multiple data types*** in integrative genomics for cancer with ***visual analytic capabilities*** for cancer biomarker discovery.

**Aim 3** – Test the completed ***software platform with cancer systems biology studies*** and build an ecosystem based on the open source framework for integrative genomics and in particular for imaging genomics in cancer.

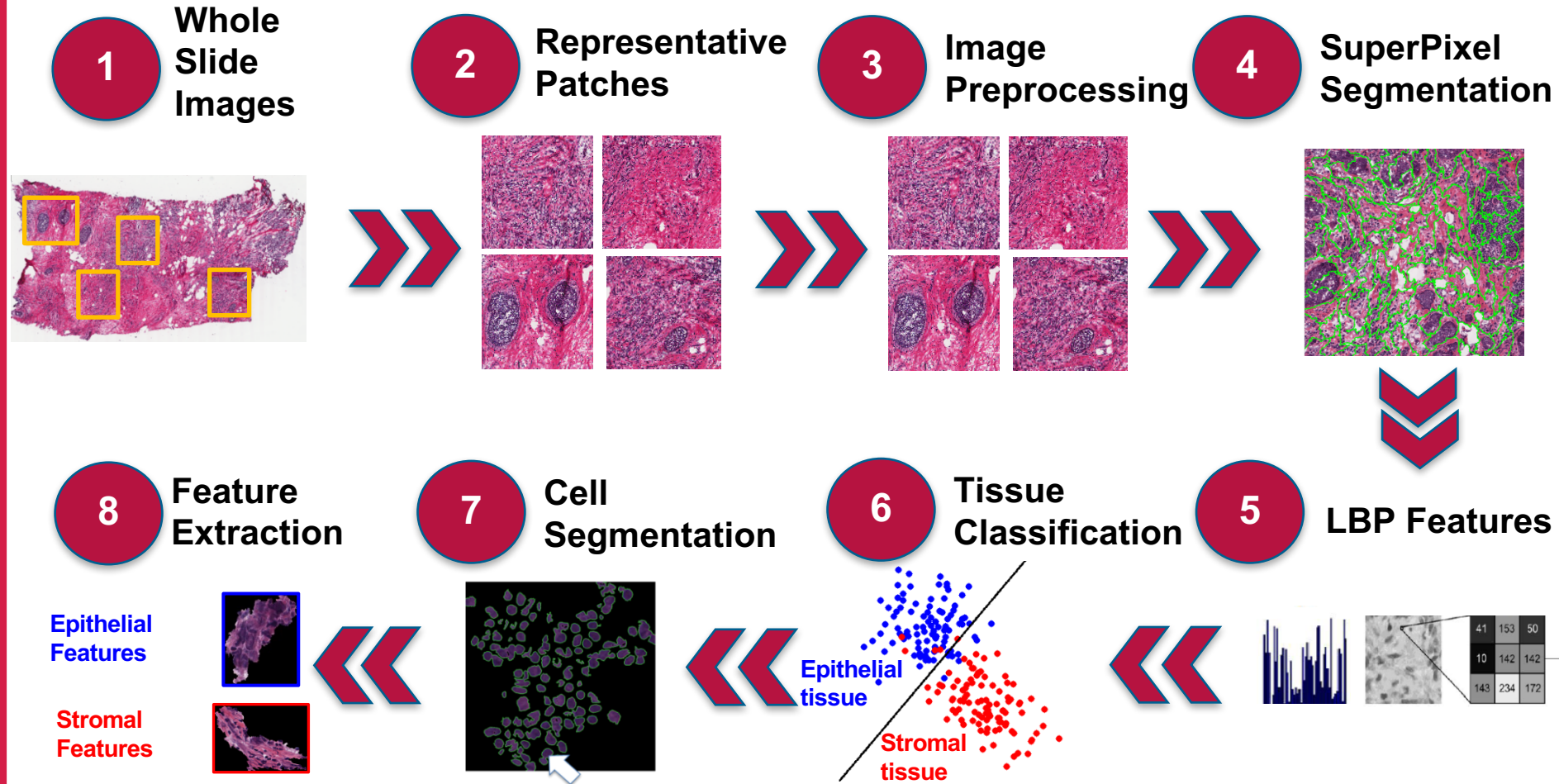


# Aim 1a - Histopathology Image Features

- **Patch-based features**
- **Whole-slide cell morphology statistics**
- **Topological features**
- **Features from other tools (e.g., CellProfiler) or collaborative groups**

