

Integrative analysis of breast cancer survival based on spatial features

Presented by

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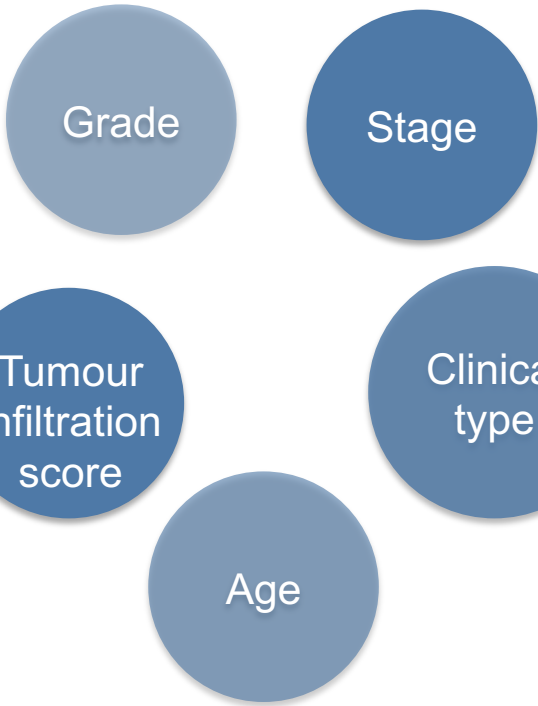


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SYDNEY

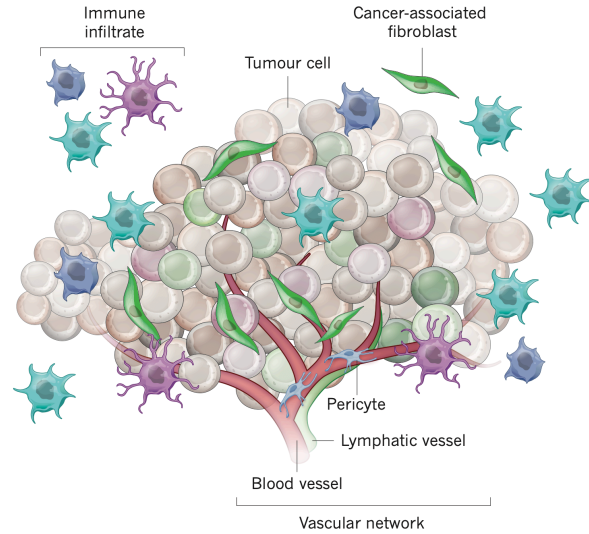


Motivation

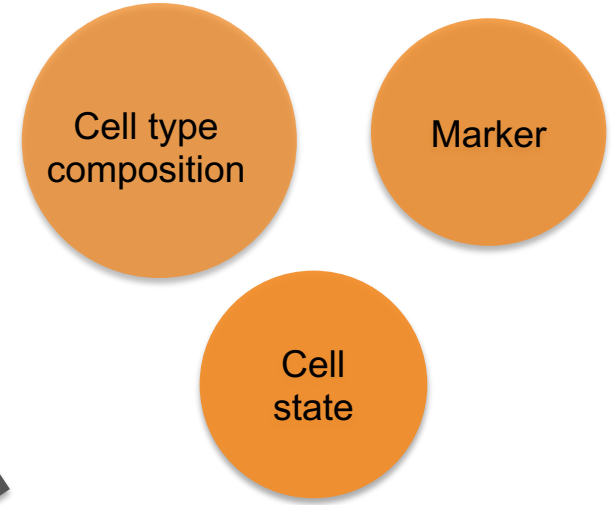
Clinical features



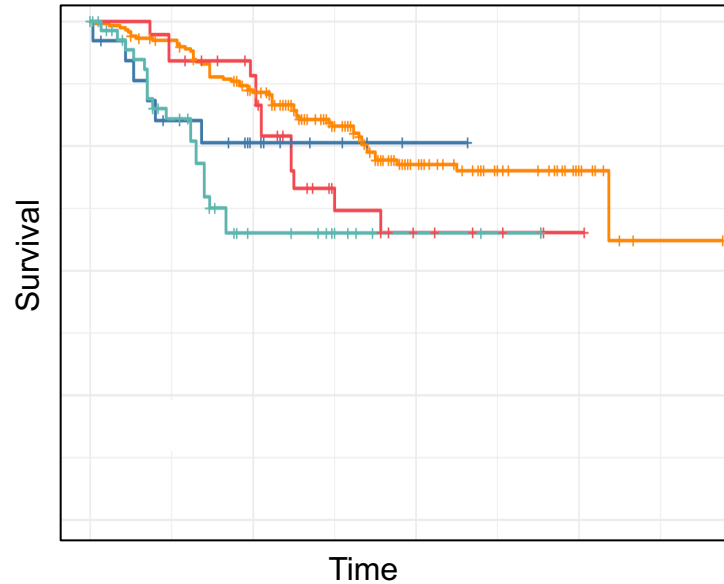
Tumour microenvironment



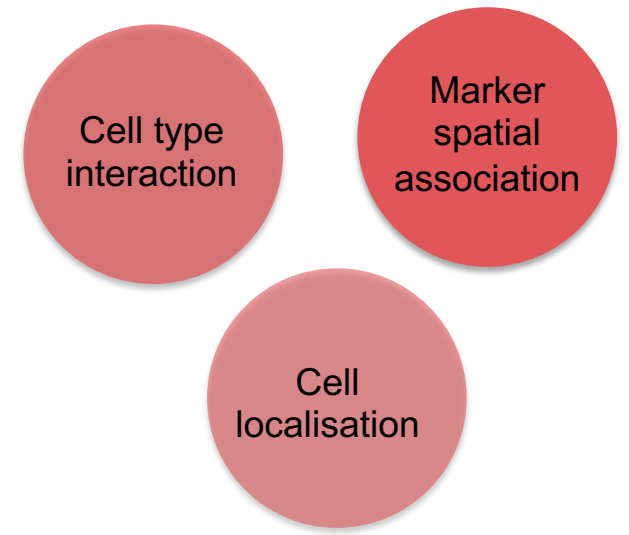
Non-spatial features



Patient survival



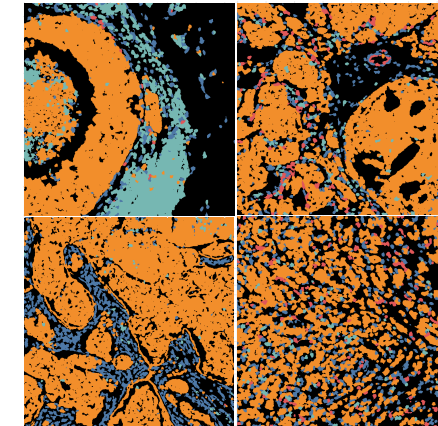
Spatial features



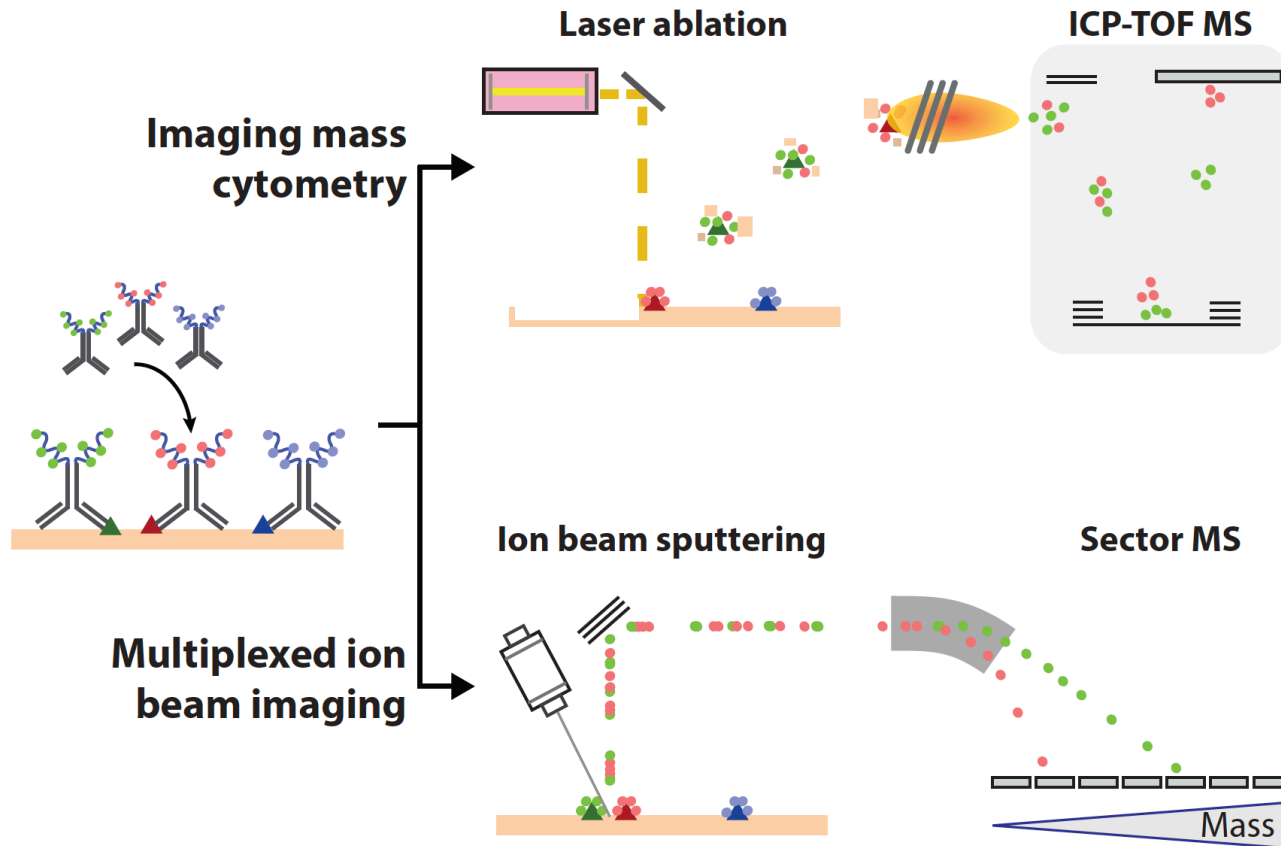
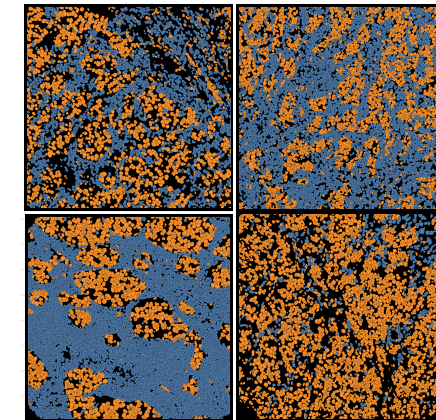
Data: Two Mass Cytometry Imaging data in breast cancer

High dimensional images

IMC (Jackson et al.)

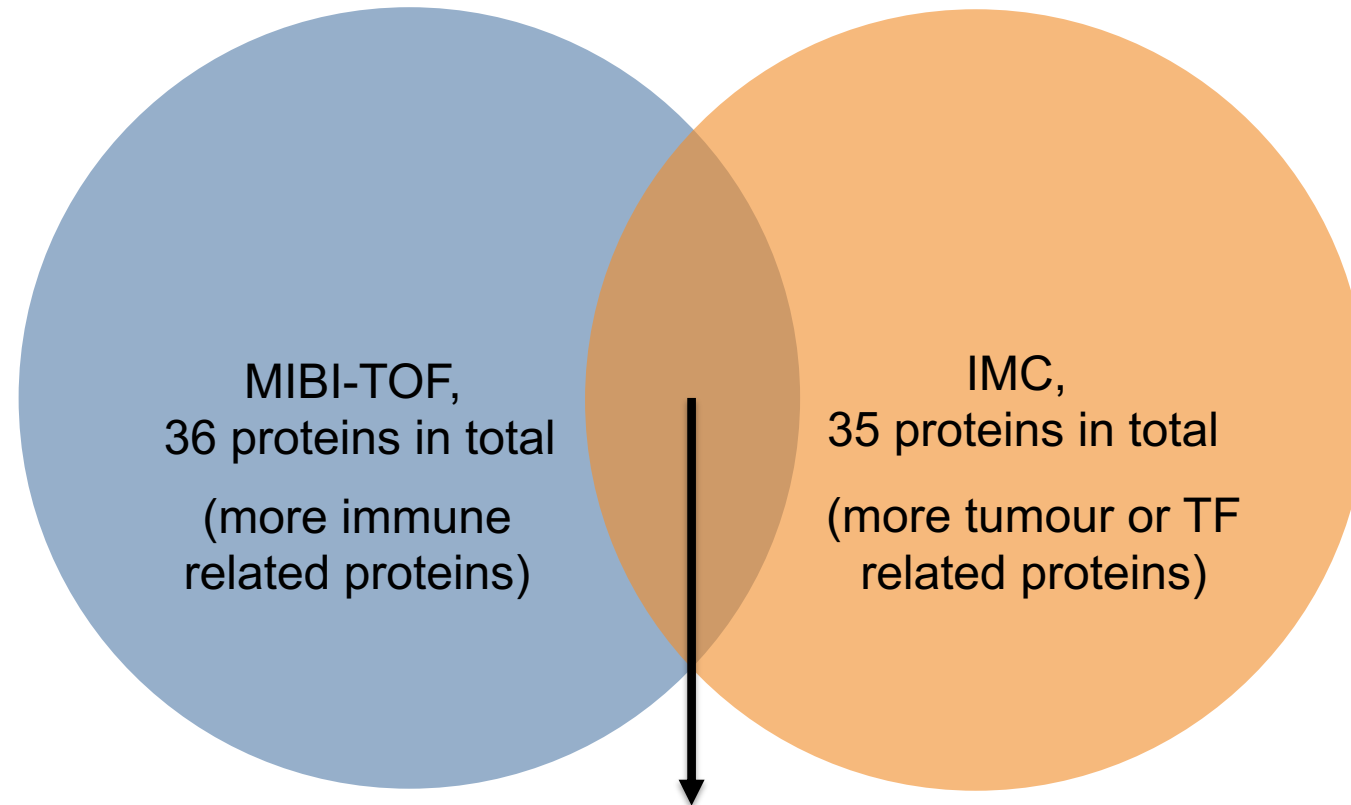


MIBI-TOF (Keren et al.)



