

Debriefing: sc targeted proteomics

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sc targeted Proteomics; Application and Future

Increasing resolution, 3D, but limited # Proteins,

Good on FFPE so many samples available

Spatial/co- expression of known molecular targets,
small molecule inhibitor


Longitudinal Clinical/Biological

Widespread use depend on clinical utility and cost

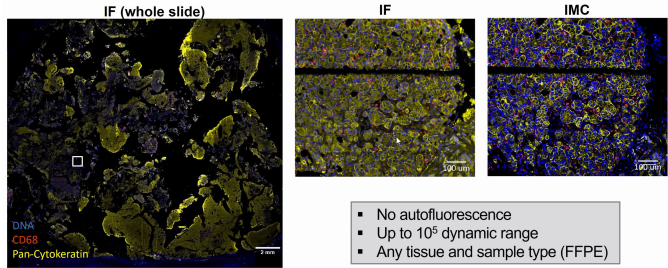
- Cell properties- shape/size, type
- Cell type proportions /composition
- Cell location, co-location analysis
- Cell higher architecture (clusters of cells)
- Cell-cell interaction (eg tumor-immune)

PowerPoint Slide Show - 2020_Bodenmiller_BeIF_Overview - PowerPoint

Imaging mass cytometry offers advantages over fluorescence-based approaches




IF (whole slide) IF IMC



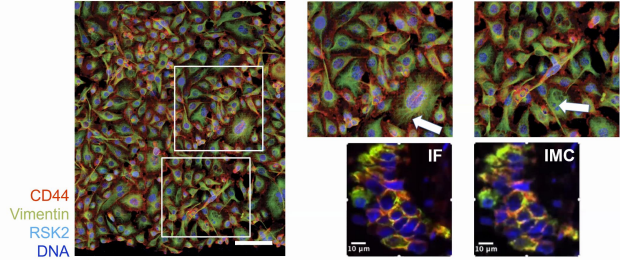
- No autofluorescence
- Up to 10^5 dynamic range
- Any tissue and sample type (FFPE)

PowerPoint Slide Show - 2020_Bodenmiller_BeIF_Overview - PowerPoint

Imaging mass cytometry images are similar to fluorescence microscopy images



CD44 Vimentin RSK2 DNA



MDA-MB-231 Breast cancer tissue

Data challenge

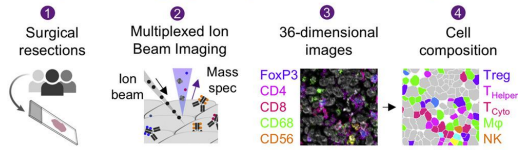
Single-cell targeted proteomics across technologies

Data from 2 studies characterizing the **breast cancer tumor immune microenvironment**, using:

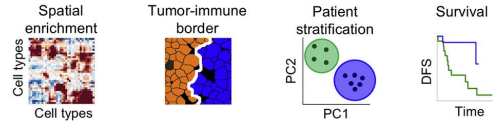
Multiplexed ion beam imaging by time-of-flight (MIBI-TOF)

- 36 proteins
- 41 TN breast cancer patients

Multiplexed imaging of 36 proteins in 41 TNBC patients

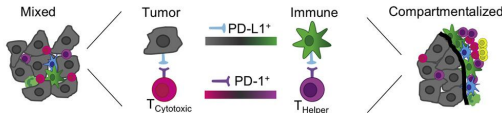


Computational analysis



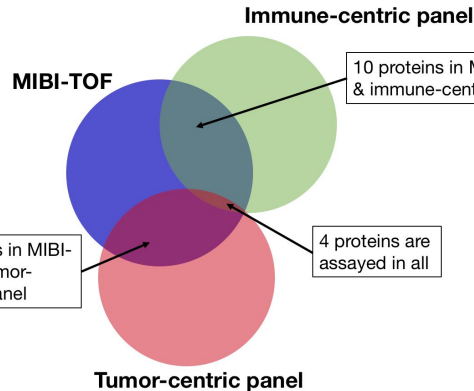
Structured tumor-immune microenvironment in TNBC

Immune organization ↔ Histology ↔ Checkpoint expression



Keren, et al. (2018)