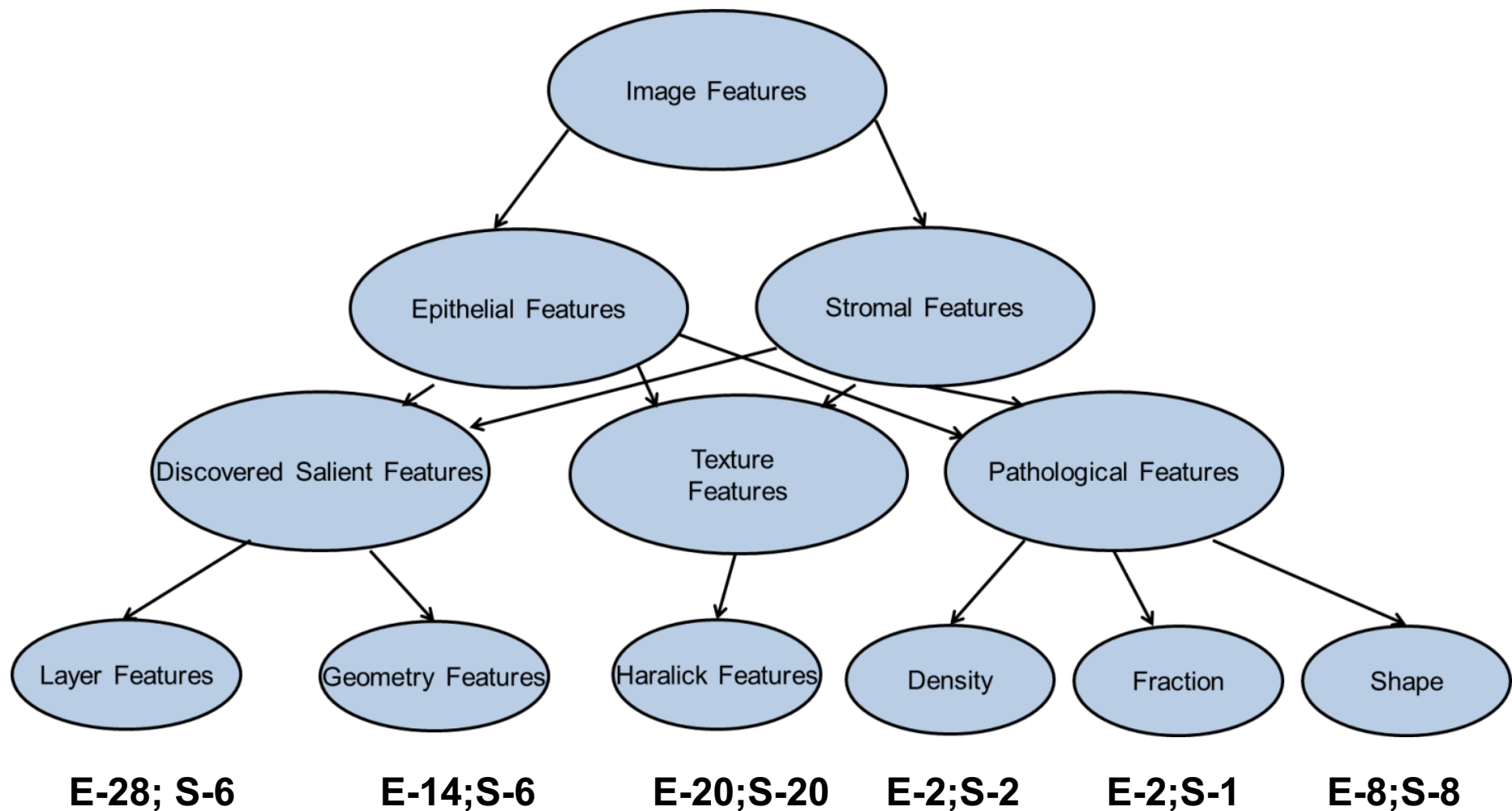


# Pipeline Overview





# Feature Extraction

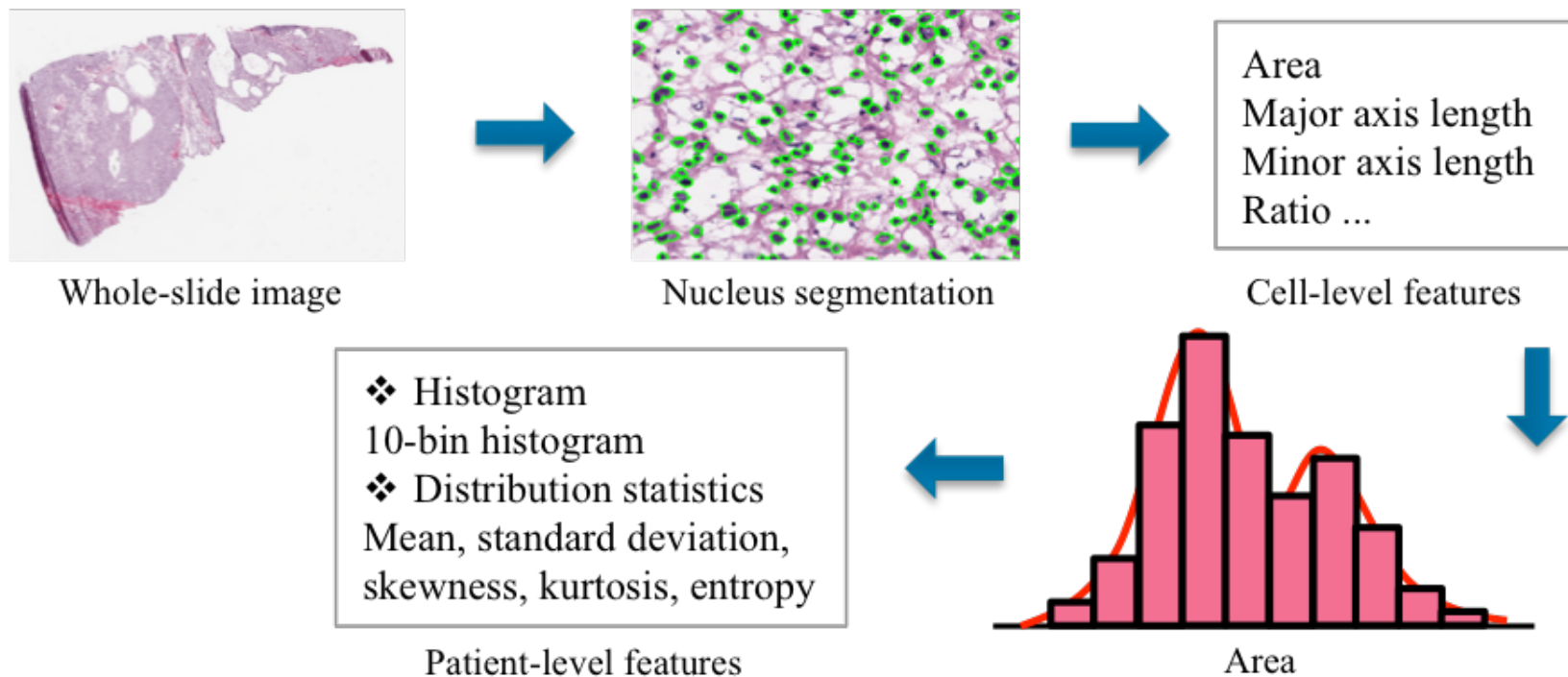


**E:epithelial features;S:stromal features**

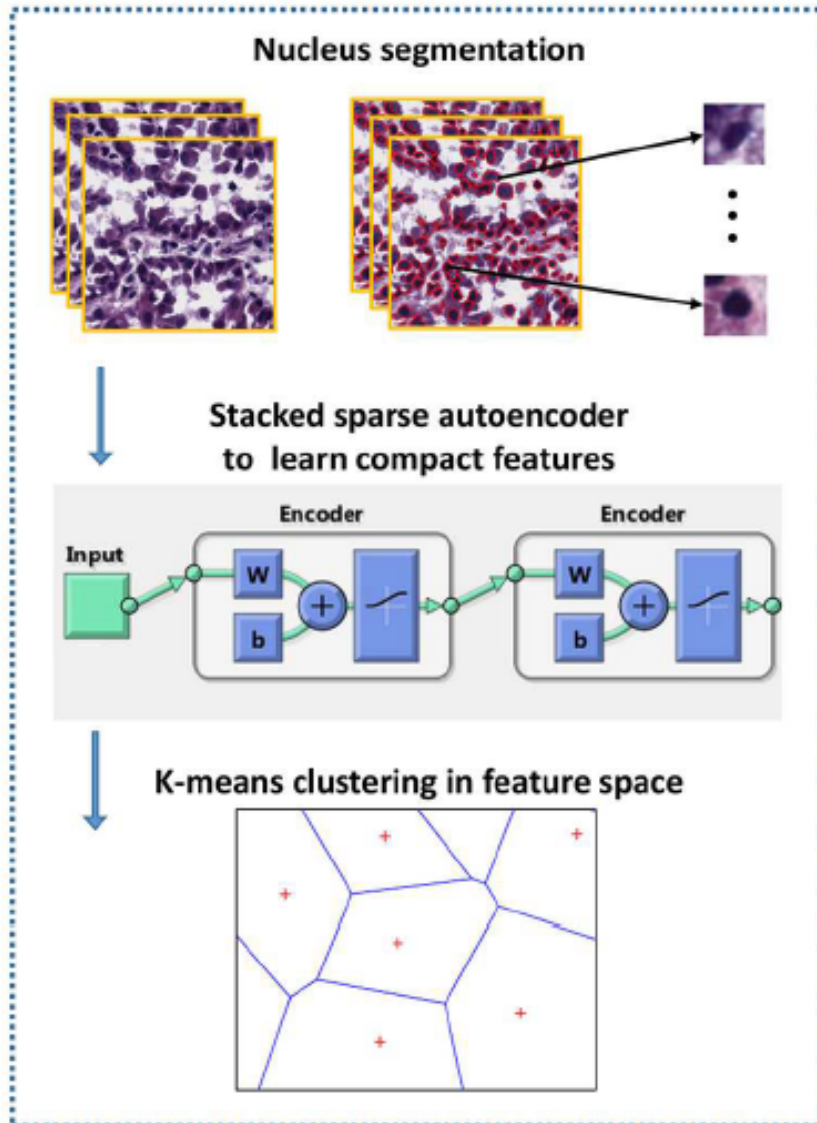


# Cell-Level Distribution Features

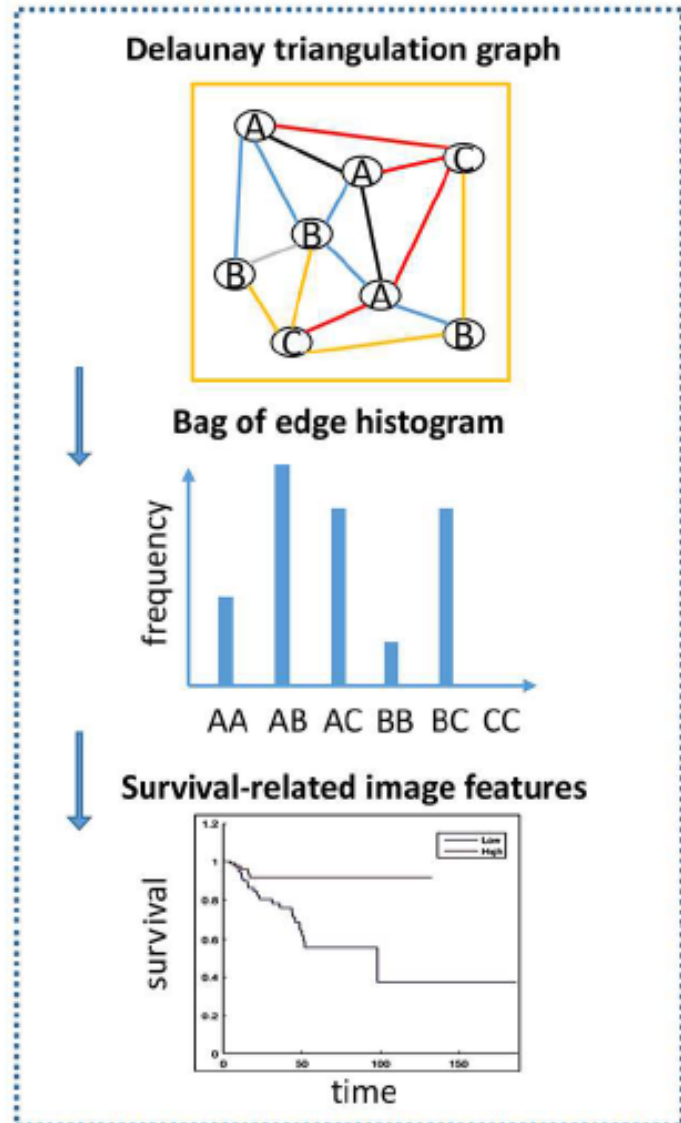
Whole-slide cell based analysis with distribution as features.



# Topological Features

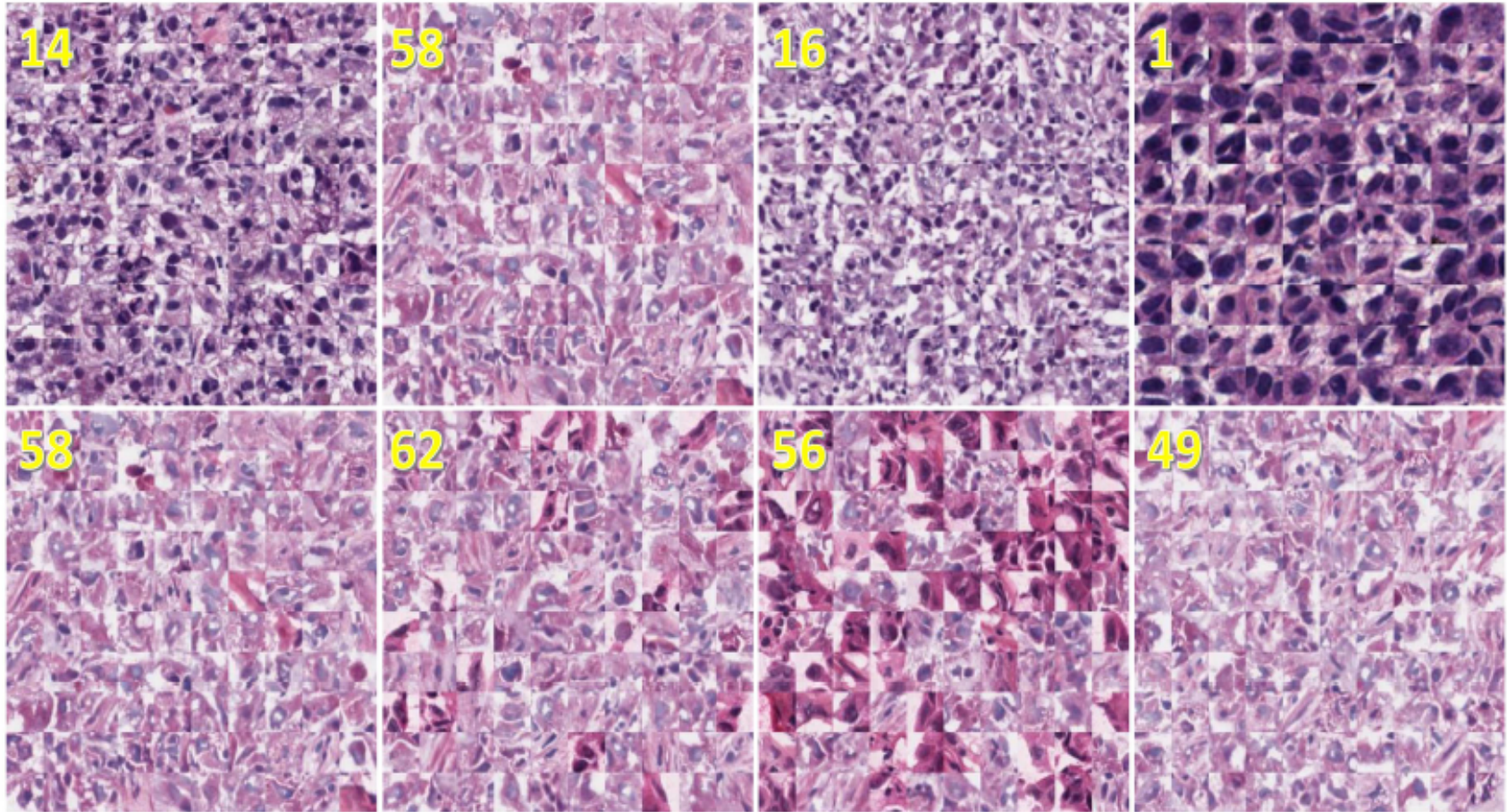


(a)



(b)

# Papillary Cell Renal Cell Carcinoma



Edge(14, 58)