Bodenmiller, B. (2016). Multiplexed epitope-based tissue imaging for discovery and healthcare applications. *Cell systems*, 2(4), 225-238.

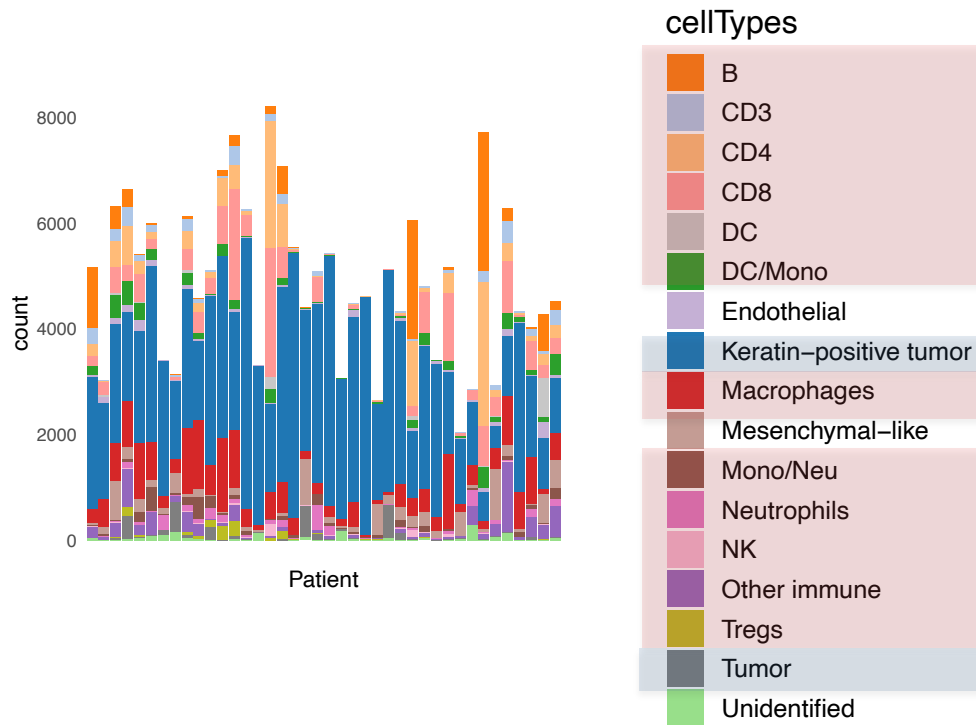
Integrative analysis challenge 1: Limited overlapped proteins



13 Common proteins:
EGFR, Ki67, SMA, Vimentin, p53,
panCK, CD20, vWF, H3K27me3,
CD45, CD68, CD3, pS6

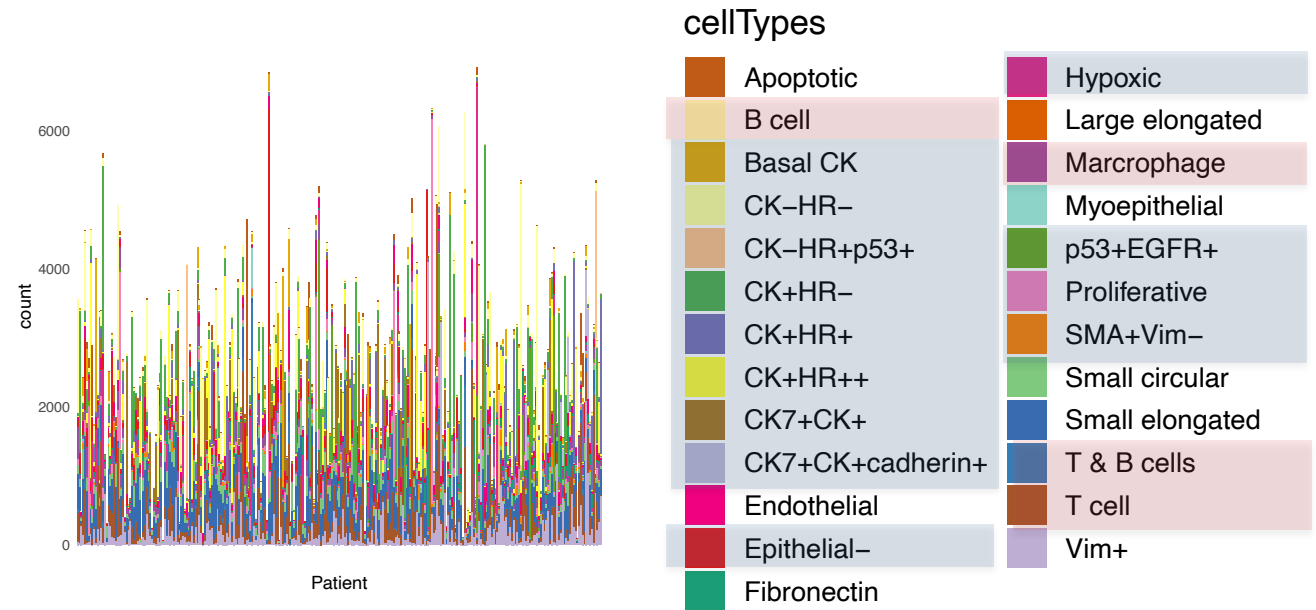
Integrative analysis challenge 2: Very different cell type annotation resolution

MIBI-TOF (Keren et al.)



Immune cell types

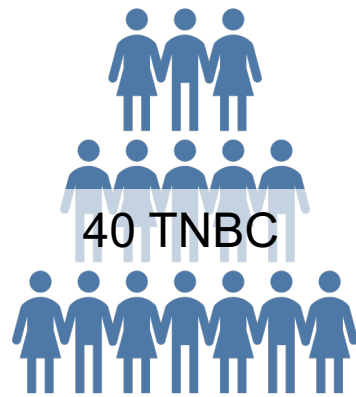
IMC (Jackson et al.)



Epithelial cell types

Integrative analysis challenge 3: Partially overlapped of clinical types between these datasets

MIBI-TOF

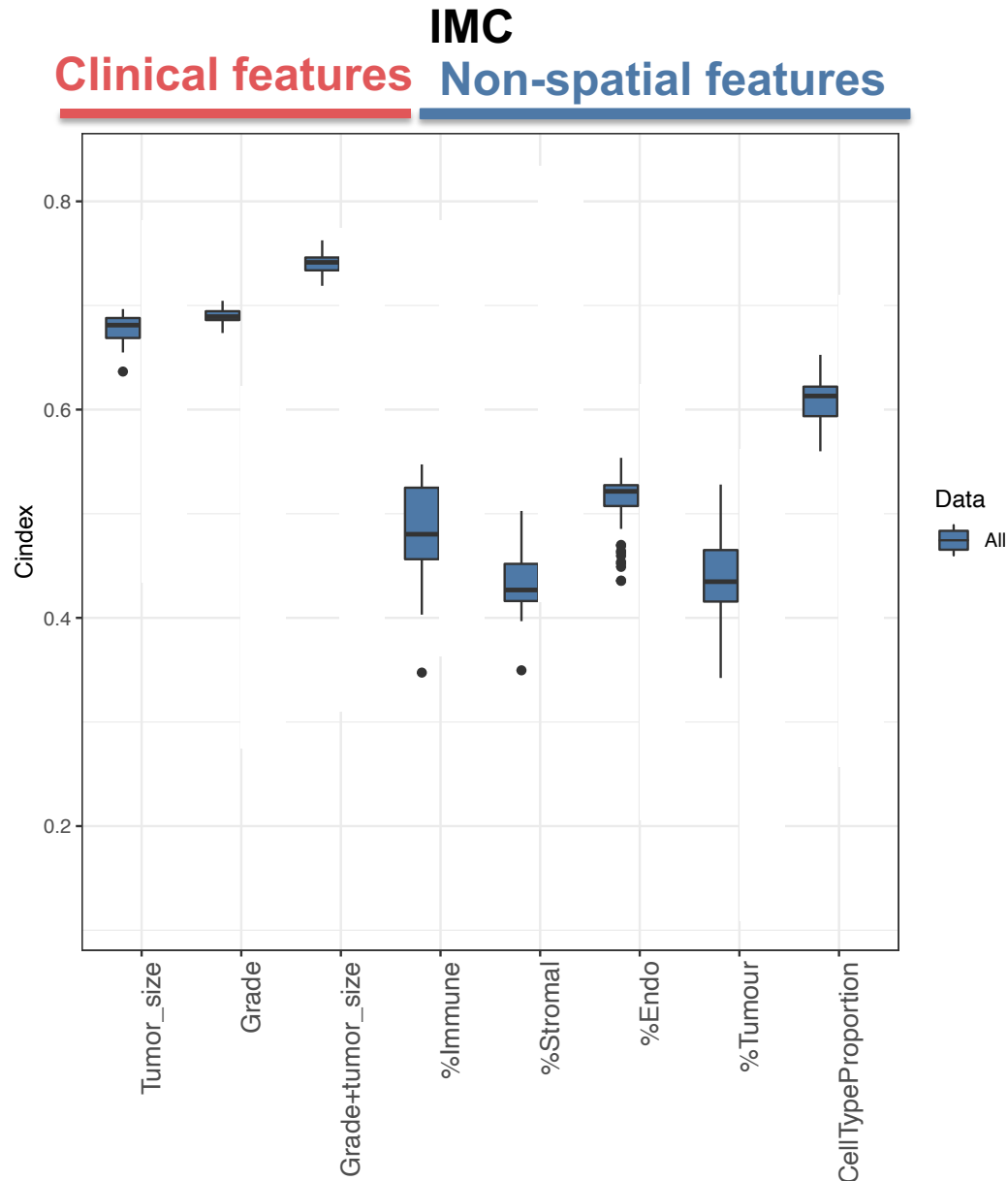


TNBC: Triple Negative Breast Cancer

IMC

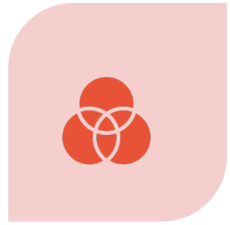


Integrative analysis challenge 4: cohort heterogeneity



- Clinical features are more predictive than features like cell type proportion
- Clinical features perform poorly in triple negative breast cancer

Challenges and Questions



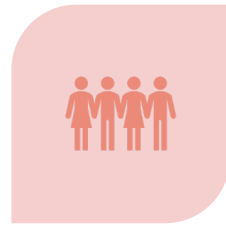
LIMITED
OVERLAPPED
PROTEIN



DIVERSE CELL TYPE
ANNOTATION



PARTIALLY
OVERLAPPED
CLINICAL TYPE



HETEROGENEOUS
COHORT

Spatial
features

- Are the spatial features extracted from the images predictive in patient's survival?

Integrative
analysis

- While integrating the two imaging data in the matrix level is challenging, are there common predictive spatial features shared between the two datasets?

Imputation

- Will other type of single-cell data information further improve the prediction in patient's survival?