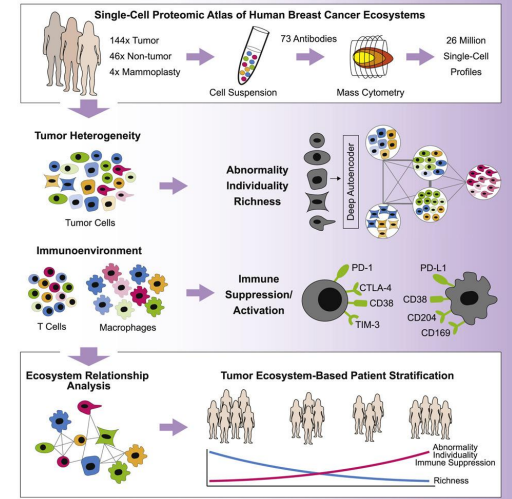
... with a total of 20 overlapping proteins



Mass cytometry

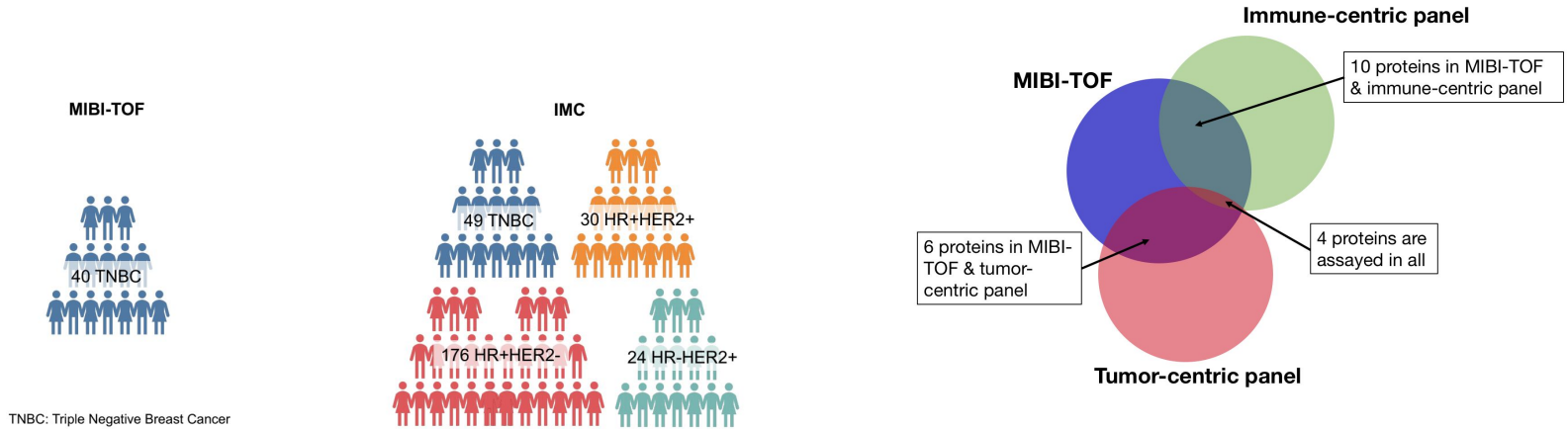
(aka mass tag, CyTOF)

- 73 proteins across 2 panels: tumor and immune
- 140 breast cancer patients, 6 TN



Wagner, et al. (2019)

Data Challenge was challenging



- Limited overlap in phenotype: only 6 TN patients in the CyTOF dataset
- Limited overlap in proteins → some cells cannot be detected in one platform
- Few features. Can't integrate features at Gene Ontology or Pathway level
- No obvious “ground truth” for validation

Hackathon Challenge Questions

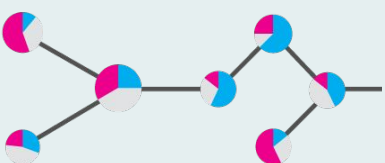
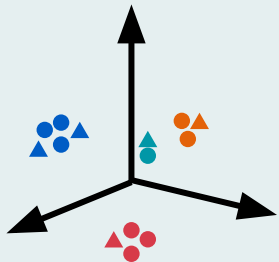
- How should we approach **integrating partially-overlapping** proteomic data collected on different patients with similar phenotypes?
- Can we **integrate** other 'omics datasets to support the results of these proteomic analyses?
- Without including the **spatial** x-y coordinate data, how well can we predict cell **co-location**?
- Can we **predict the spatial expression patterns** of proteins measured on mass-tag but not measured in the MIBI-TOF data?
- What additional information can we learn about the different **macrophage and immune populations** in breast cancer by conducting integrated analyses of these datasets?