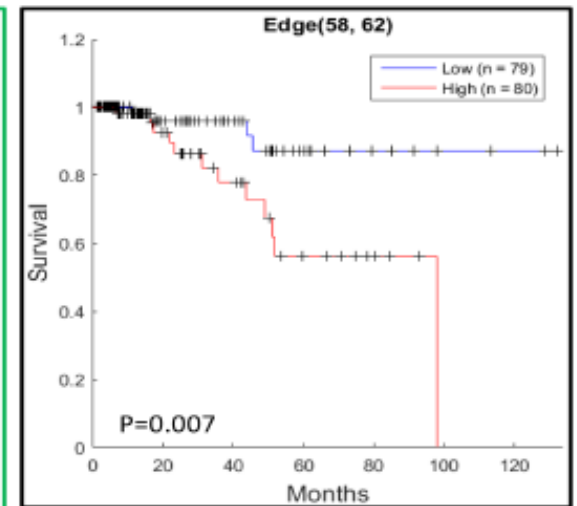
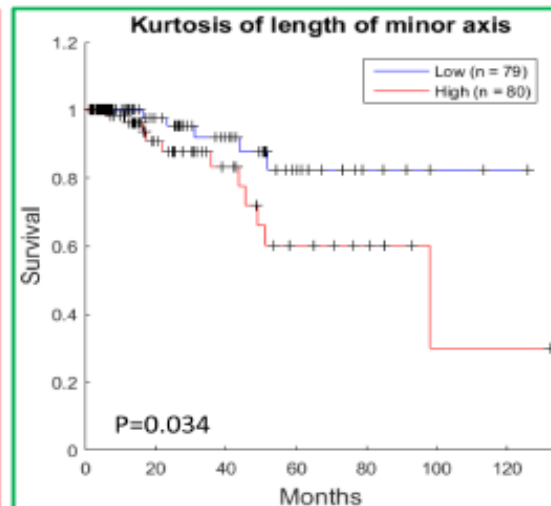
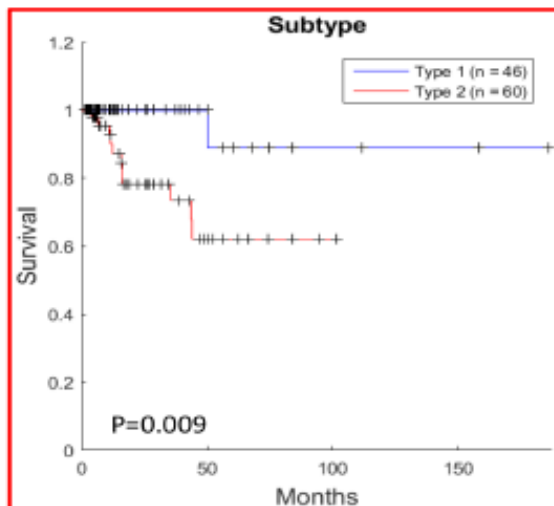
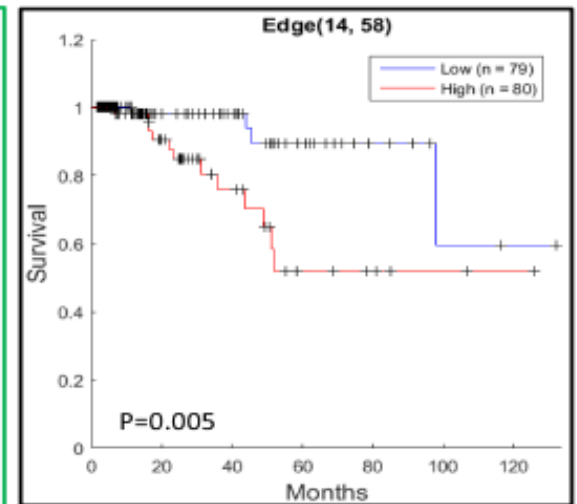
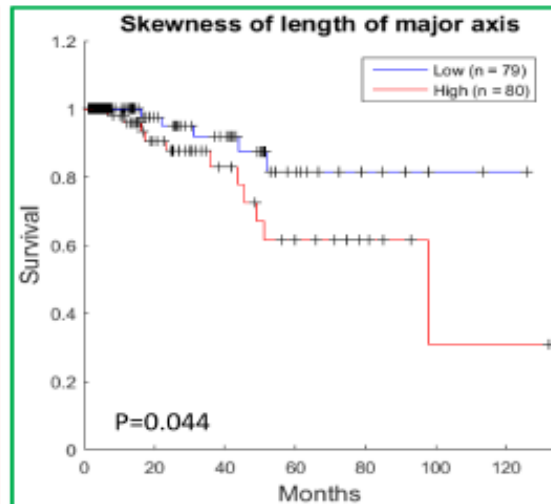
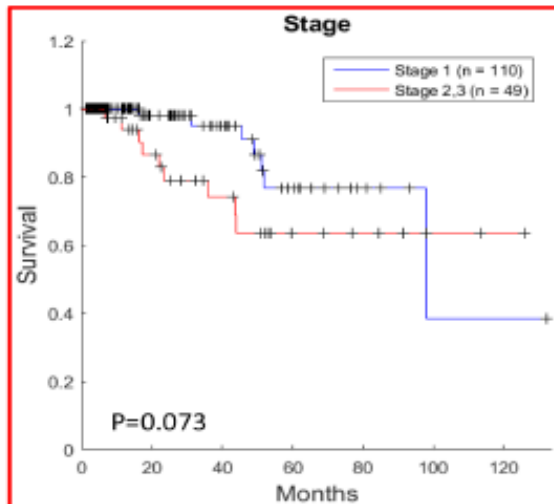
Edge(58, 62)

Edge(16, 56)

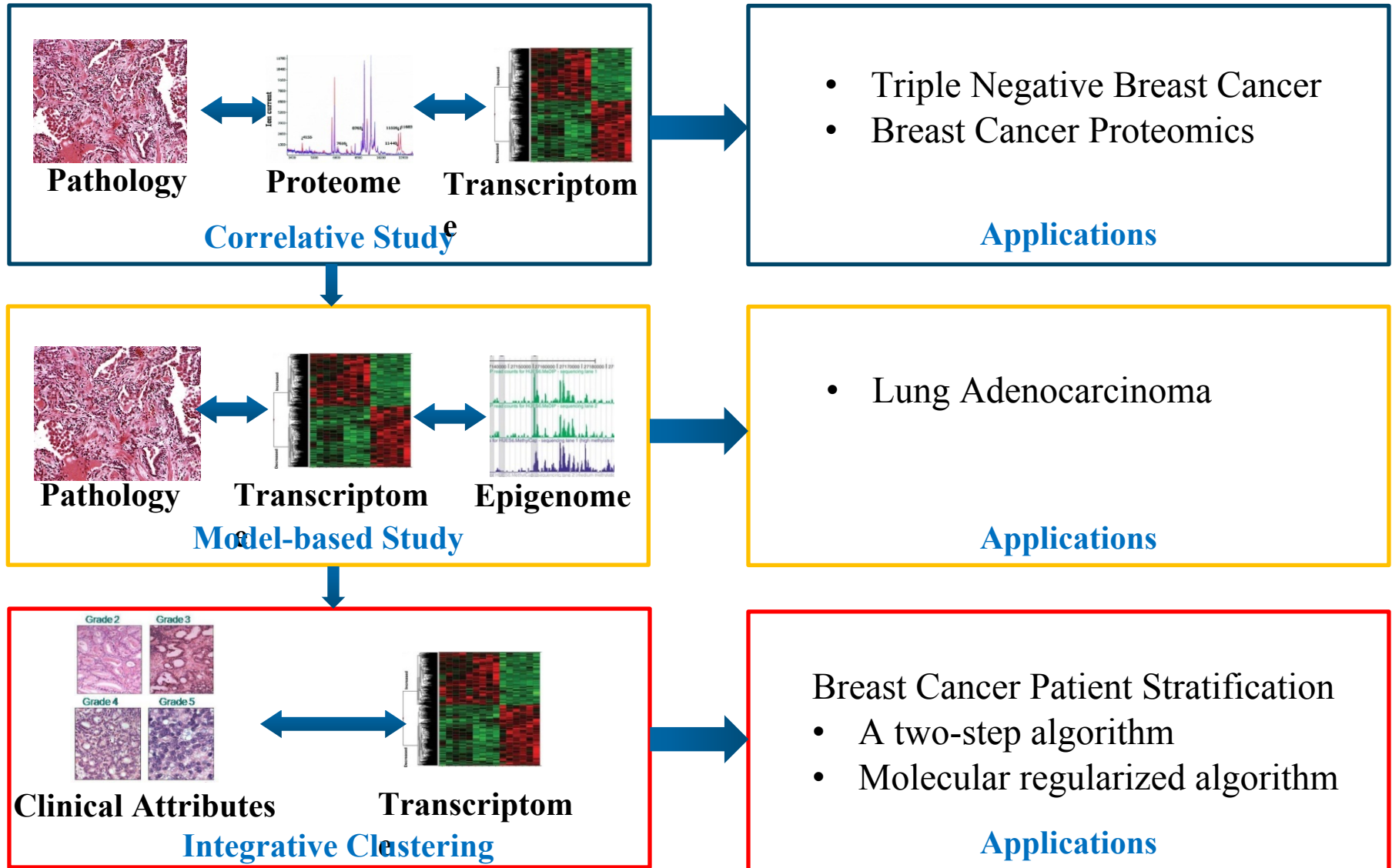
Edge(1, 49)