Challenges and Questions

Spatial features

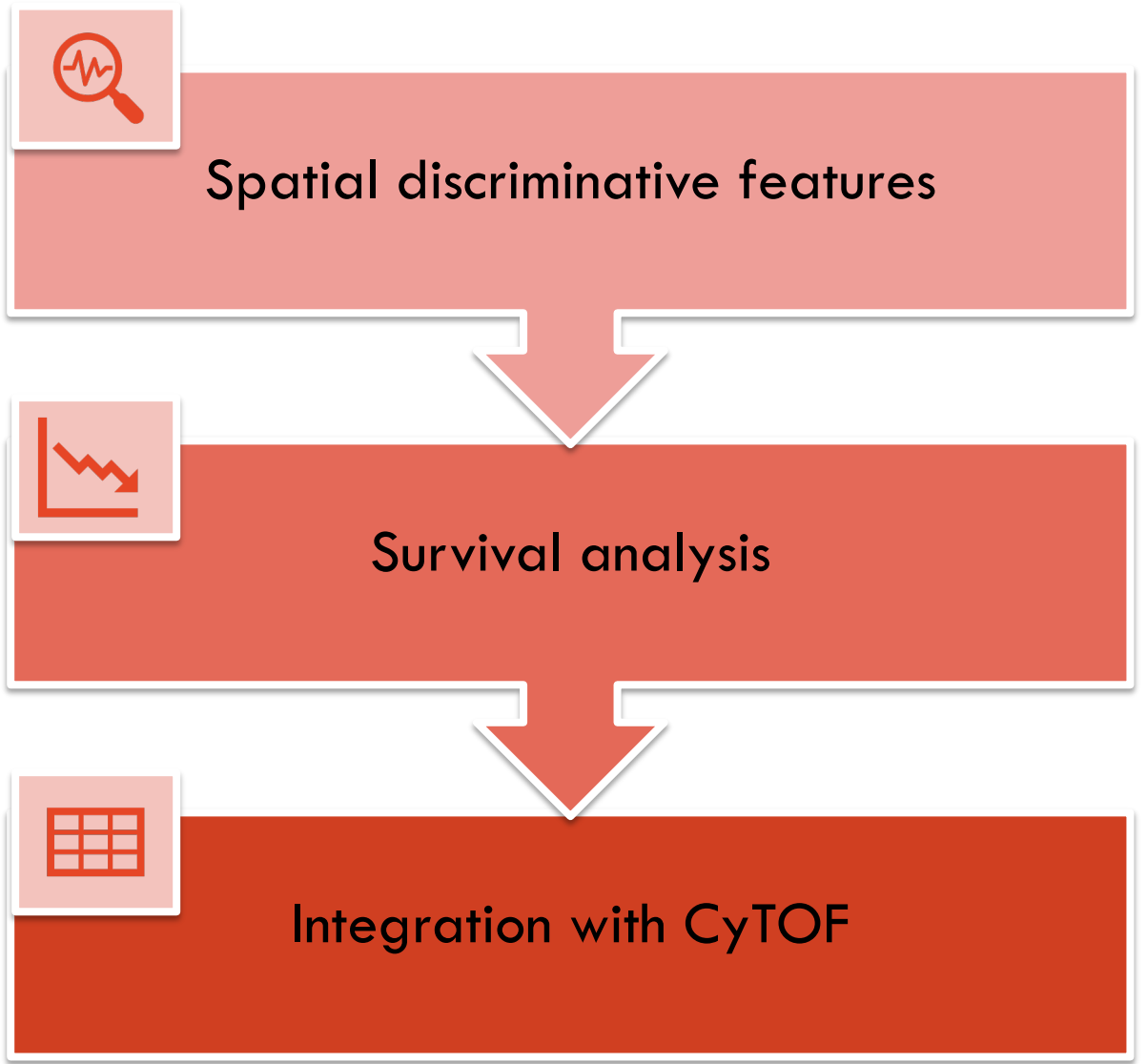
- Are the spatial features extracted from the images predictive in patient's survival?

Integrative analysis

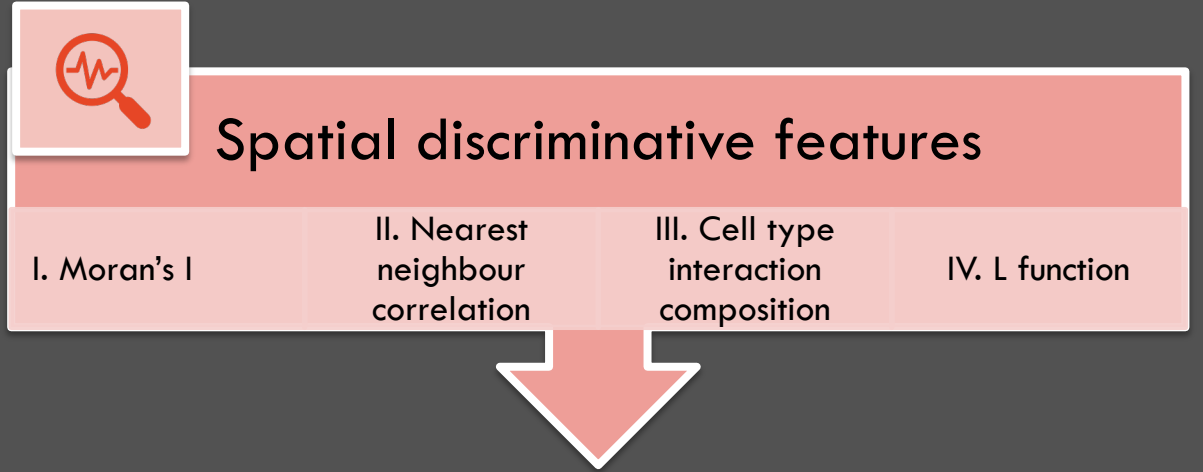
- While integrating the two imaging data in the matrix level is challenging, are there common predictive spatial features shared between the two datasets?

Imputation

- Will other type of single-cell data information further improve the prediction in patient's survival?



Spatial features

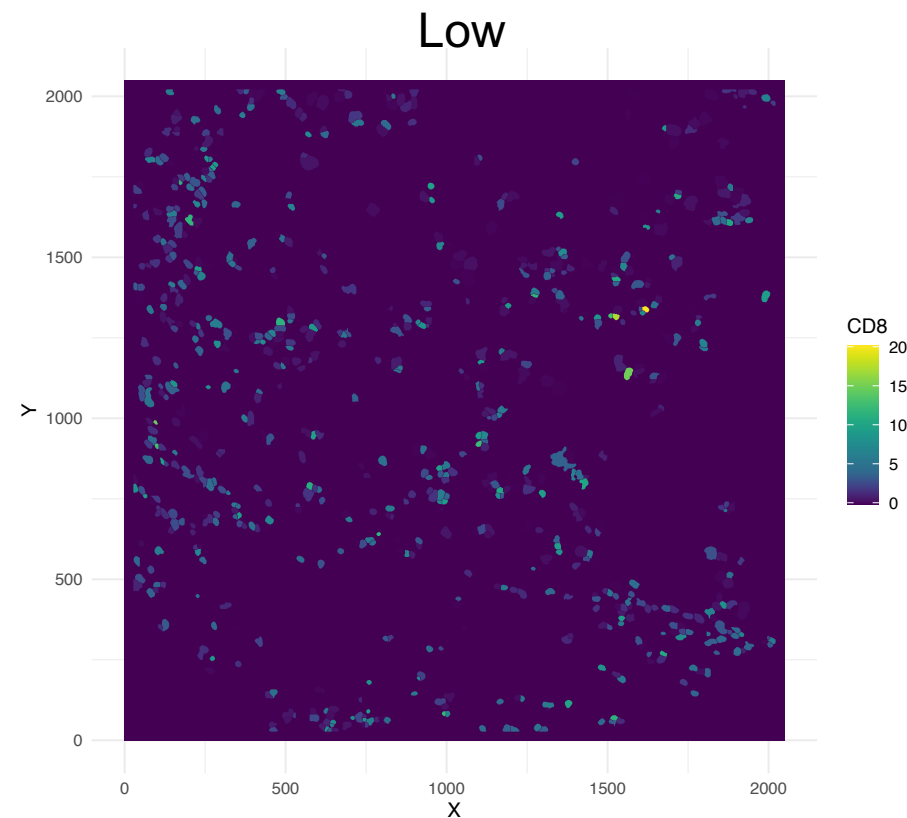
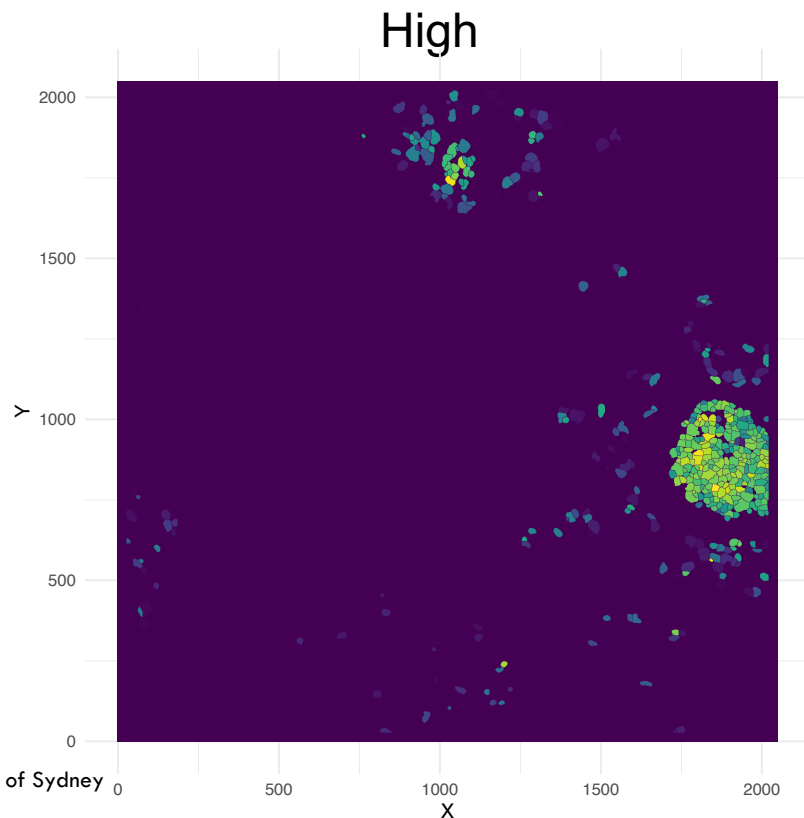


Spatial metrics I: Spatial autocorrelation - Moran's I

Moran's I measures spatial autocorrelation based on both feature locations and values simultaneously:

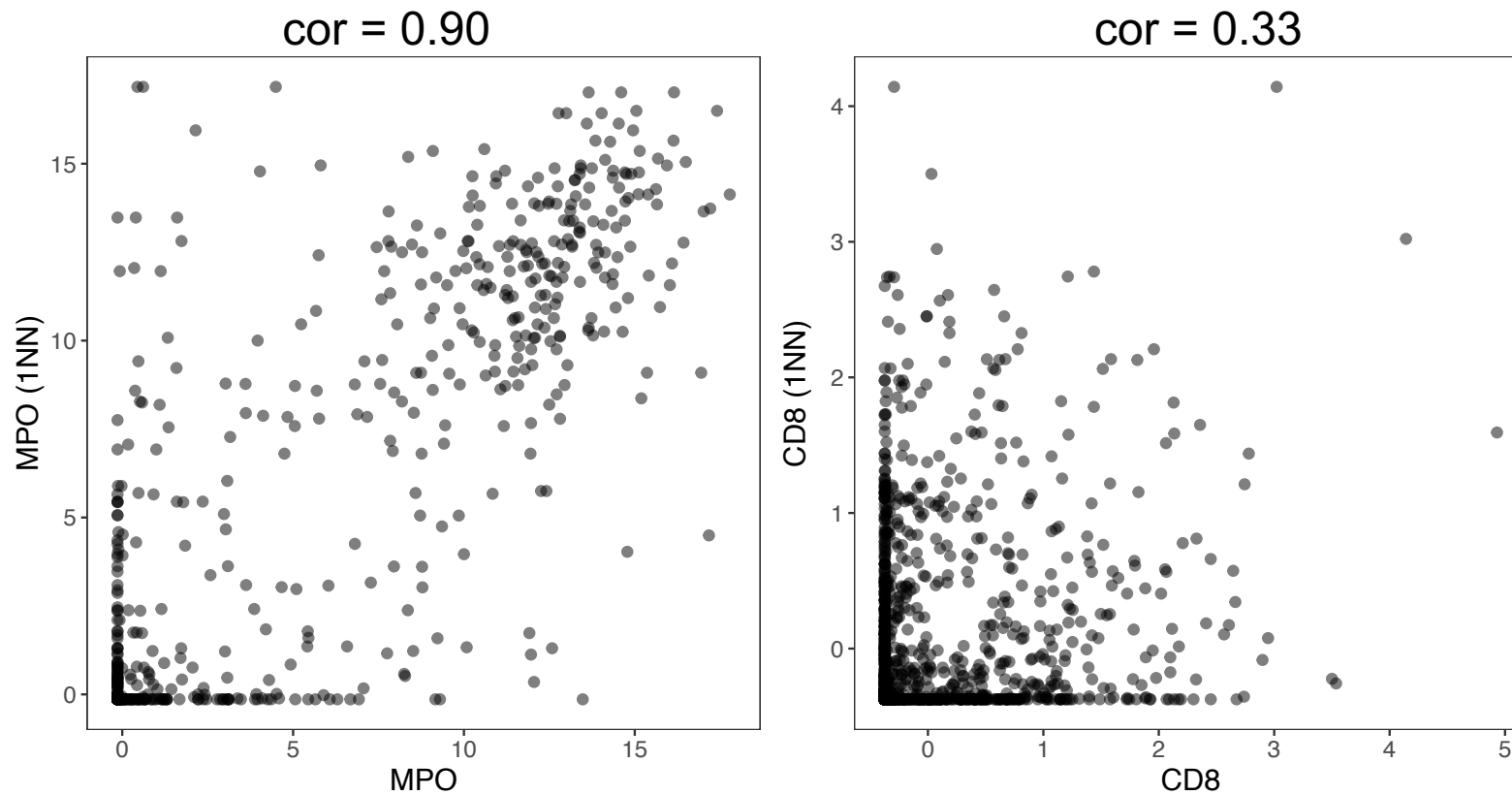
$$I = \frac{N}{\sum_{ij} w_{ij}} \frac{\sum_i \sum_j w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2}$$

where N is the total number of cells indexed by i and j ;
 x is one epitope expression;
 w_{ij} is a matrix of spatial weights