Challenges

Integration of features

Cross-platform

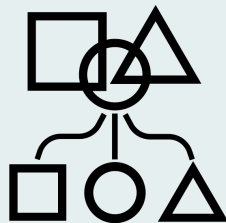
Transfer Imputing
features across
datasets



Prediction

Transferring
cell labels
between
datasets

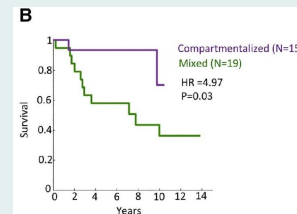
Spatial
co-location
, structure



Spatial structure
co-location,
autocorrelation








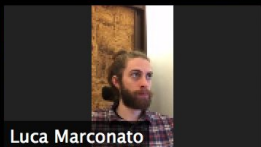



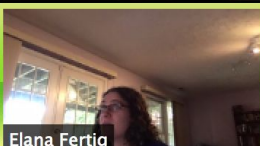

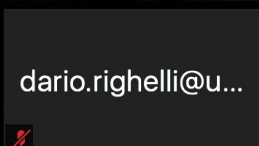
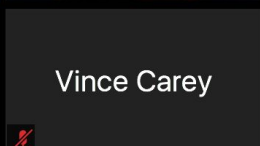
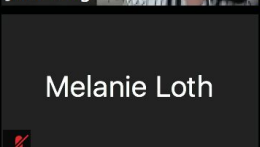


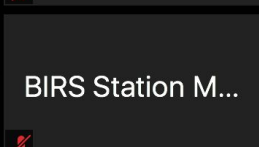
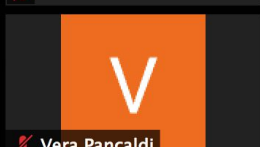
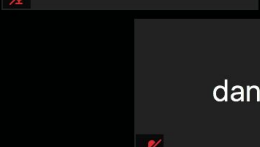
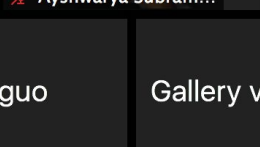
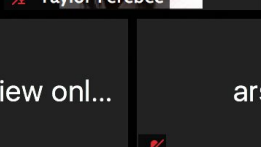



clinical significance



sc targeted Proteomics Brainstorm

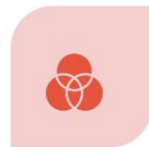
A screenshot of a Zoom meeting grid with 20 participants. The participants are arranged in a grid, with some having video off. The names and status of the participants are as follows:

 Atul Deshpande	 Aedin Culhane	 Duncan Forster	 Lauren Hsu	 krissankaran
 Meng Chen	 pratheepa jeganat...	 Luca Marconato	 Yingxin Lin	 susan holmes
 Jean Yang	 Elana Fertig	 Genevieve Stein-O'...	 dario.righelli@u...	 Vince Carey
 Melanie Loth	 Ayshwarya Subram...	 Taylor Ferebee	 BIRS Station M...	 Vera Pancaldi
 danguo	 Gallery view onl...	 arshi	 Marcel Ramos	

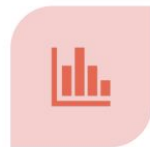
Challenges in Data Integration

- Connecting partially overlapping datasets (feature)
 - Gene Ontology (Duncan- cell type specific map)
 - Combining different scales
 - Normalization
-
- Scale - connecting partially overlapping datasets (cell)
 - Coarse and fine grained resolution
 - (single cell-> bulk-> spatial->communities)
 - Hierarchical , layers
 - Integration at clinical level

Challenges and Questions



LIMITED
OVERLAPPED
PROTEIN



DIVERSE CELL TYPE
ANNOTATION



PARTIALLY
OVERLAPPED
CLINICAL TYPE



HETEROGENEOUS
COHORT

Data Challenges: Normalization

Transform - log, arcsinh, sqrt?