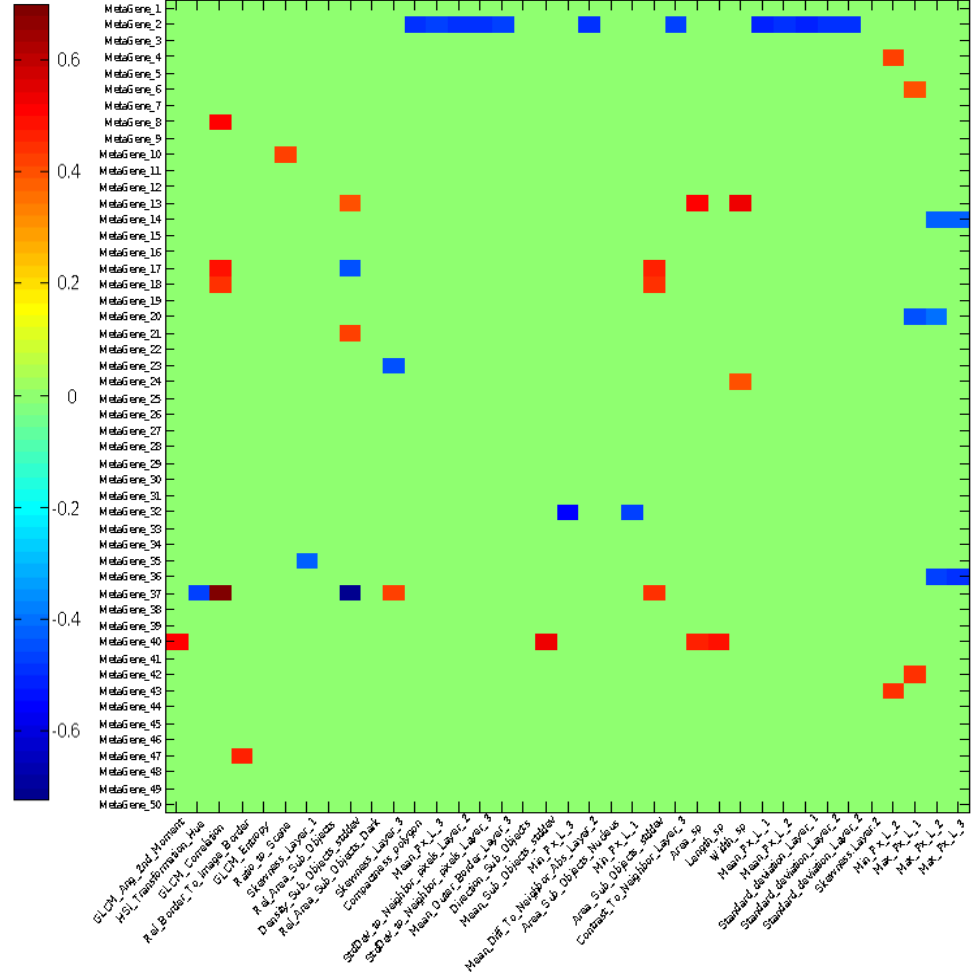
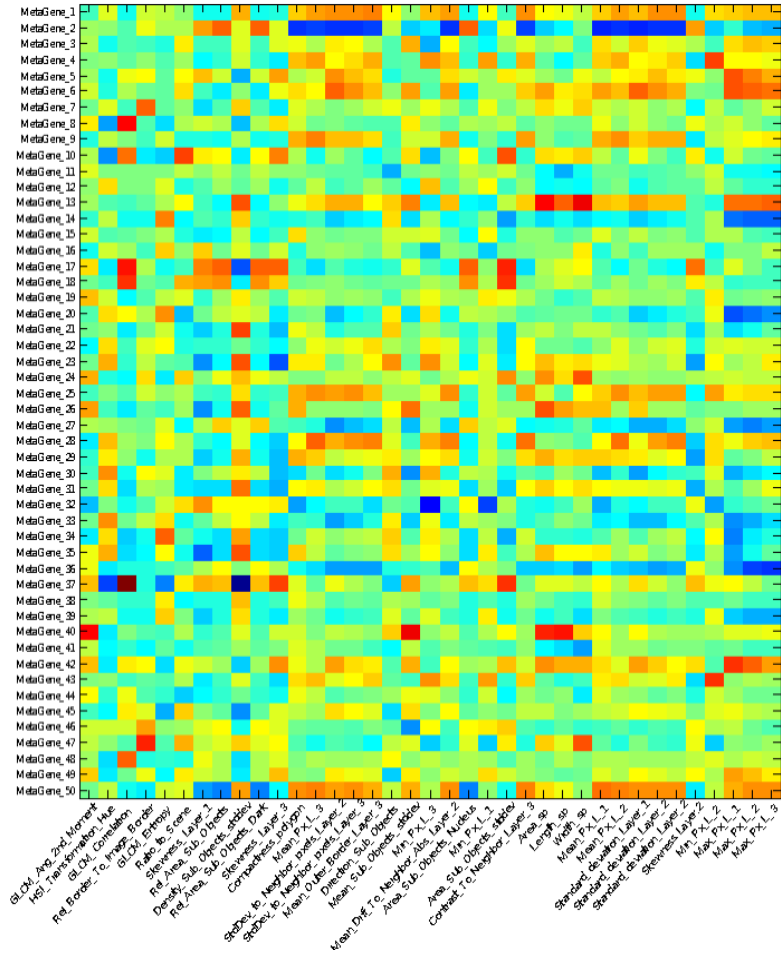
# Papillary Cell Renal Cell Carcinoma