Spatial metrics II: Nearest Neighbour Correlation

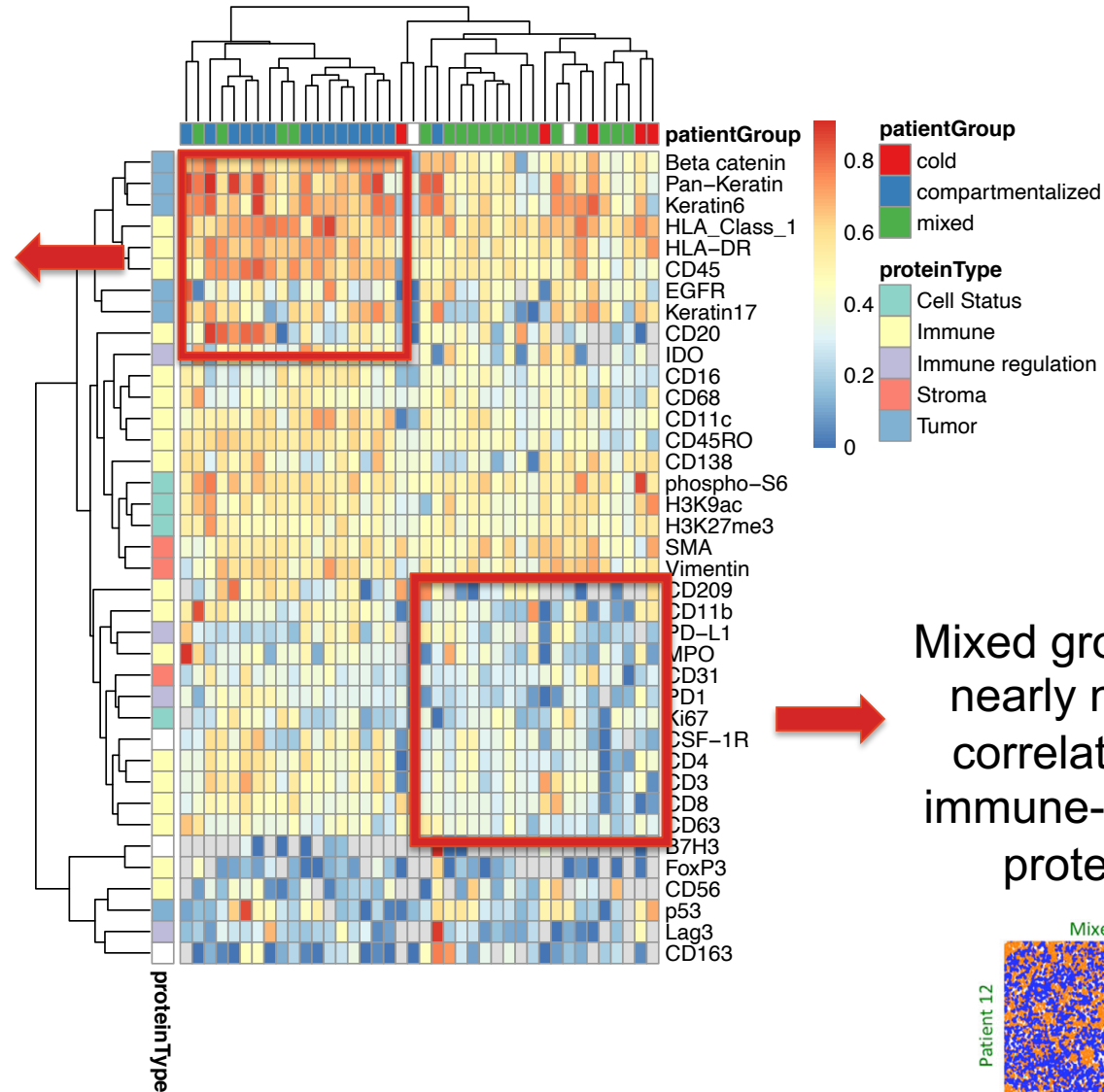
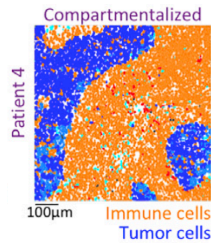
Nearest Neighbour Correlation: Correlation of protein expression between of cells with their nearest neighbours



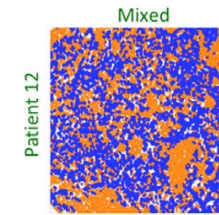
Spatial metrics II: Nearest Neighbour Correlation

MIBI-TOF (Keren et al.)

Compartmentalized group has high NN correlation in tumor and immune related proteins

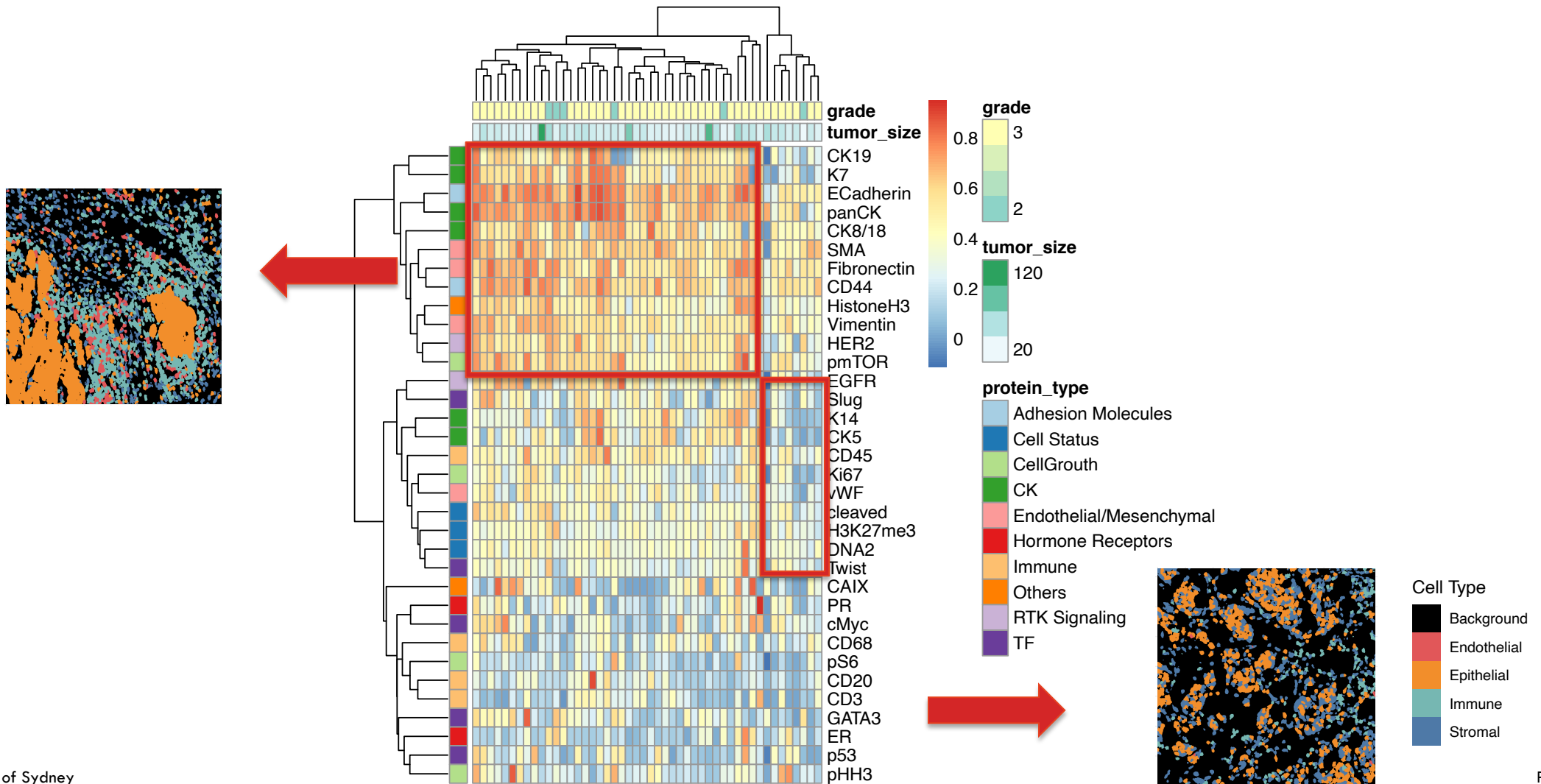


Mixed group has nearly no NN correlation in immune-related proteins



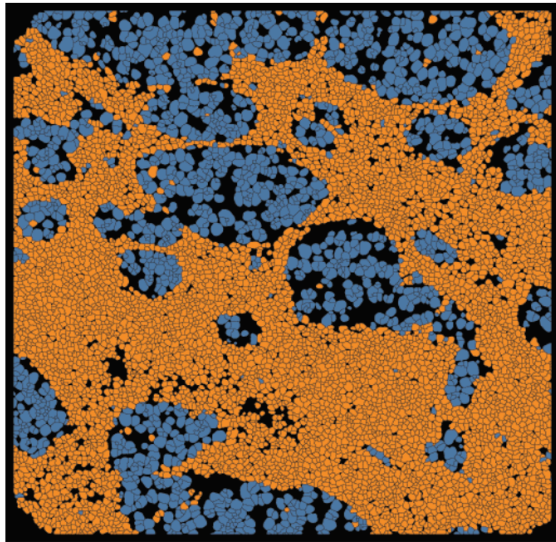
Spatial metrics II: Nearest Neighbour Correlation

IMC (Jackson et al.)

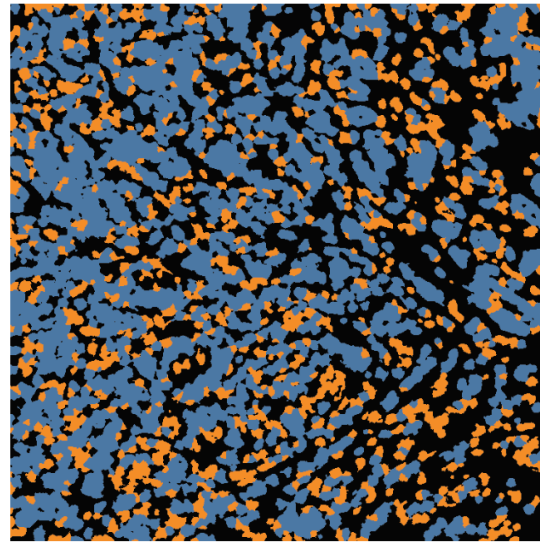


Spatial metrics III: Cell type interaction composition

Patient 1



Patient 2



Tumour



Microenvironment



Proportion of spatial interaction pairs



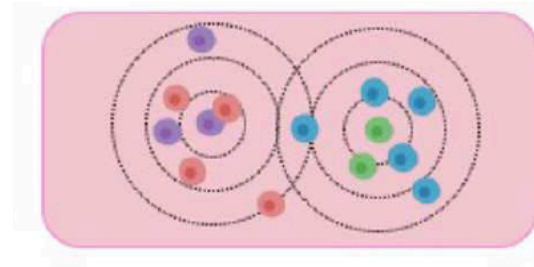
Microenvironment

Tumour-Microenvironment

Tumour

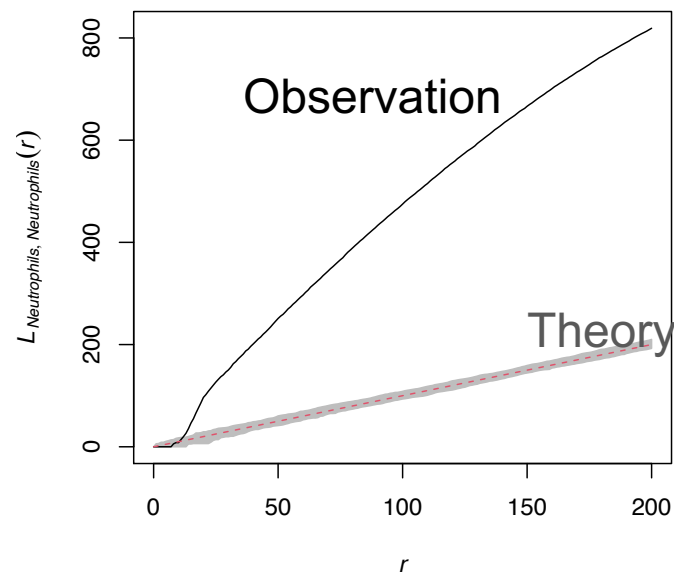
Spatial metrics IV: L functions

L functions: to assess the significance of cell-cell interactions



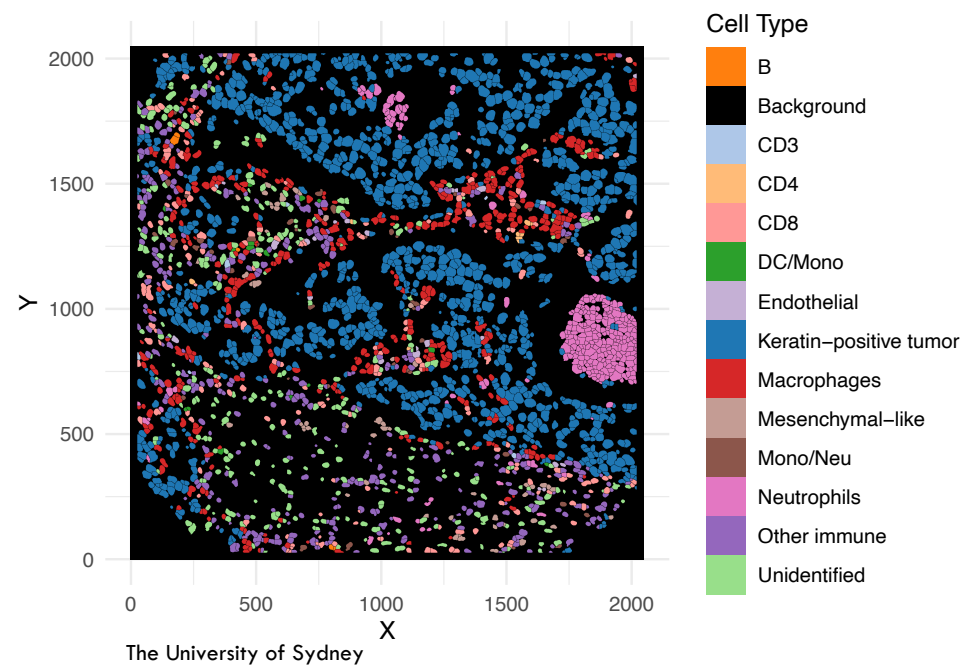
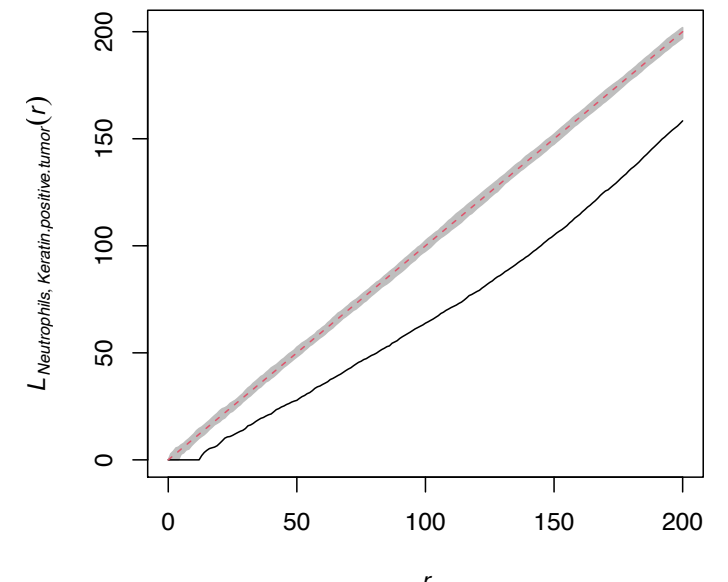
Association