Order of magnitude in scale

Questions about the validity of normalizing by Cell Size (neurons v leukocytes)

Cell type markers maybe only 1 cell type

Quantile -can't assume composition or sum of expression uniform

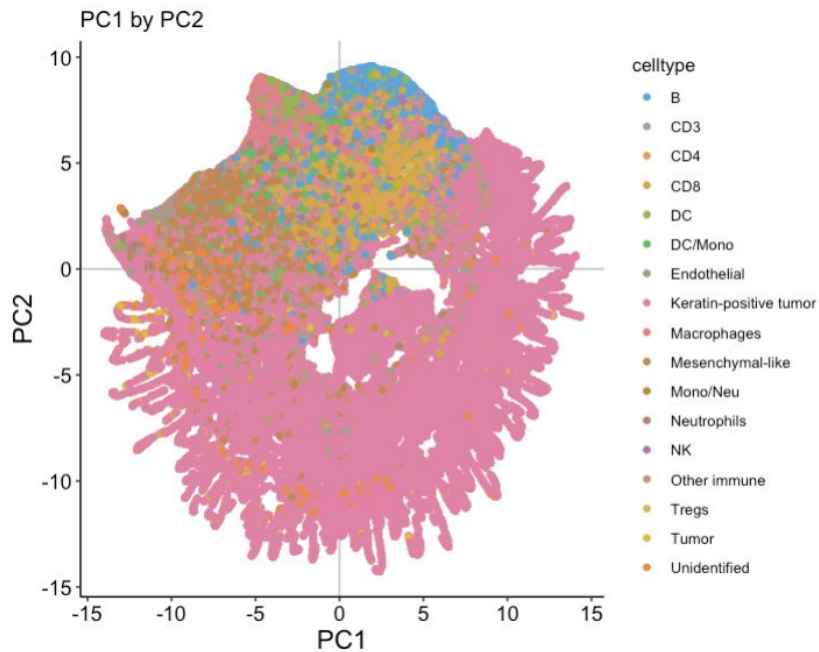
Different physical technologies, strong batch effects

Funky MIBI not mass Tag Umap - Why?

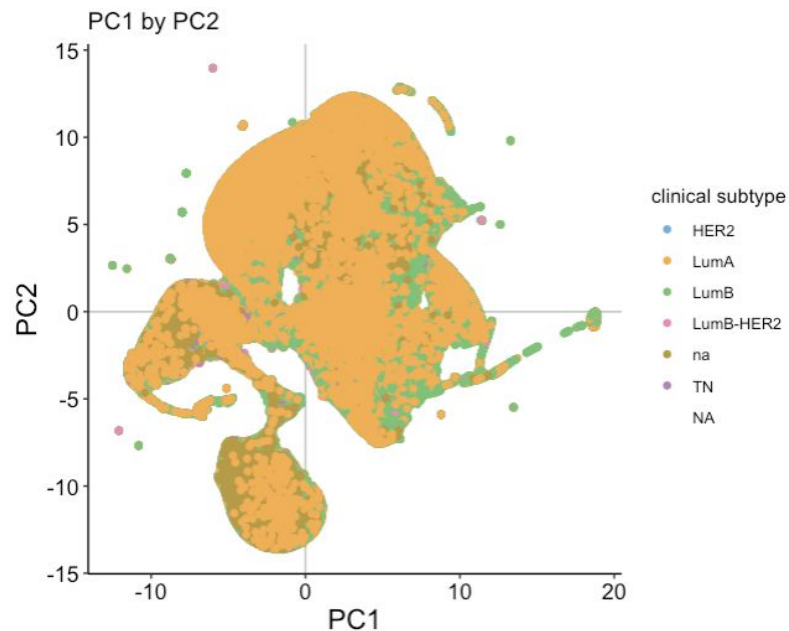
Outlier effect of cell type marker in low feature space, where markers unique to cell?