# Aim 1b - Correlation to Integration

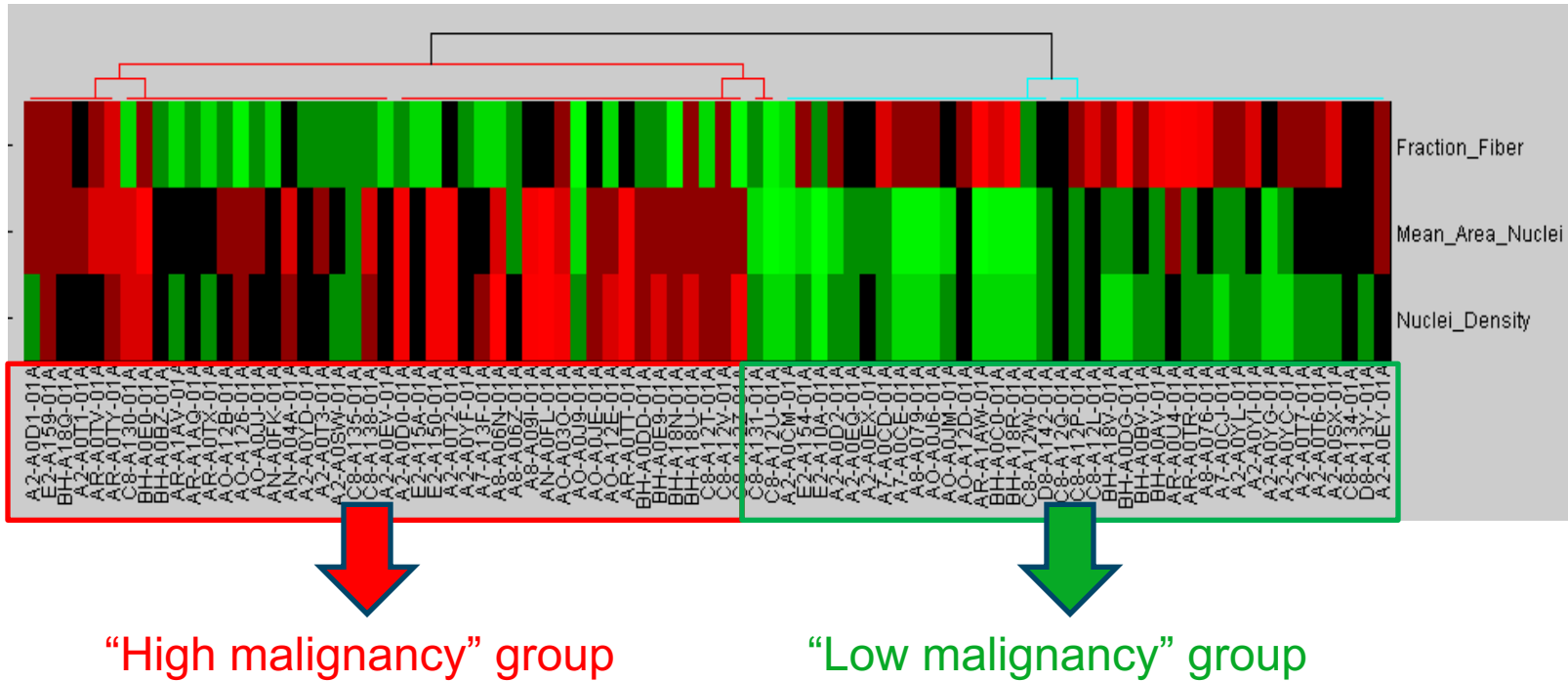


# Eigengene – Imaging Feature Correlation



# Breast Cancer

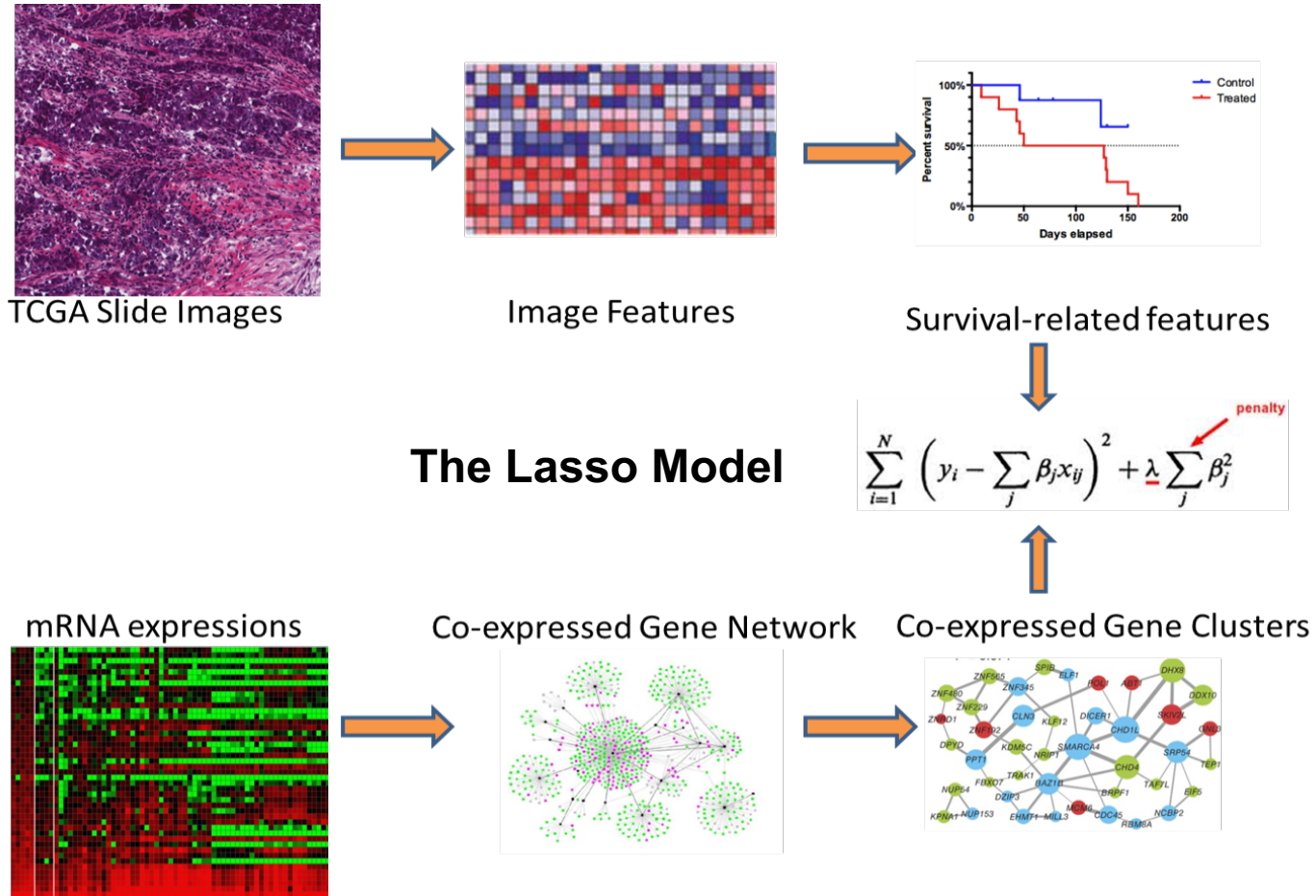
## Patient Stratification on Morphology



**Hierarchical clustering of breast cancer patients based on imaging features.**



# Lung Adenocarcinoma



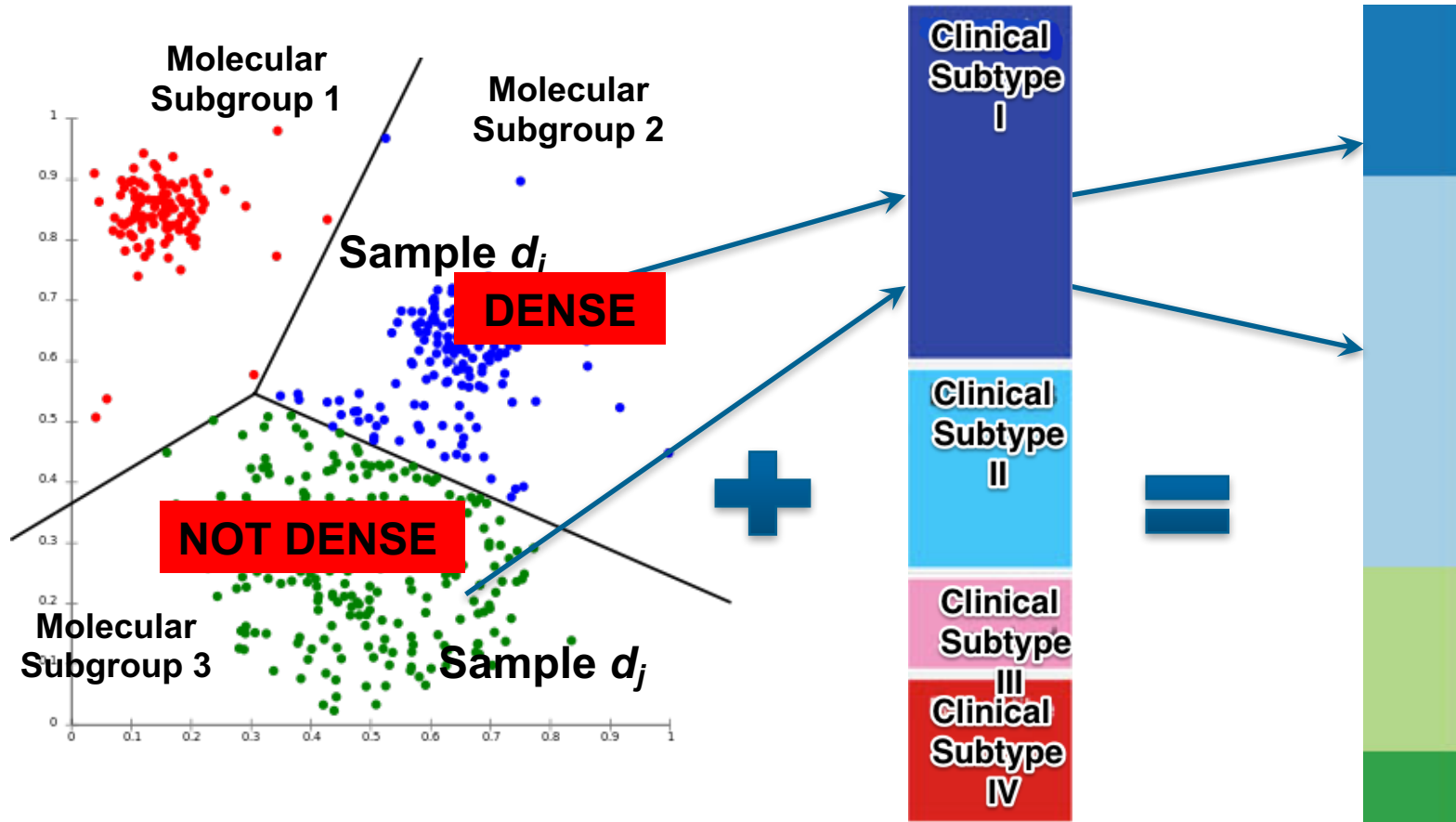
Schematic overview of constructing gene networks and analyzing correlations between gene networks and morphological features

# Morphology and genetic variations

Gene Cluster (size)	beta	GO Biological Process/p-values	Cytobands/p-values	Notes:
4 (59)	-1.1558	GO:0006614 SRP-dependent cotranslational protein targeting to membrane / 9.105E-98		
31 (10)	1.3894			Genes down-regulated in nasopharyngeal carcinoma relative to the normal tissue (p = 5.074e-19, all 10 genes)
33 (10)	-1.7213		19q13.42/5.525e-6	All 10 genes on 19q13.3-4
40 (8)	1.2977		8q24.13/3.263e-5	Seven genes on 8q21-24, one on 8q13
59 (7)	-1.5729		16p11.2/1.364e-10	All seven genes on 16p11
60 (7)	1.2103		Xq28/1.982e-13	All seven genes on Xq27-28
61 (7)	-1.6639		6p21.1/4.436e-7	Six genes on 6p21-22, one on 6p12
70 (6)	2.1783		17q21.31/5.532e-10	All six genes are on 17q21
74 (6)	-2.0544		8p11.2/1.048e-9	All six genes are on 8p11.2
75 (6)	-1.0093	GO:0050680 negative regulation of epithelial cell proliferation / 3.290E-6	17q11.2/6.880e-7	All six genes are on 17q11-12
87 (5)	1.9569		19q13.2/1.131e-6	All five genes on 19q13
95 (5)	2.5783		18q12.1/1.175e-9	All five genes on 18q12



# Concept



Wang et al, Methods, 2013



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# The Algorithm

## Algorithm 1: Molecular Regularized Consensus Patient Stratification

**Data:** Similarity Matrix  $\tilde{S}$ , Molecular Density Weight Matrix  $W$ , the number of clusters in final consensus  $k$ ,  $MaxIter$ , precision  $\epsilon$

**Result:** Cluster indicator matrix  $U$ .

initialize  $\tilde{U}^{(1)} > 0$ ,  $t = 1$ ,  $\Delta = +\infty$ ;

**while**  $t < MaxIter$  and  $\Delta > \epsilon$  **do**

$$\text{Update } \tilde{U}_{ij}^{(t+1)} \leftarrow \tilde{U}_{ij}^{(t)} \sqrt{\frac{[(W \circ S)\tilde{U}D]_{ij}}{[(W \circ \tilde{U}D\tilde{U}^T)\tilde{U}D]_{ij}}};$$

$$\text{Update } D_{ij}^{(t+1)} \leftarrow D_{ij}^{(t)} \sqrt{\frac{[\tilde{U}^T(S \circ W)\tilde{U}]_{ij}}{[\tilde{U}^T(\tilde{U}D\tilde{U}^T \circ W)\tilde{U}]_{ij}}};$$

$$\text{Compute } \Delta = \|\tilde{S} - W \circ (\tilde{U}D\tilde{U}^T)\|_F^2;$$

$t = t + 1$ ;

**end**

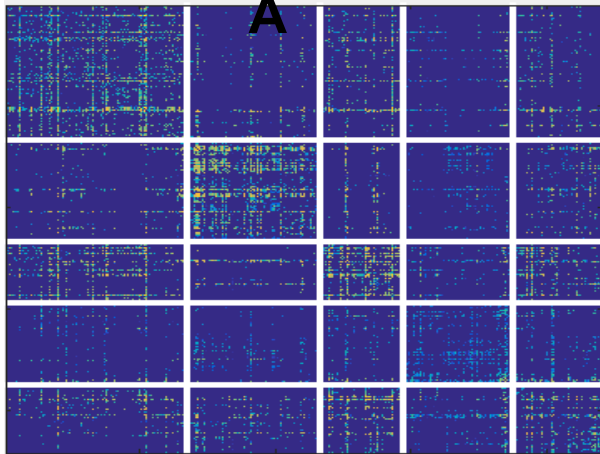
Discretize  $\tilde{U}$  to binary membership matrix.