(Neutrophils - Neutrophils)

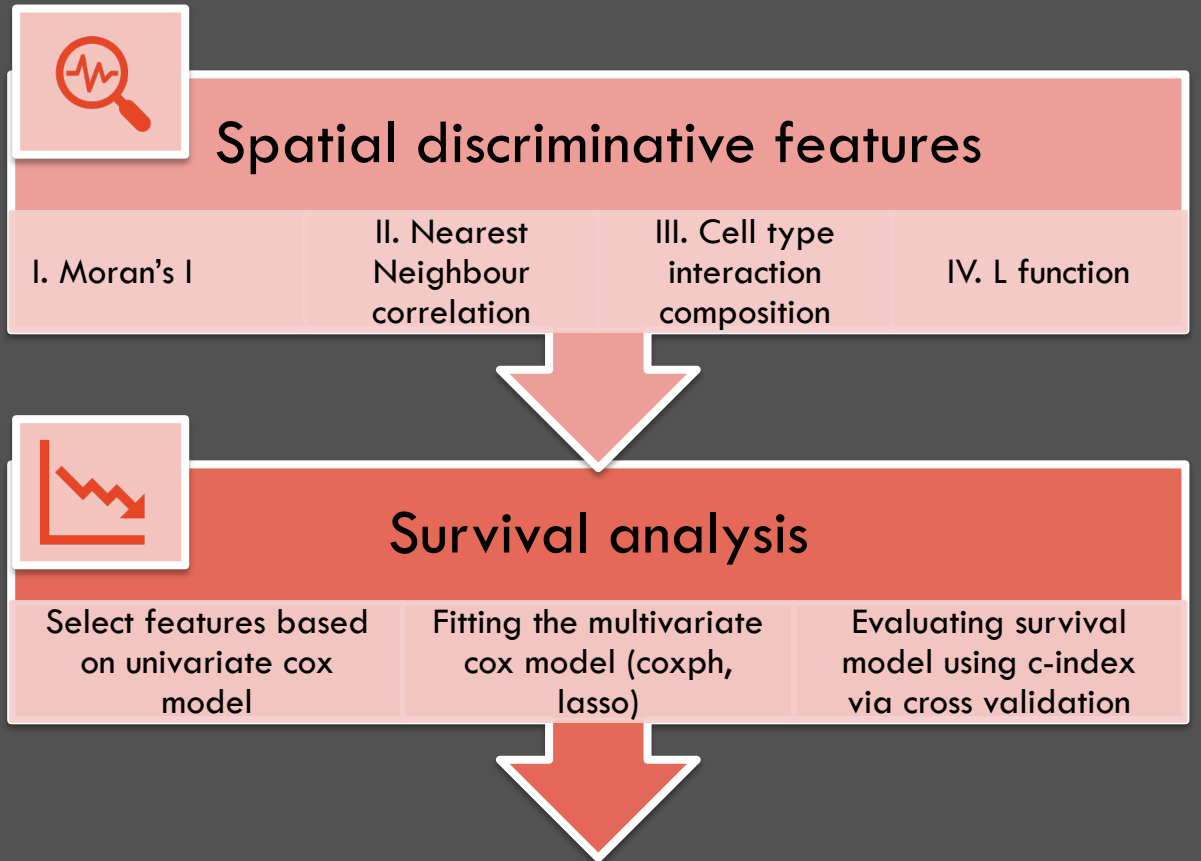


Avoidance

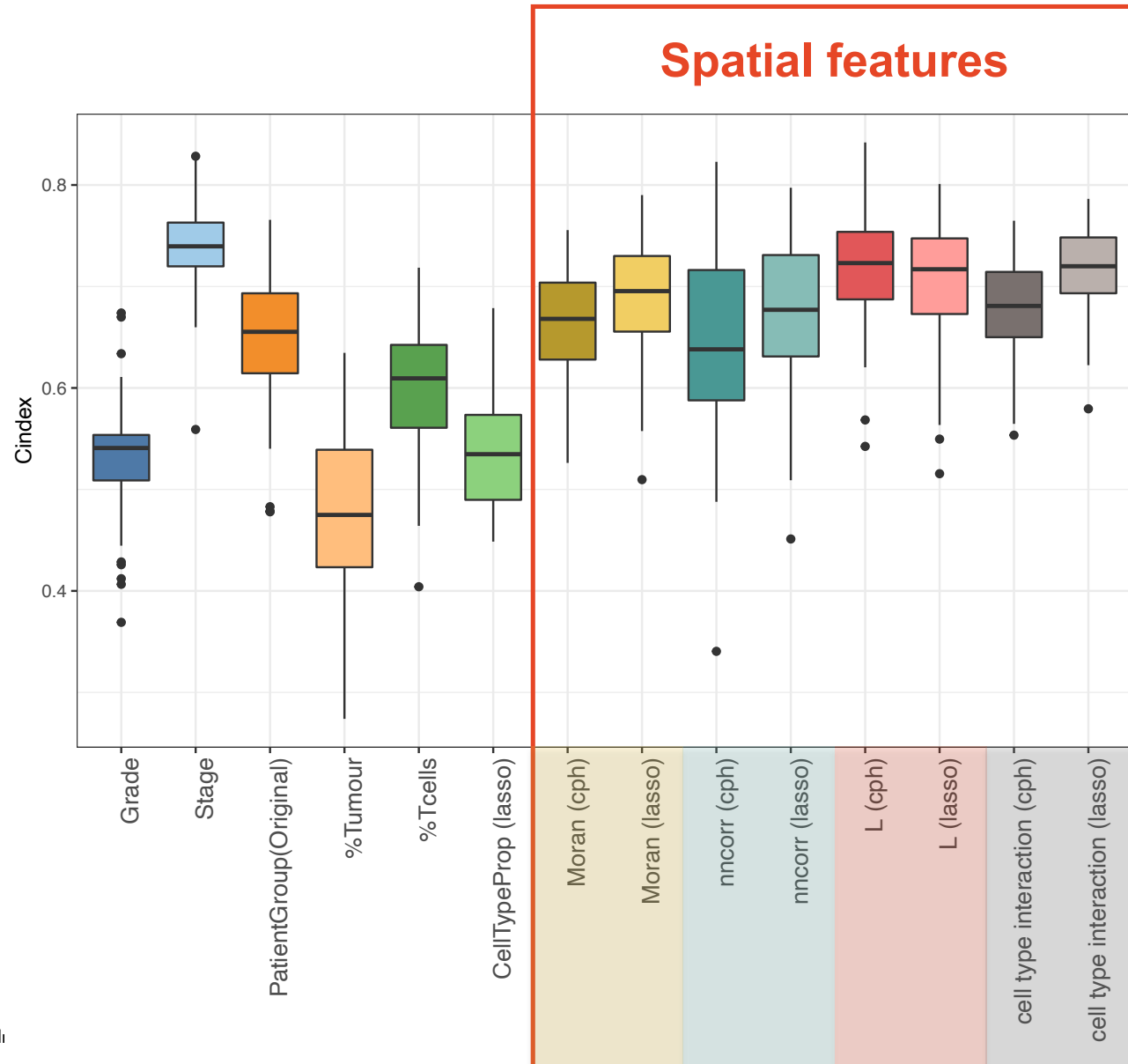
(Neutrophils - Keratin+Tumour)



Survival analysis using spatial features



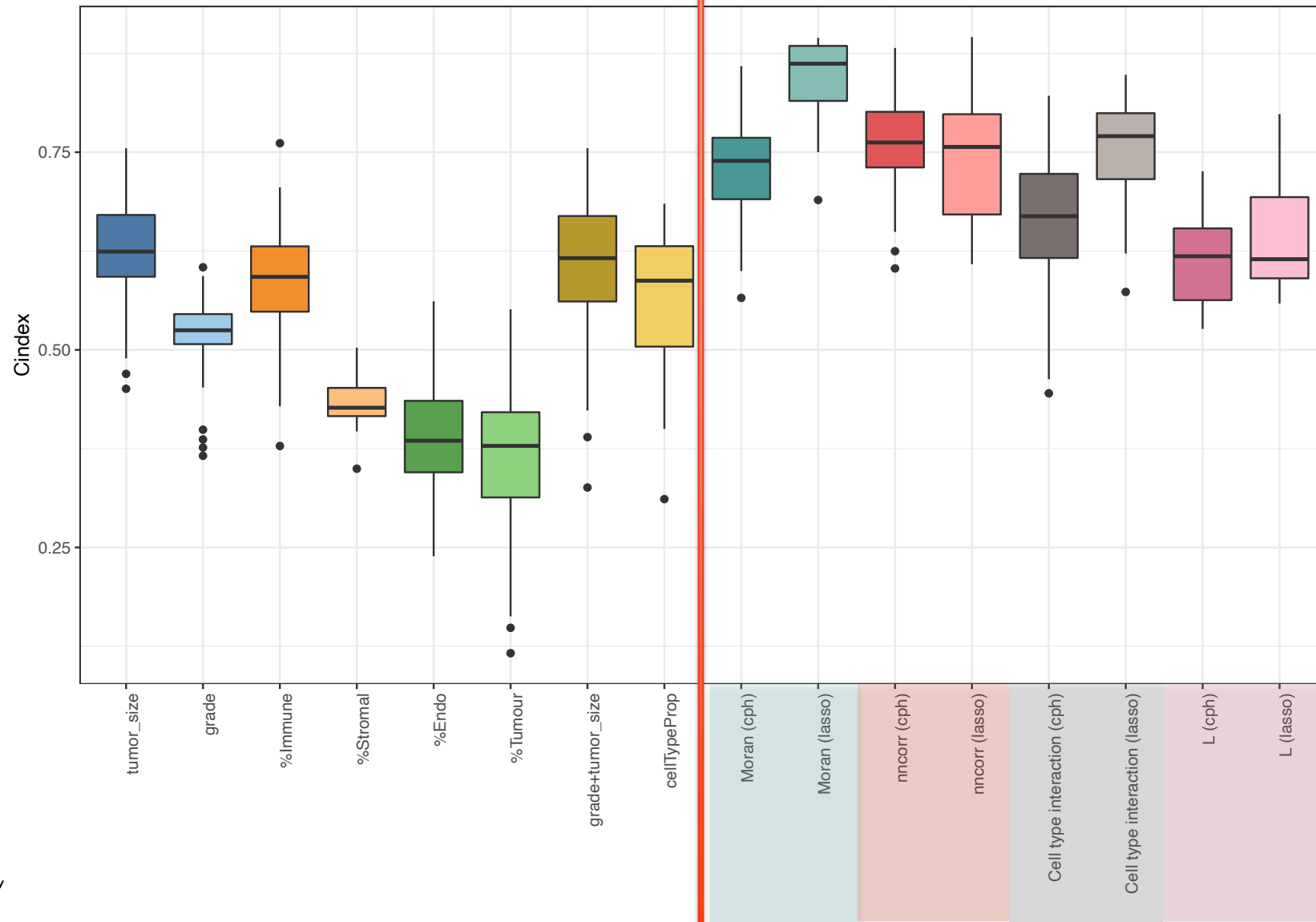
Survival analysis (MIBI-TOF)



Spatial features perform relatively well in survival outcome prediction in MIBI-TOF data.

- Moran's I
- Nearest neighbour correlation
- L functions
- Cell type interaction composition

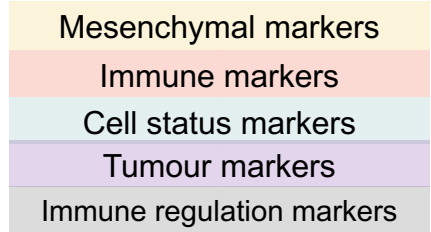
Spatial features (IMC TNBC)



Similar outperformance of spatial features can be found in TNBC cohort of IMC data.