The UGLY MIBI UMAP!!!

mibi



cyTOF



Bridge to connect data with partial/little overlap

Proteins as cell type or state marker

“BRIDGE”

- Presence/Absence of Cell States
- Cell compositions/proportions
- Spatial Structure (eg Morans)
- Biological Sample Phenotype
- Clinical features
- Survival (interval/right censored discussion)



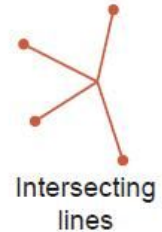
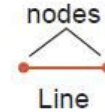
Integration of Spatial data - Scale, SWM

Scale and space in biological systems

How to define spatially- points, lines, polygons

XY centroid may poorly capture

- Cell size or shape (neuron)
- Neighbours may depend on cell size/shape
- Community
- Partially overlapping



I.16 Spatial objects

Spatial objects in a GIS can include points, lines of various types, intersecting lines, and polygons.

Integrating Spatial Data - Biological data have always been spatial

Spatial statistics already well established in other fields

- GIS, Ecology, Plant science (Taylor Ferebee), Weather (Elana Fertig)
- Statistics based on Euclidean distance (Sphere), graph triangulation (Moran, Gabriel), K-NN etc
- 15 years ago applied Ripley's K factor on biopsy (Susan Holmes)
- Test statistics to associate spatial patterns with covariates

Connecting features to spatial across platforms

Need to unify scaling (Vera Pancaldi)

Limited expected map of

- The physical structure
- Cell composition in structure
- Expected level of protein expression

How to connect Coarse v Fine
resolution neighborhoods ?

Connecting features to spatial across platforms

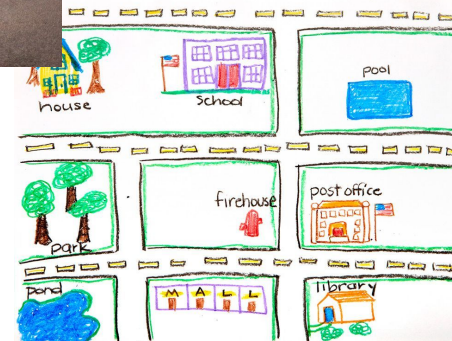
Need to unify scaling (Vera Pancaldi)

Limited expected map of

- The physical structure
- Cell composition in structure
- Expected level of protein expression



NEED



How to connect Coarse v Fine resolution neighborhoods ?

Have - Digital 'Omics + Analog Map

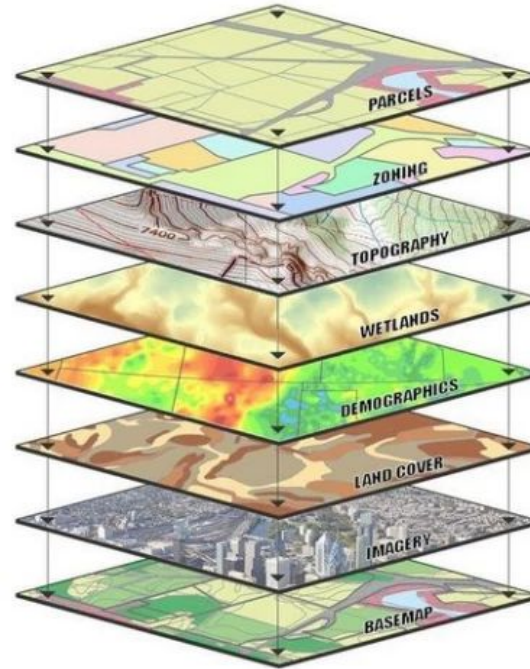
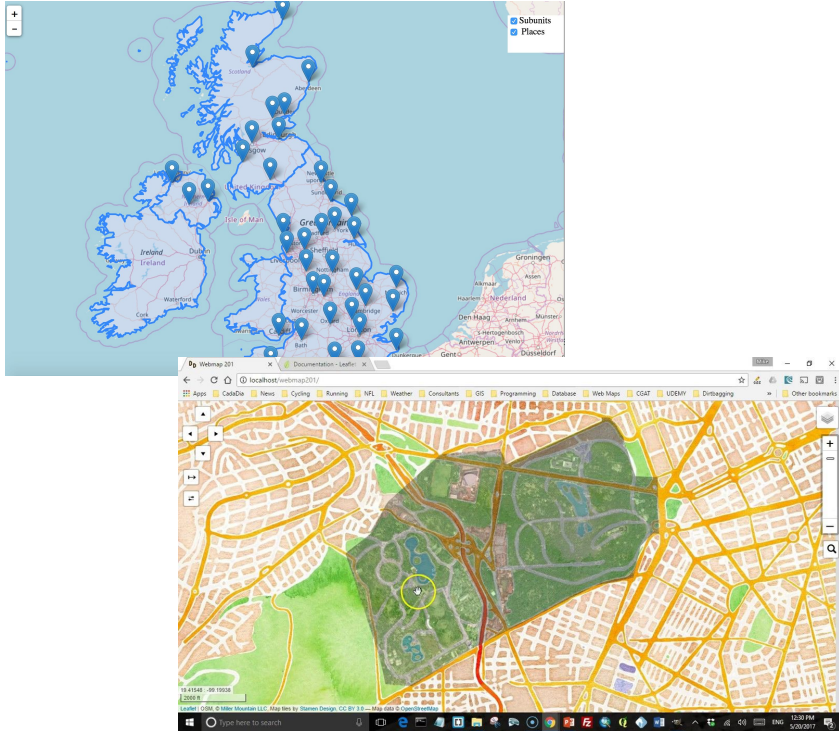