**Algorithm 1:** Molecular Regularized Consensus Patient Stratification

# Ongoing – Grassmanian Integration

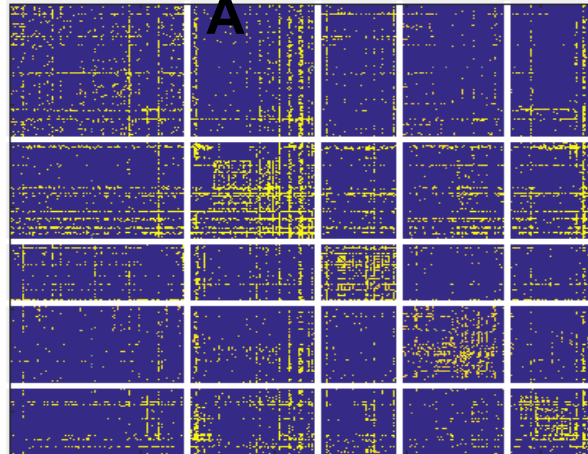
mRN

A

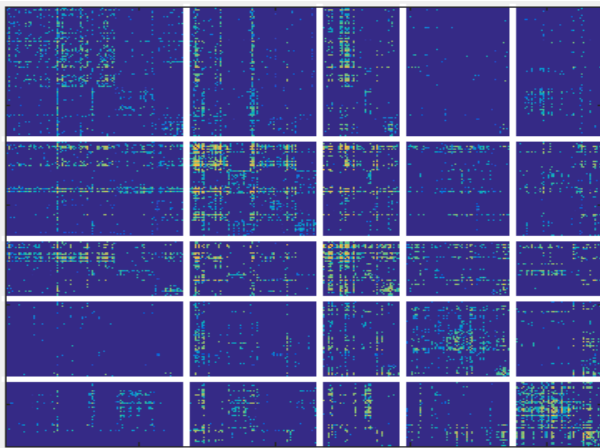


miRN

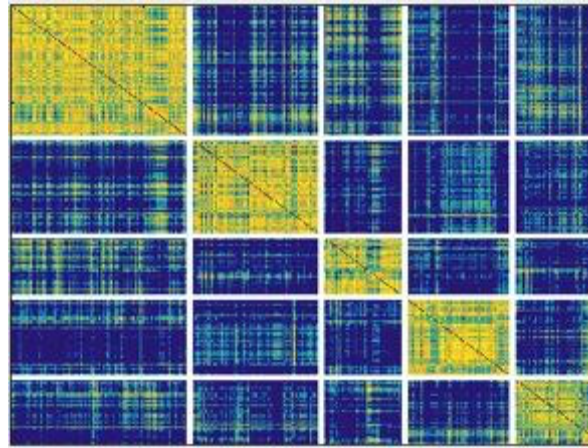
A



DNA methylation



Integration



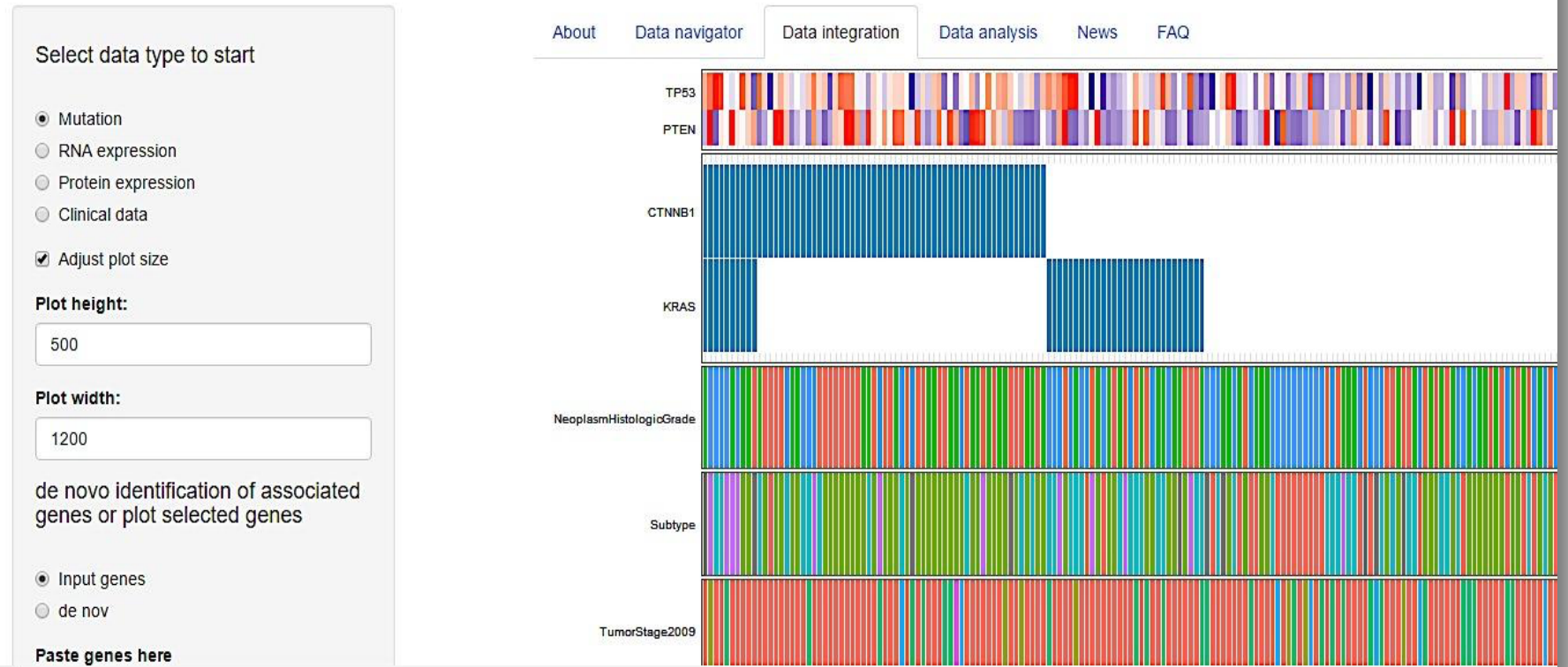
## Aim 2 - Software

- **OSUMO (Ohio State University Multi-Omics tool)**
- **iGenomicsR (R/Shiny)**
- **WINGS (in collaboration with Dr. Parag Mallick)**
- **GRAPHIE**
- **AnnoPeak**
- **ImQCM**

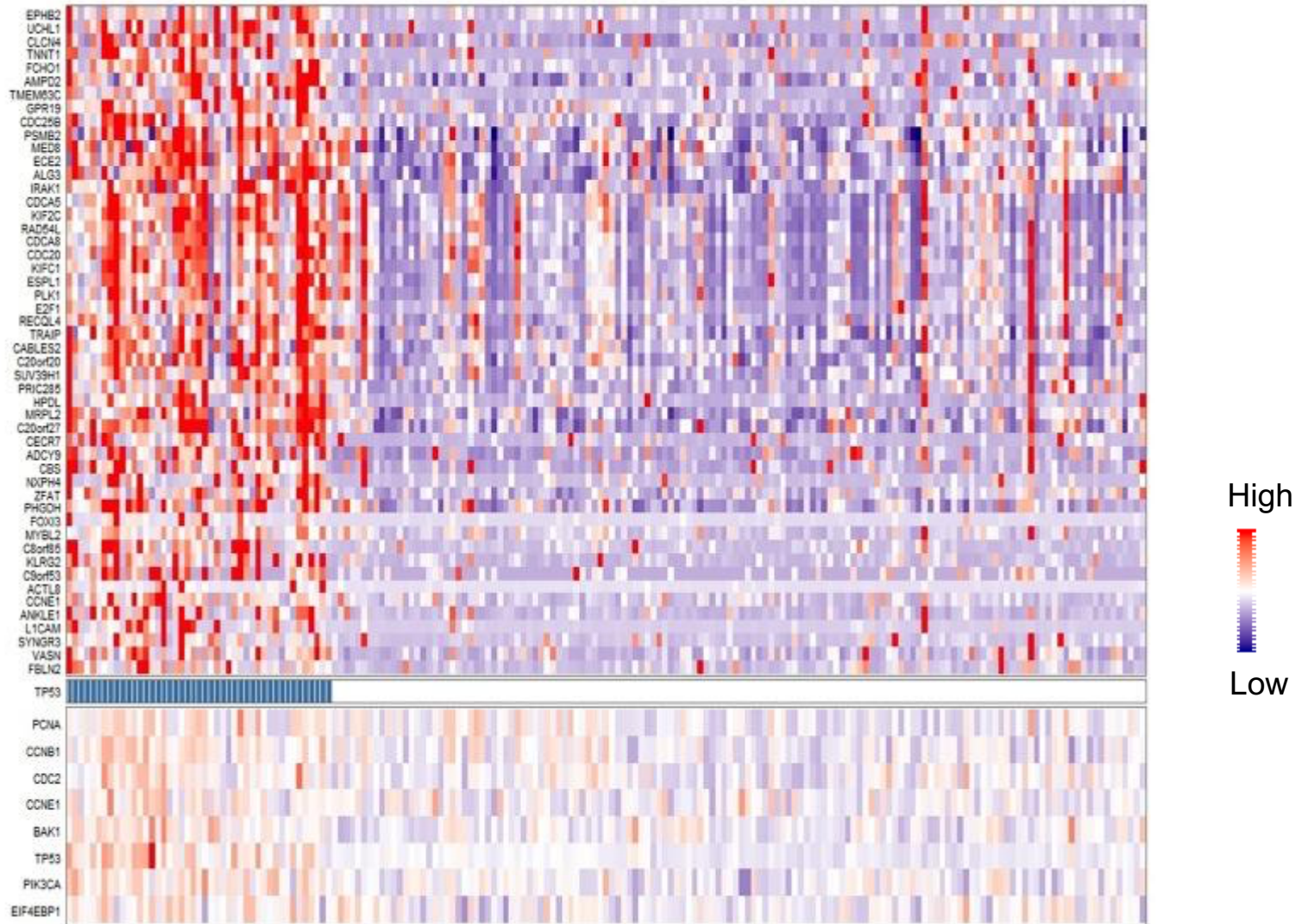


# iGenomicsR

iGenomicsR: an integrative platform to explore, visualize, and analyze multidimensional genomics data for disease



# Cell cycle genes is highly expressed in TP53 mutated patients





# WINGS

**Wings Portal**

Home Analysis Advanced Admin spellbook ravali

Templates

- AnalyzeAffyData
- BCFVarCaller
- BCFVarCaller\_MultiSample
- BasicProteogenomicAnalysis
- CalcRPKMFromFASTQ
- CalcRPKMfromBAM
- GenerateHeatmap
- GenomicVariantCaller
- ImageFeatureExtractionAnalysis
- IndexBamFile
- ProteinIdentification
- SNPIndelAbstractCaller
- SNVCaller\_Mutect
- TranscriptomicsOnly
- VarscanCaller
- ZhangProteogenomicAnalysis
- ZzDaniel\_example1
- test\_daniel\_CW1\_HB
- zzzztest
- zzzzztest
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Run Workflows ImageFeatureExtractionAnalysis BasicProteogenomicAnalysis ZhangProteogenomicAnalysis

Template Documentation Provenance

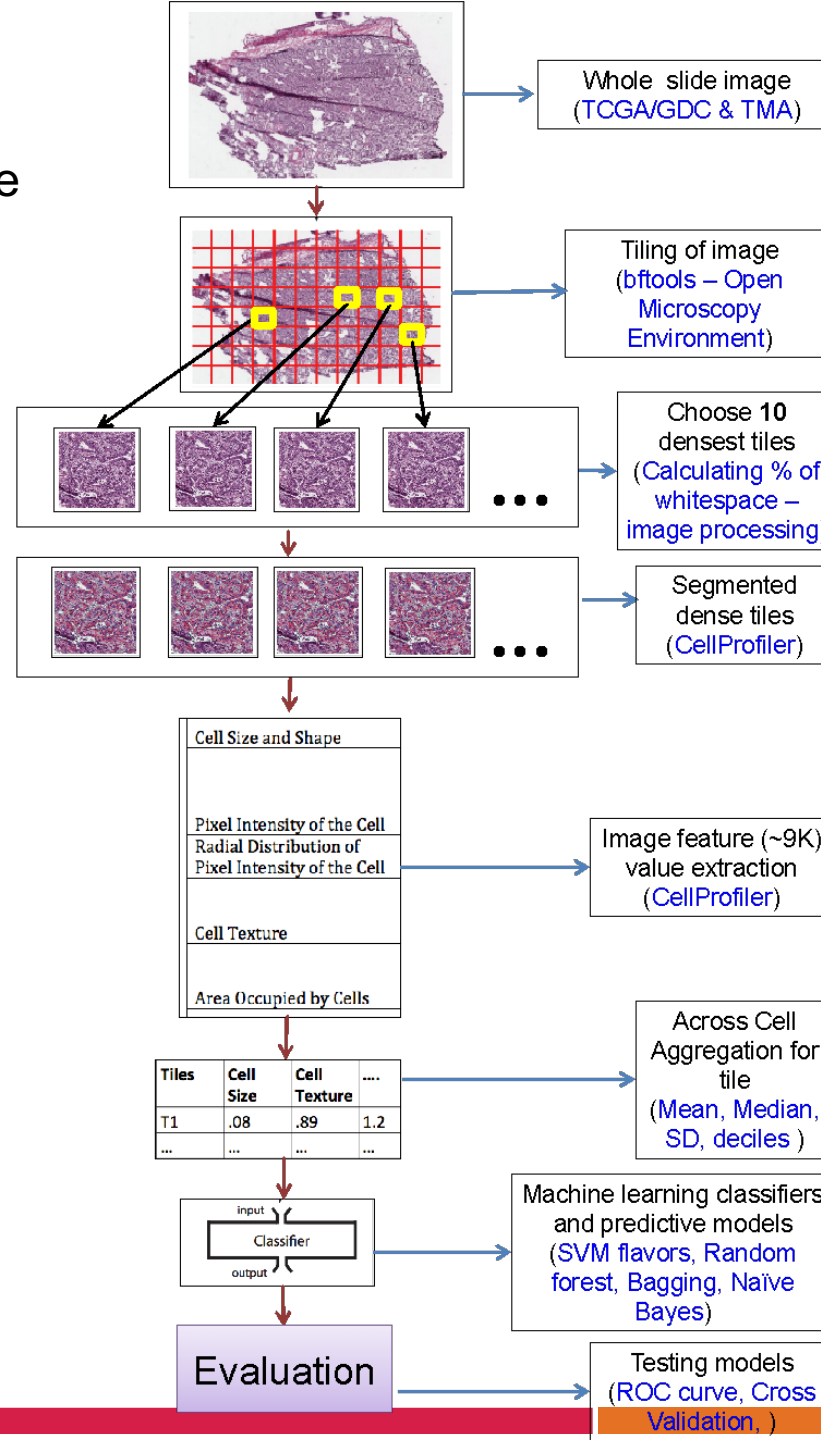
Suggest Data Suggest Parameters Plan Workflow Clear Reload