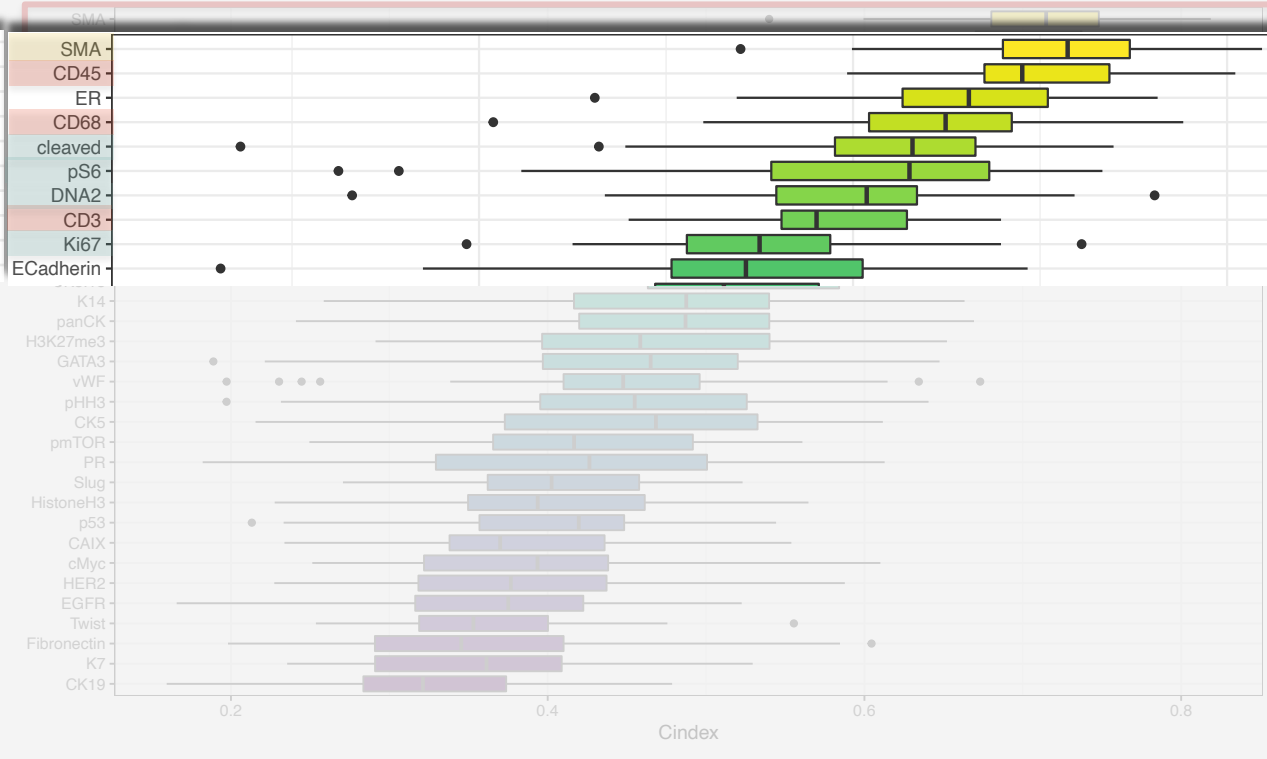
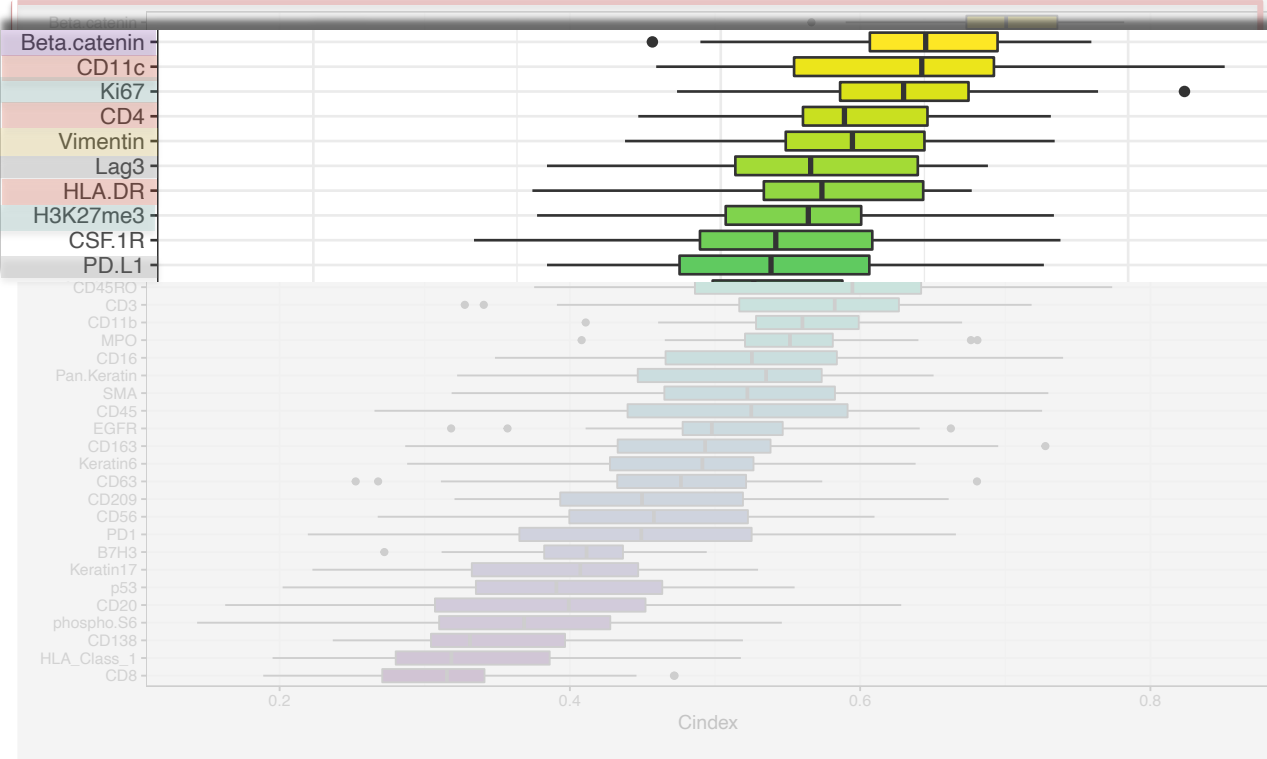
- Moran's I
- Nearest neighbour correlation
- L functions
- Cell type interaction composition

Moran's I



MIBI-TOF

IMC

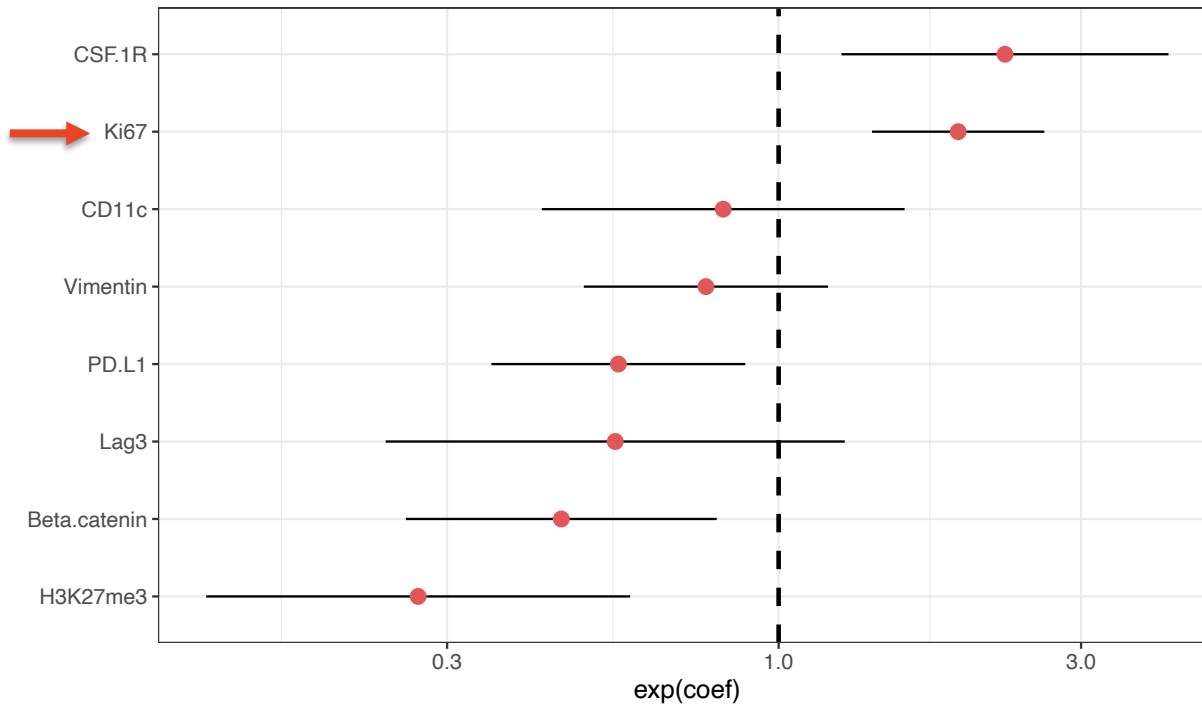


Top features are from diverse marker categories.

Moran's I

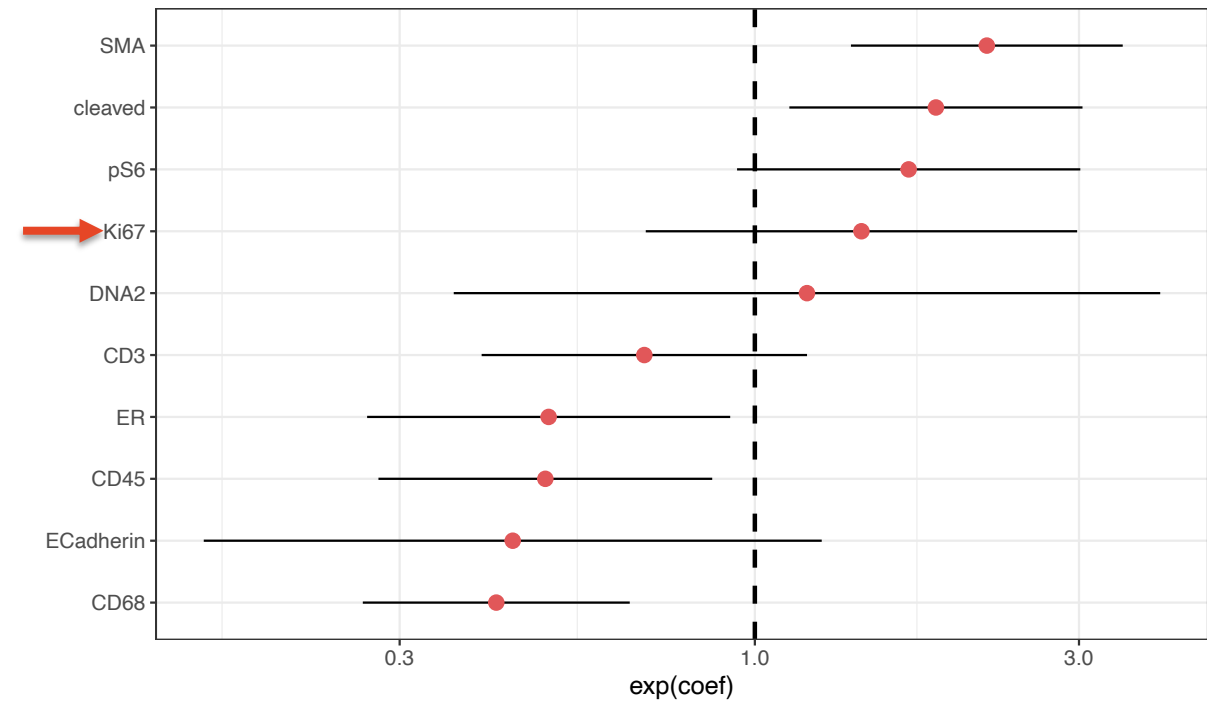
MIBI-TOF

Cox proportional hazards regression model (Moran's I)