Library, Trinity College Dublin, Ireland



Will be “driving” blindly until we have a digital cell location map

Have layers in GIS data (Susan Holmes)



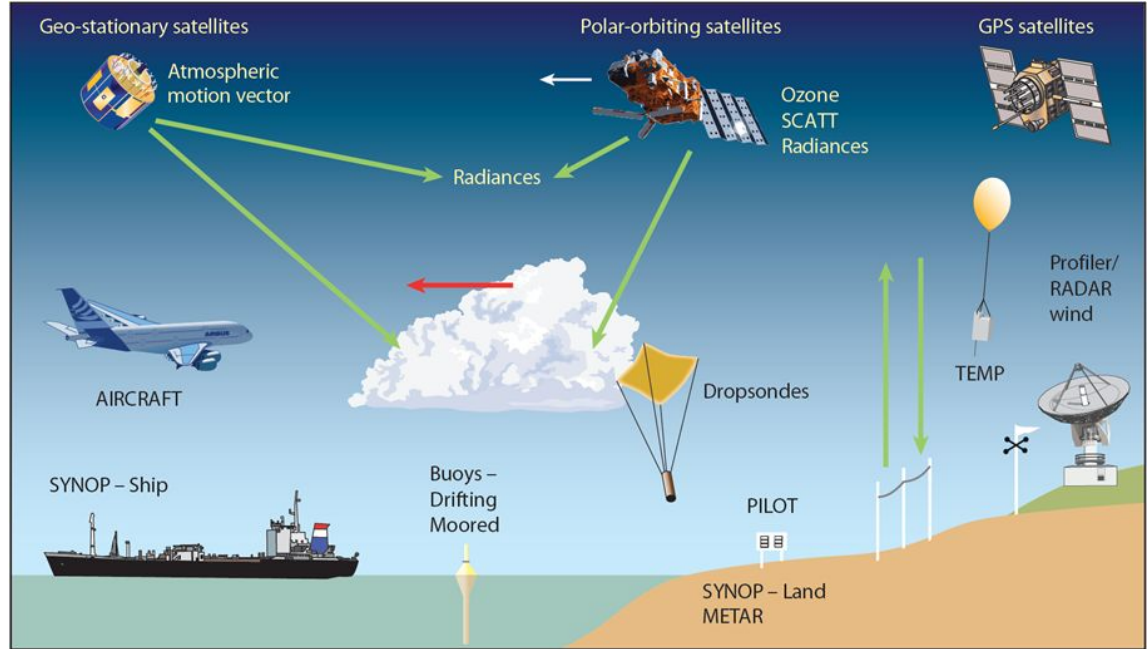
GIS DATA LAYERS

Many different types of data can be integrated into a GIS and represented as a map layer.

Examples can include: streets, parcels, zoning, flood zones, client locations, competition, shopping centers, office parks, demographics, etc.

When these layers are drawn on top of one another, undetected spatial trends and relationships often emerge. This allows us to gain insight about relevant characteristics of a location.