alignParams: Select a file... refFasta: Select a file...  
rawNGSData: Select multiple files... pileupParams: Select a file...  
refFastaBundle: Select a file... varfiltParamFile: Select a file...  
translateAAParams: Select a file... snpIndelParams: Select a file...  
refFastaAnnot: Select a file... spectraFile: Select a file...  
protAssemblyParams: Select a file... LCMS2Params: Select a file...  
searchEngine: Enter a string value...

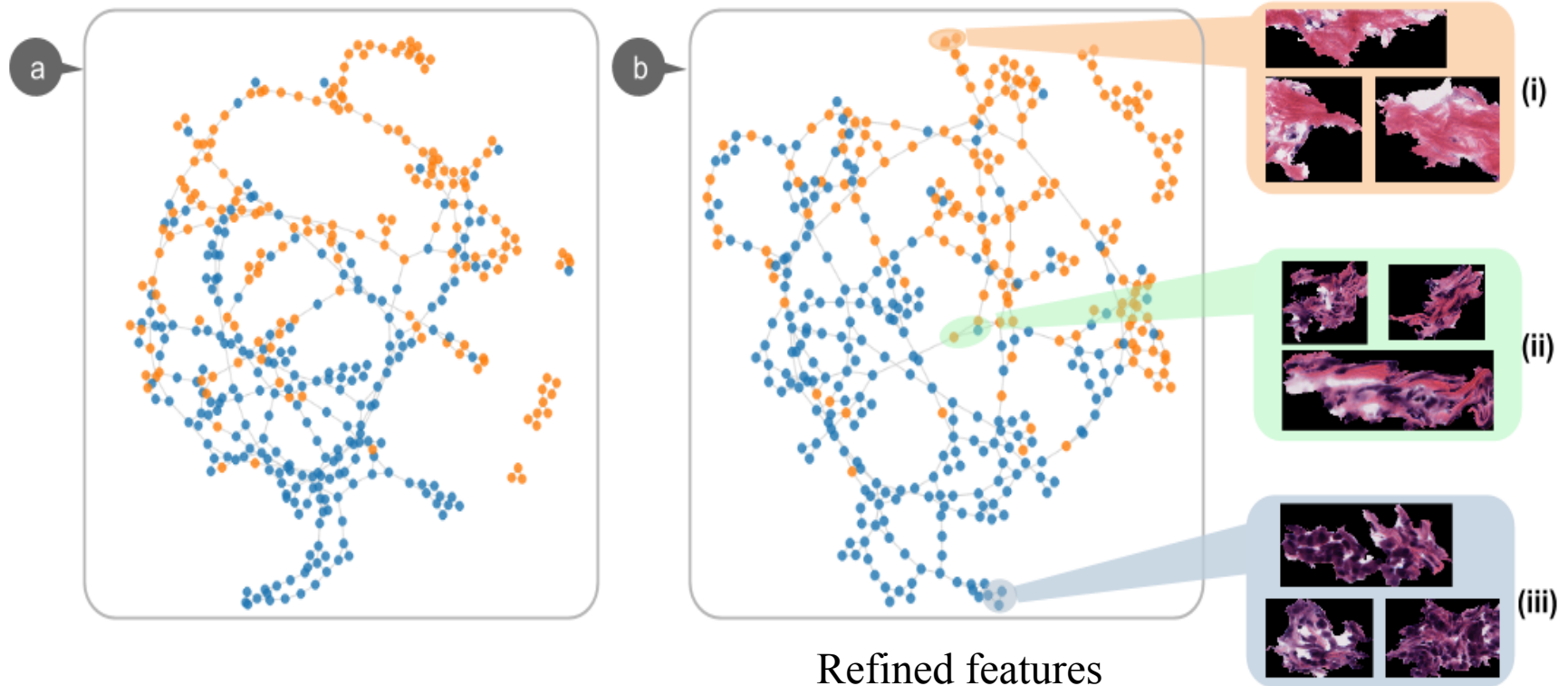
Layout 🔍 🔍 🖨️ Grab Image



# Workflow for Nature Communications publication



# Graphie – Visual Analytics of Imaging Features



Refined features

Ding et al. *BMC Bioinformatics* 2015, **16**(Suppl 11):S10  
<http://www.biomedcentral.com/1471-2105/16/S11/S10>



RESEARCH

Open Access

## GRAPHIE: graph based histology image explorer

Hao Ding<sup>1</sup>, Chao Wang<sup>3</sup>, Kun Huang<sup>2\*</sup>, Raghu Machiraju<sup>1\*</sup>

From 5th Symposium on Biological Data Visualization  
Dublin, Ireland. 10-11 July 2015

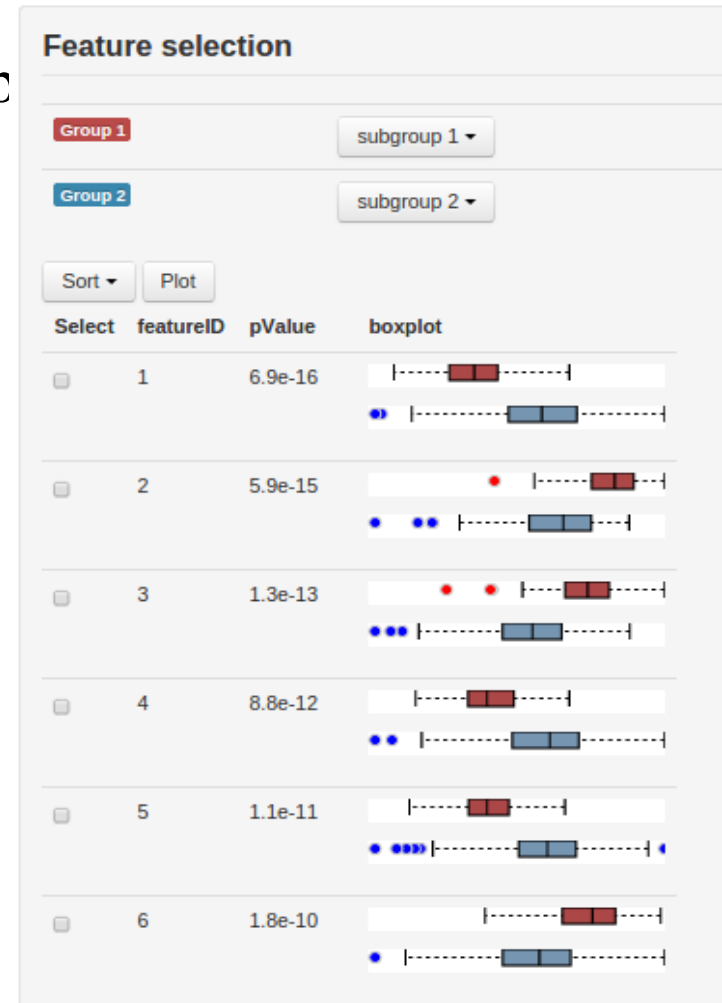


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# Graphie –Feature Selection

Examine feature distinctiveness for group of images.

- Student's t-test
- Boxplots
- Re-generate with selected feature subset



# Aim 3 – Translational Applications

- Triple negative breast cancer biomarker discovery (Drs. *Charles Shapiro, MSMC*)
- Triple negative breast cancer neoadjuvant therapy outcome prediction (Dr. *Zaibo Li - OSU, Yuan Zhang – Harbin Cancer Hospital*)
- Lung adenocarcinoma immune therapy response prediction (Drs. *David Carbone - OSU, Yilong Wu – Guangdong Lung Cancer Inst.*)
- Lung adenocarcinoma prognosis prediction and subtyping (Dr. *Lin Yang – UFL, David Foran – Rutgers U*)
- Papillary cell renal cell carcinoma (Dr. *Anil Parwane - OSU*)
- Clear cell renal cell carcinoma (Dr. *Anil Parwane - OSU*)
- Thyroid cancer SPORE (Drs. *Matt Ringel, Kevin Coombes - OSU*)
- Gastric cancer (Dr. *Jiafu Ji – Beijing Cancer Hospital*)
- Liver cancer (Dr. *Lei Liu – Fudan University*)
- Neuroblastoma (CAMDA)
- Cytology image classification for cancers (Dr. *Zaibo Li - OSU*)

# Aim 3 – Basic Science Applications

- **Cancer cell cycle pathway characterization (Dr. Gustavo Leone, MUSC)**
- **Cancer genome stability gene mutation (Dr. Jeffrey Parvin, OSU)**
- **Cancer epigenetics / CCSB U54 (Drs. Tim Huang, UTSA)**
- **Cancer drug repurposing (Drs. Philip Payne, WashU)**
- **Cancer co-methylation markers (Dr. Jie Zhang, OSU)**
- **Systems modeling of breast cancer (Dr. Lang Li, IU)**
- **Functions of STUB1 gene (Dr. Yufeng Yang, Fuzhou U)**