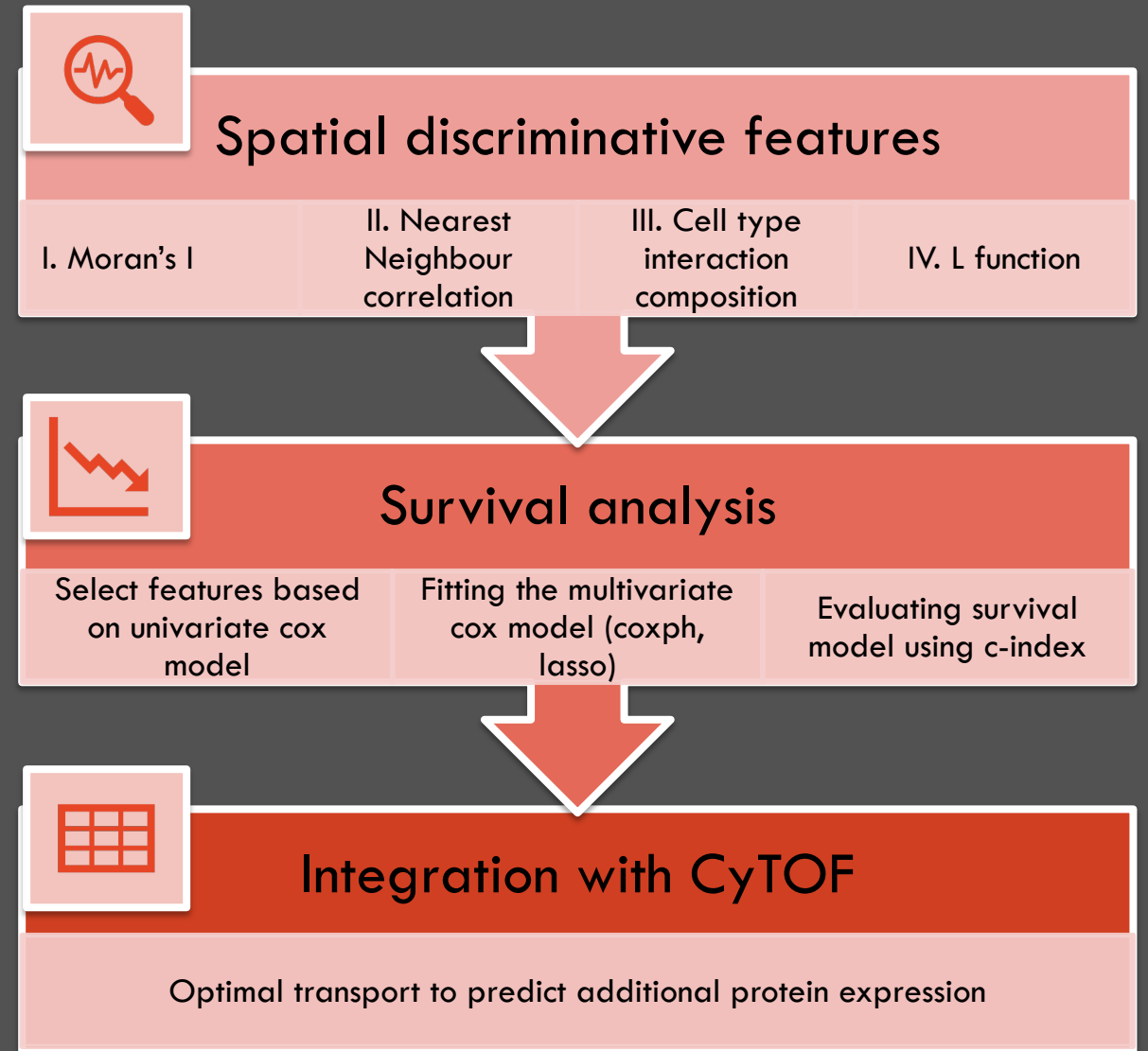
IMC

Cox proportional hazards regression model (Moran's I)



Only one common selected top features (Ki67, a cell proliferating marker) in two models

Optimal transport to impute imaging data using CyTOF data



Optimal transport

Optimal transport problem setting

$$\arg \min_{\gamma} \langle \gamma, M \rangle_F + \lambda \sum_{i,j} \gamma_{ij} \log(\gamma_{ij})$$

s.t.

$$\sum_i \gamma_{ij} = a_j$$

$$\sum_j \gamma_{ij} = b_i$$

$$\gamma \geq 0$$

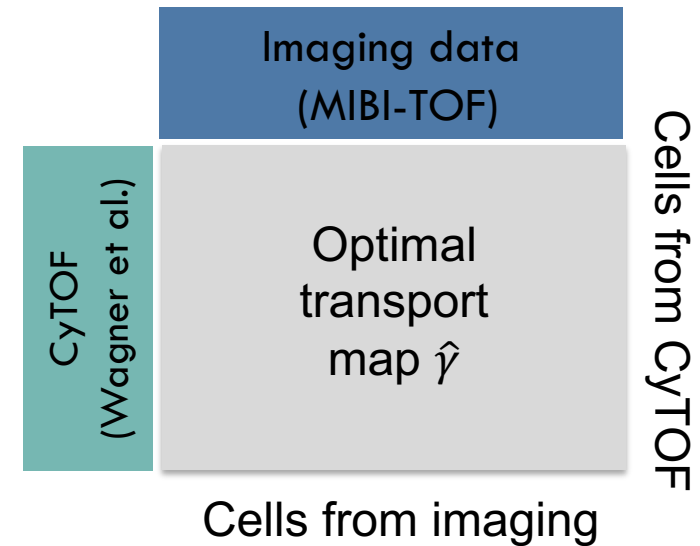
where M is the cost matrix for the dissimilarity of cells between CyTOF and imaging data;

a_j is the weight for cell j in imaging data; and b_i is the weight for cell i in CyTOF data.

The prediction of a protein expression at position j in imaging using the CyTOF protein expression $g \in R^n$ is

$$\frac{\sum_i \hat{\gamma}_{ij} \times g_i}{\sum_i \hat{\gamma}_{ij}}$$

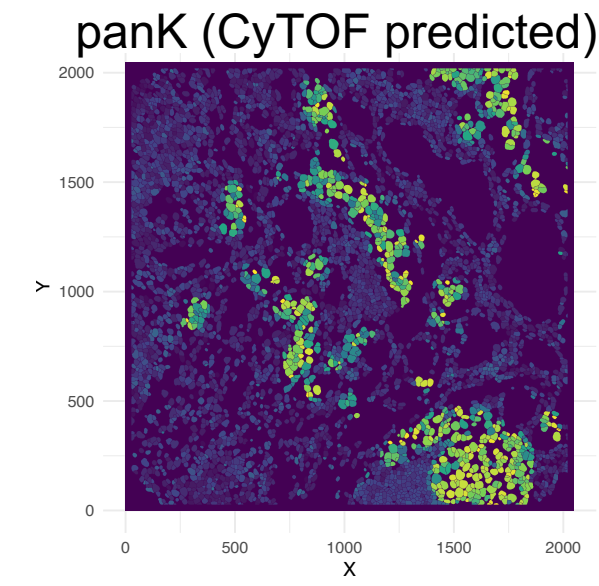
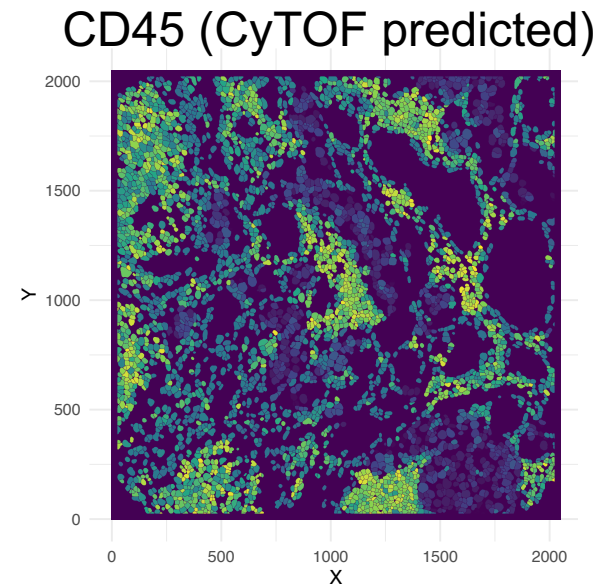
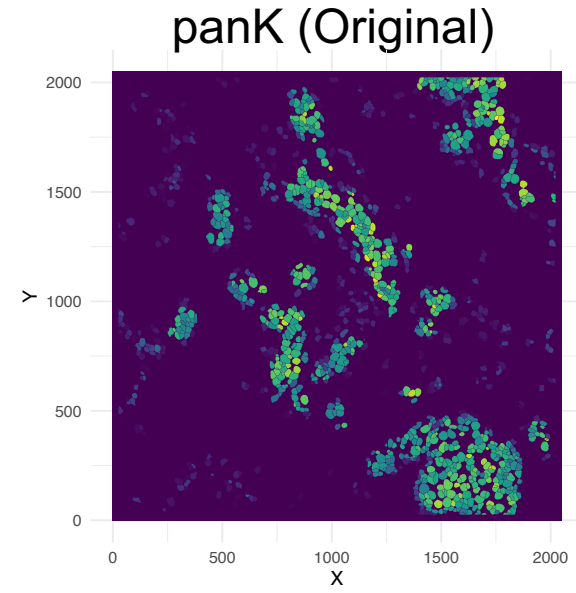
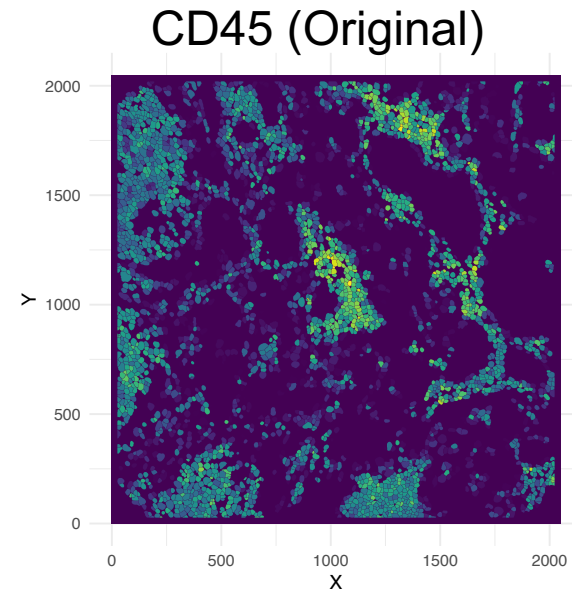
Optimal transport plan



Challenges:

- Wagner et al. CyTOF data only has ~14 proteins common with MIBI-TOF data

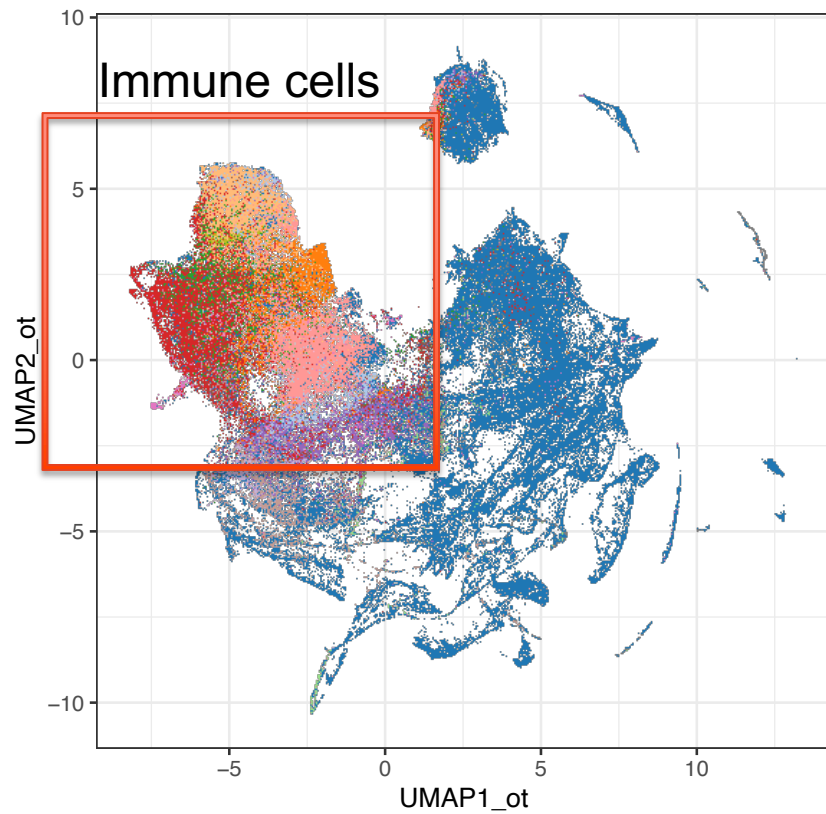
Protein prediction



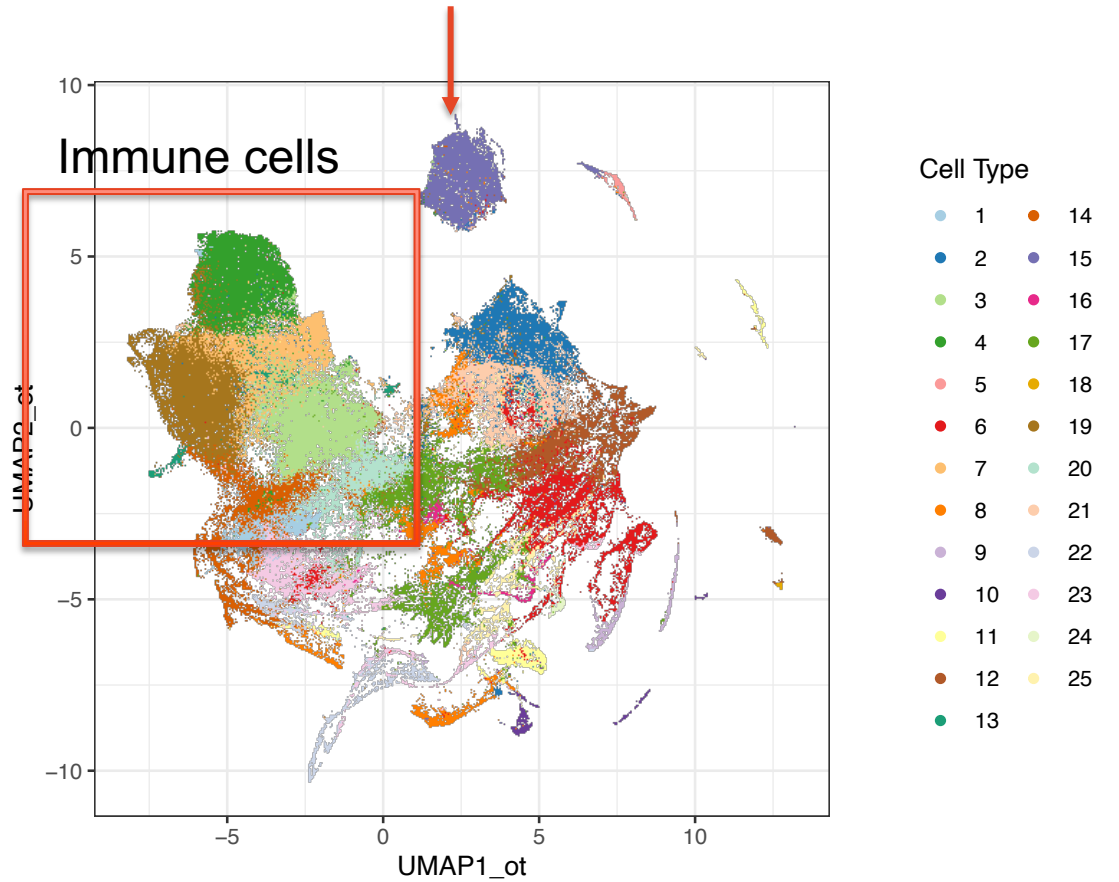
cor = 0.85

cor = 0.94

Identification of new sub cell type

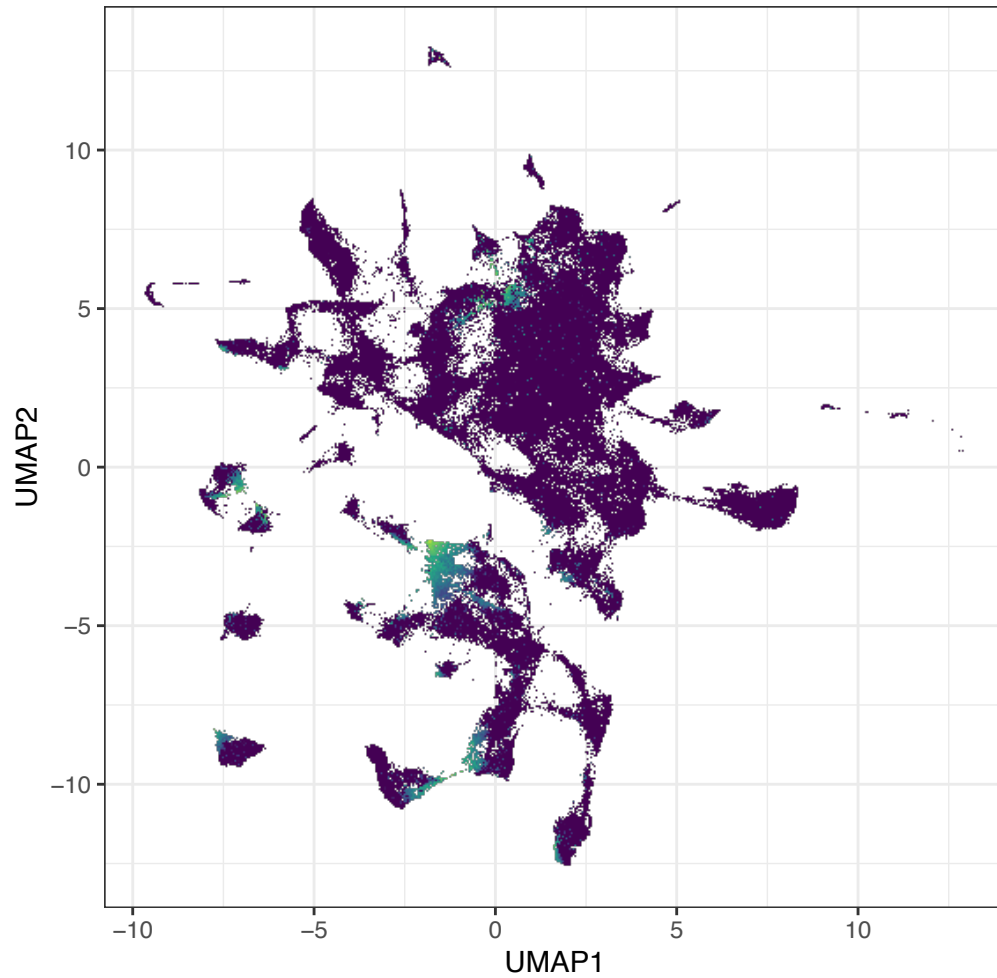


- Cell Type
- B
 - CD3
 - CD4
 - CD8
 - DC
 - DC/Mono
 - Endothelial
 - Keratin-positive tumor
 - Macrophages
 - Mesenchymal-like
 - Mono/Neu
 - Neutrophils
 - NK
 - Other immune
 - Tregs
 - Tumor
 - Unidentified

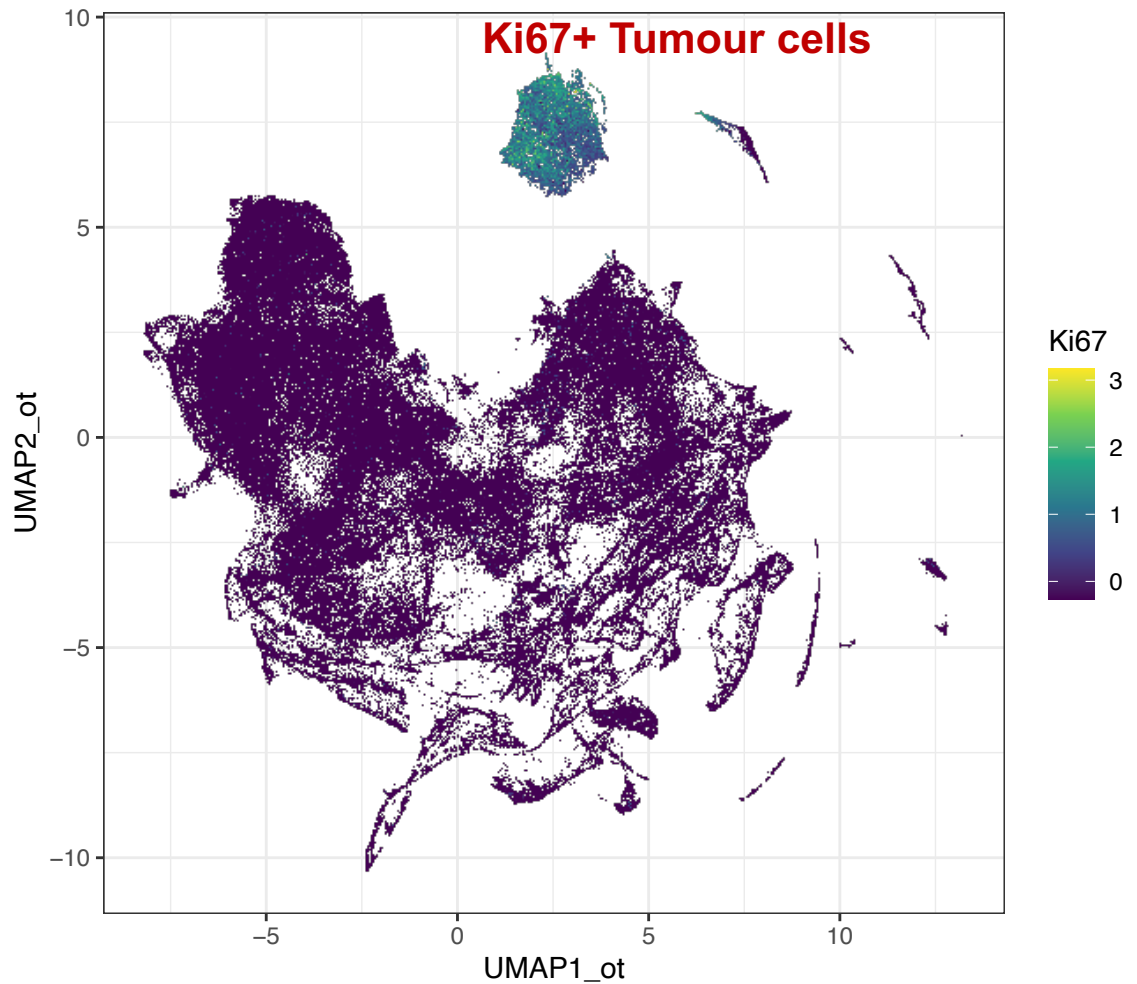


Identification of new sub cell type

Original

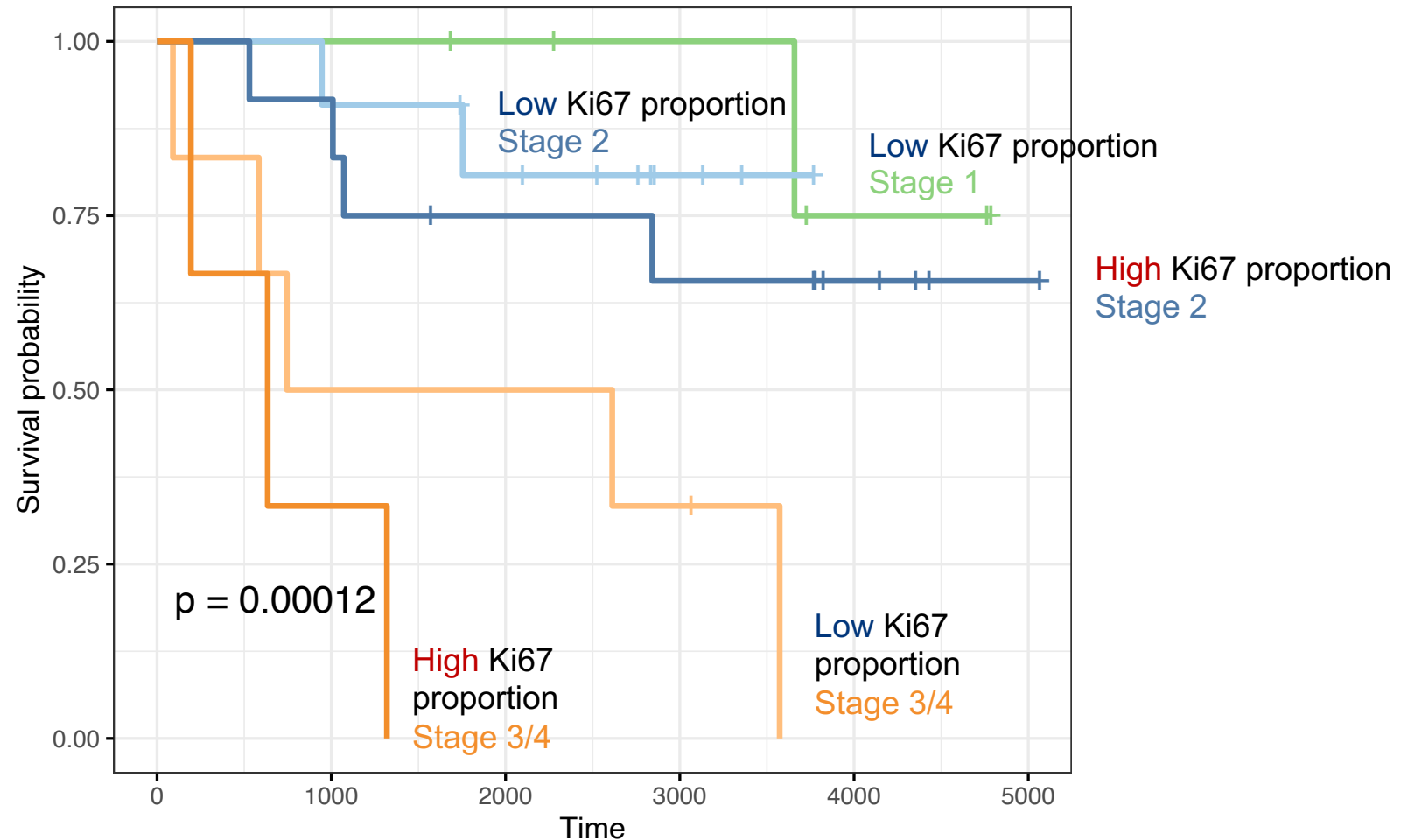


After Optimal Transport Imputation



Survival analysis based on new annotations

Strata + ki67_class=Low, STAGE=1 + ki67_class=Low, STAGE=2 + ki67_class=Low, STAGE=3_4 + ki67_class=High, STAGE=2 + ki67_class=High, STAGE=3_4



Yerushalmi, R., Woods, R., Ravdin, P. M., Hayes, M. M., & Gelmon, K. A. (2010). Ki67 in breast cancer: prognostic and predictive potential. *The lancet oncology*, 11(2), 174-183.

Inwald, E. C., Klinkhammer-Schalke, M., Hofstädter, F., Zeman, F., Koller, M., Gerstenhauer, M., & Ortmann, O. (2013). Ki-67 is a prognostic parameter in breast cancer patients: results of a large population-based cohort of a cancer registry. *Breast cancer research and treatment*, 139(2), 539-552.

Conclusion

- Spatial features especially spatial association of the protein expression improve the survival prediction in both imaging datasets.
- Limited common feature is found between the survival models due to the limited common proteins measured in two datasets.
- Imputation of additional protein expression improved the cell type identification, and have potentials to increase the commonality between two datasets and further improve the survival prediction.

Acknowledgment

The University of Sydney
School of Mathematics and Statistics
Sydney Precision Bioinformatics Research Group

Jean Yang
Pengyi Yang
Samuel Mueller
John Ormerod
Rachel Wang
Ellis Patrick
Garth Tarr
Dario Strbenac

Yue Cao
Hani Kim
Thomas Geddes
Taiyun Kim
Mengbo Li
Connor Smith
Andy Tran
Andy Wang
Kevin Wang
Xiangnan Xu
Yunwei Zhang

Lauren Hsu and Aedin Culhane for providing the processed MIBI-TOF and CyTOF data