Weather layers: Satellites, Weather Balloons (Elana)



Single Cells -> Bulk -> Communities

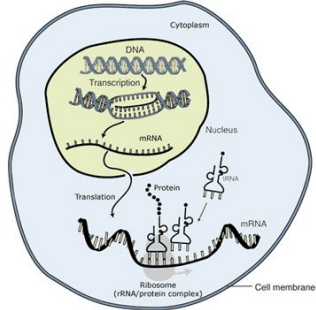


Image adapted from: National Human Genome Research Institute.

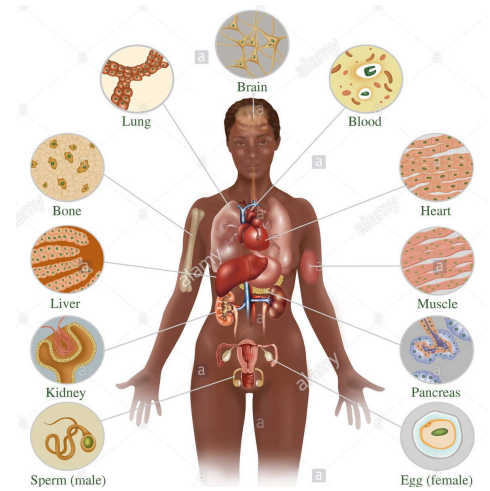
'Omics DNA Chromatin
RNA Protein
Glycosylation-
metabolites etc

Forms of Chemical Signaling	
Autocrine	A cell targets itself.
Signaling across gap junctions	A cell targets a cell connected by gap junctions.
Paracrine	A cell targets a nearby cell.
Endocrine	A cell targets a distant cell through the bloodstream.

Connected by signaling
(paracrine, endocrine
Gap junctions, autocrine)



Composed of organized
Cells types, polarity



Human Phenotype
defined by
Systems,
Organs that are
composed of Cell
Communities

Spatial Proteomics Future Directions

- Need a digital map and to define variables of interest
- Can this be built from existing data
- New benchmark datasets
- Methods - leverage existing, build new
- spatial scale measures
- Other methods for validation (prediction strength, can we large number of “observations” cells)
- What are the limitations of the physical technologies and what directions are the technologies headed?
 - Limited channels

Output

- Table of Data types
- Table/Figure of Spatial measures
- Table of Taxonomy of methods
- (there was support for packaging up data/code vignettes in an R package)

Figures :

- Bridging Studies: mapping between datasets: pheno, cells, features
- Methods: Embed/Graph - Optimal Trans/Matrix Factor/Topic Modelling/Forests
- Communities Clusters/UMAP → Spatial Structure: XY- Line-Polygon. SWM (distance/grid/graph tri, neighbors, etc)
- Annotation (Duncan)

Table? Descriptors of different data types (sc'OMICS)

N Typical number of features (proteins/genes) measured

P Typical number of samples/cells measured

Distributions/orders of magnitude

Sample type (single-cell, multi-cell, bulky)

NA Missing values (% , the typical way to impute missing values)

Count data/intensity (continuous)

Omics : genomics/transcriptomics/proteomics/PTM/metabolomics

Typical normalization method (log transform)

State of the art publications

Clinical data -- potentially following clinical trials can help control for diversity of patients; also incorporating EHR

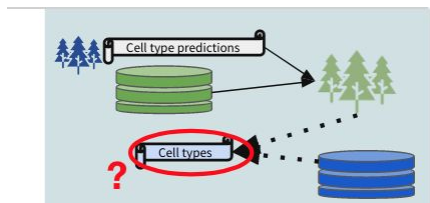
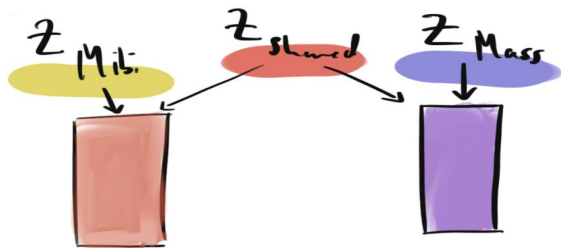
Spatial info (no, 2D, 3D)