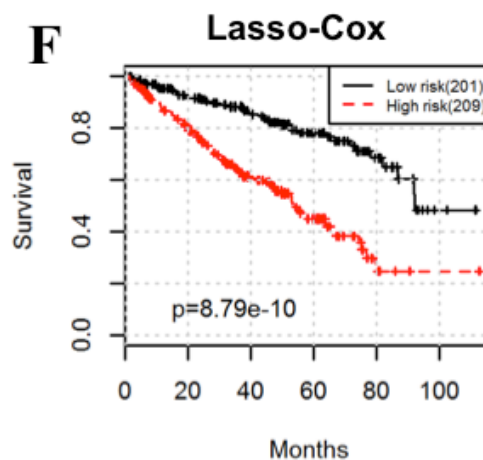
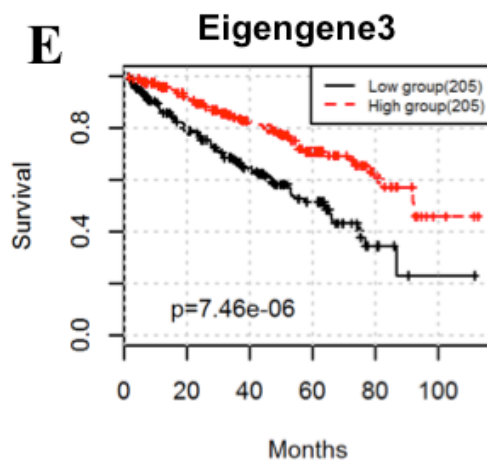
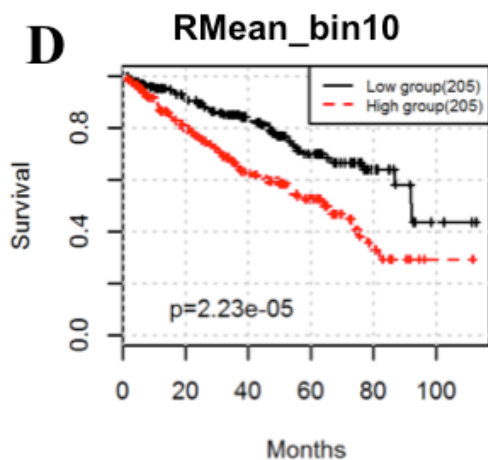
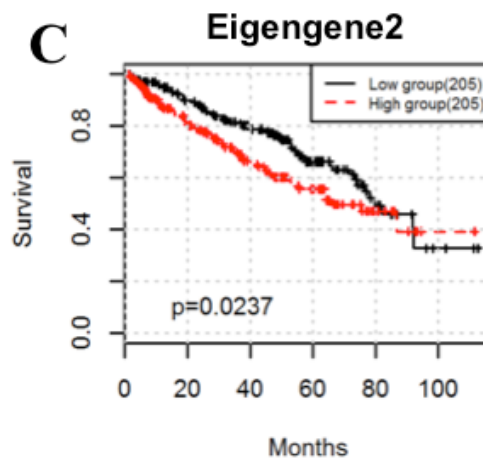
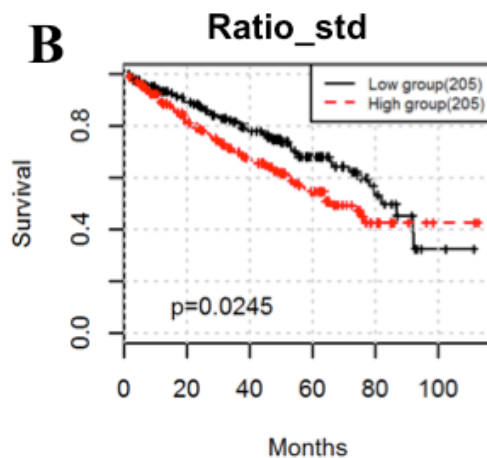
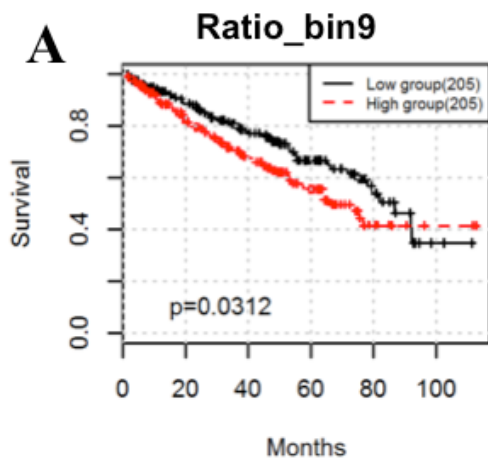
# Aim 3 – Informatics Collaborations

- **Integrative analysis of cancer proteogenomics data (Dr. Parag Mallick, Stanford U)**
- **Integrative analysis and visualization of CPTAC data (Dr. Bing Zhang, Baylor College of Medicine)**
- **Integrative visualization tool development (Dr. Xing Tang, St. Jude Children's Hospital)**
- **Integrative tool evaluation (Dr. Simon Lin, Nationwide Children's Hospital)**
- **Integration with TPCA (Dr. Han Liang, MD Anderson)**
- **Morphological feature extraction (Dr. Lee Cooper, Emory U)**



# Clear Cell Renal Cell Carcinoma

Question – Can these features do better when combined?





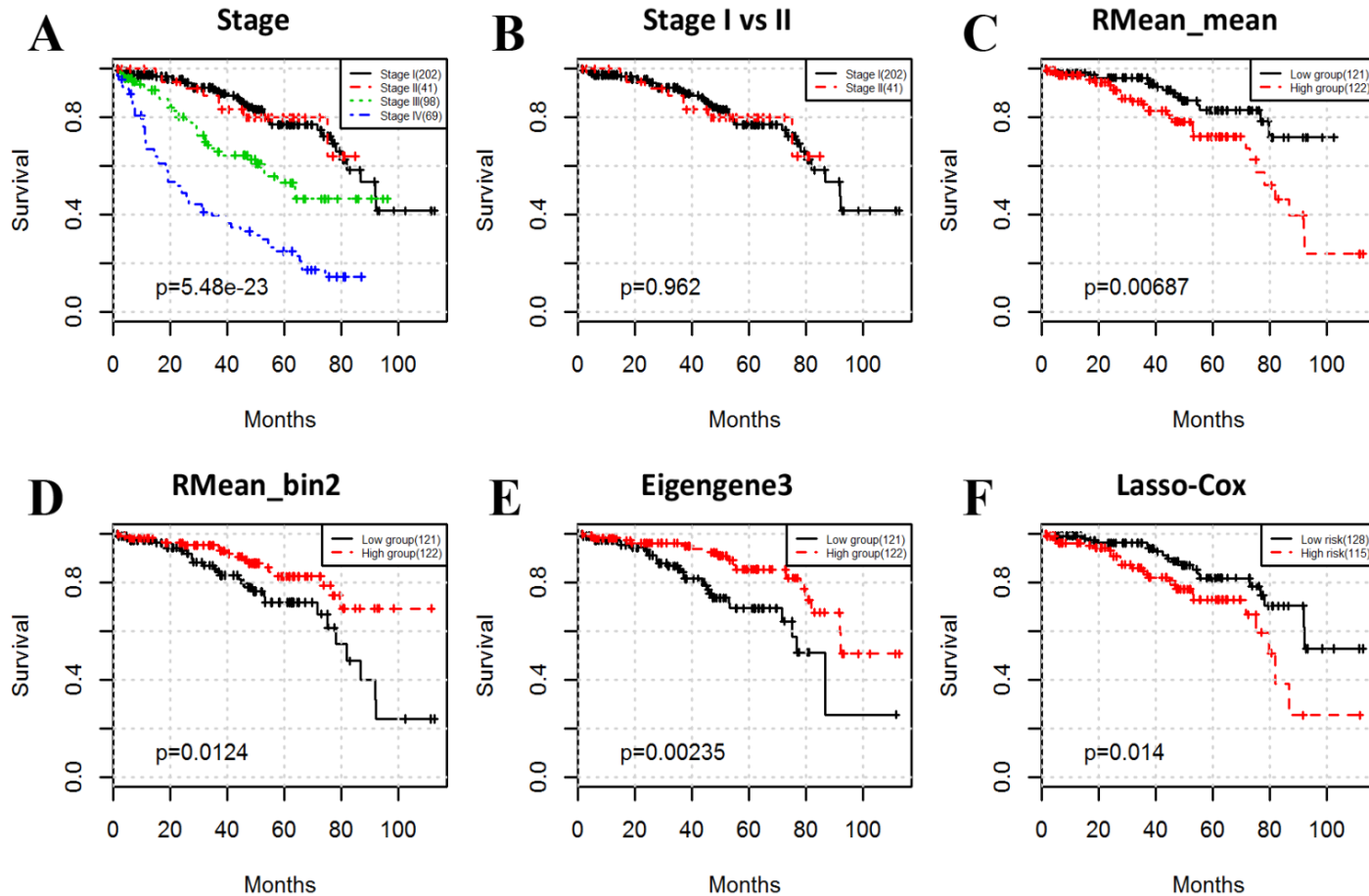
# Clear Cell Renal Cell Carcinoma

**Question – Can these features do better when combined?**

Variable	Univariate Cox regression		Multivariate Cox regression	
	HR (95% CI)	P value	HR (95% CI)	P value
Lasso-Cox	3.06 (2.10-4.45)	5.02e-9	2.26 (1.46-3.49)	2.31e-4
Clinical				
Grade	2.38 (1.63-3.5)	8.45e-6	1.46 (0.95-2.23)	8.22e-2
Stage	3.68 (2.57-5.27)	1.12e-12	3.00 (2.00-4.49)	9.23e-8
Gene expression				
CSNK2A1	0.90 (0.64-1.26)	5.34e-1	1.07 (0.74-1.56)	7.11e-1
SPP1	1.15 (0.82-1.61)	4.14e-1	1.10 (0.75-1.63)	6.20e-1
DEFB1	1.41 (1.00-1.98)	4.99e-2	1.36 (0.95-1.95)	9.71e-2
PECAM1	0.77 (0.55-1.09)	1.40e-1	1.04 (0.69-1.58)	8.45e-1
EDNRB	0.50 (0.35-0.71)	9.10e-5	0.96 (0.59-1.57)	8.77e-1
TSPAN7	0.54 (0.38-0.76)	5.12e-4	1.03 (0.64-1.67)	9.07e-1
Somatic mutation				
VHL	0.99 (0.70-1.38)	9.33e-1	1.23 (0.86-1.75)	2.57e-1
PBRM1	0.85 (0.58-1.24)	3.94e-1	1.03 (0.69-1.54)	8.85e-1
BAP1	1.49 (0.78-2.85)	2.22e-1	1.49 (0.74-3.00)	2.60e-1
SETD2	1.29 (0.77-2.14)	3.29e-1	1.03 (0.62-1.74)	9.00e-1
TP53	2.26 (1.00-5.15)	5.13e-2	2.86 (1.19-6.86)	1.85e-2

# Clear Cell Renal Cell Carcinoma

**Question** – What features are correlated with patient outcome in early stage (stages I, II)?



# Features and Workflow Released on GitHub

All processed data for clear cell renal cell cancer project (extracted quantitative imaging features, combined gene expression data, etc) and codes with annotations, comments and instructions are available at <https://github.com/chengjun583/image-mRNA-prognostic-model>.



# Next

- **Multiple releases of web portal and tools**
- **Extensive user evaluations**
- **Outreach - CCSB, ITCR, AMIA, AACR, PSB, ICIBM, ...**
- **Interpretation and validation of discoveries from applications**