Table - “Taxonomy” of methods

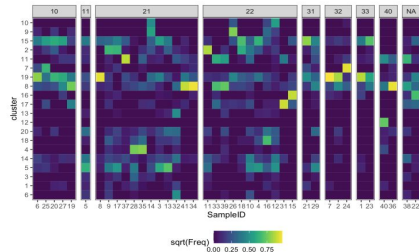
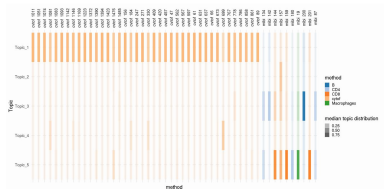
- Represent as a Table, or decision tree figure to manuscript?
- Matrix factorization
- NN graphs
- Technology specific methods
 - Still want consensus
 -
- Methods broadly divided into
 - Embedding
 - Graph
- Hierarchical Bayesian

Figures Aligning data/Learning Across Studies

INSERT FIGURES????



Estimated topic distribution



Optimal transport plan

Imaging data (MIBI-TOF)

Optimal transport map $\hat{\gamma}$

Cells from imaging

Tumor panel RF model:

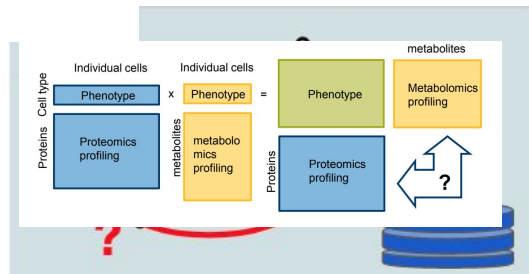
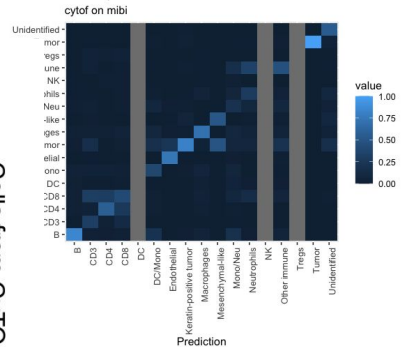
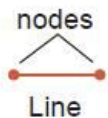
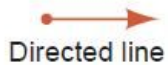


Figure: Spatial → Biology

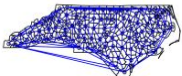
Measures XY/Lines/Polygons



SWM Sphere (distance)/GRID/ Graph



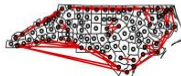
Delauney triangulation



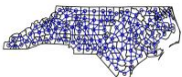
Sphere of influence



Difference between DT and SOI



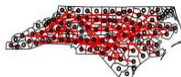
Gabriel graph



Relative graph



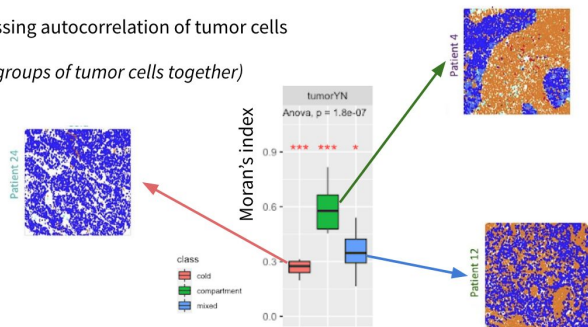
Difference between GG and RN



Moran's index: Tumor cells

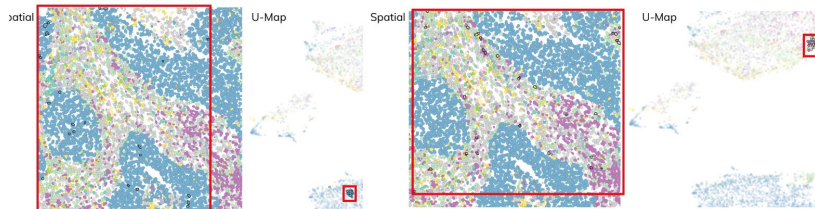
Assessing autocorrelation of tumor cells

(i.e., groups of tumor cells together)



Interactive Visualization

- Linked Brushing: Combine (literal) spatial map with abstract (U-)map
- Within cell-types, some U-Map clusters are spatially co-located, but far from universal



Examples where U-Map clusters are spatially diffuse. Immune cells highlighted in left pair, tumor on right.