

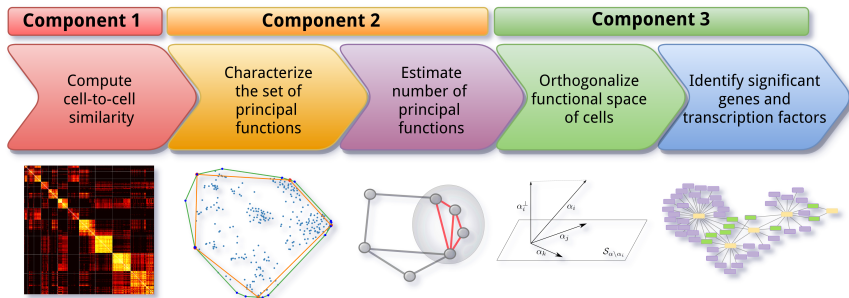
Tumor Heterogeneity, Signaling Cascades, and Drug Targets

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Overall Workflow



Underlying hypothesis

Transcriptional profile of cells is dominated by housekeeping genes, whereas their functional identity is determined by a combination of weak but preferentially expressed genes.

Component 1

Supporting evidence

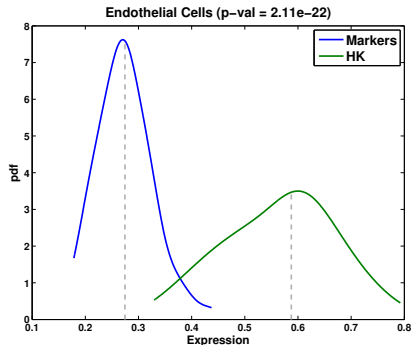


Figure: Endothelial Cells

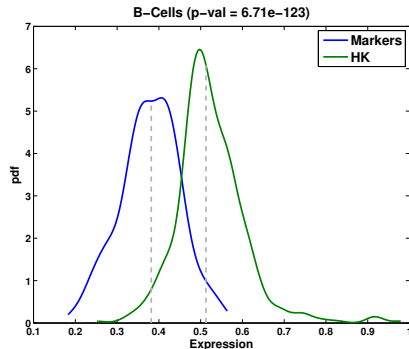


Figure: B-Cells

Component 1

Supporting evidence

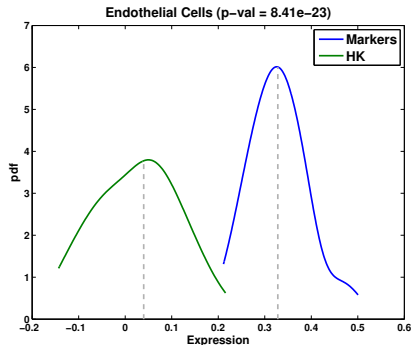


Figure: Endothelial Cells

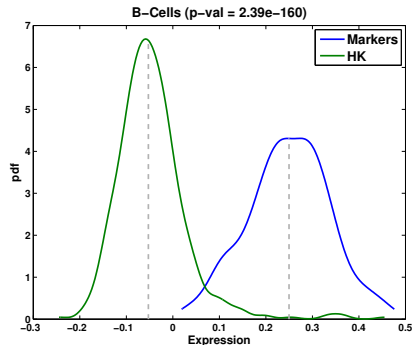
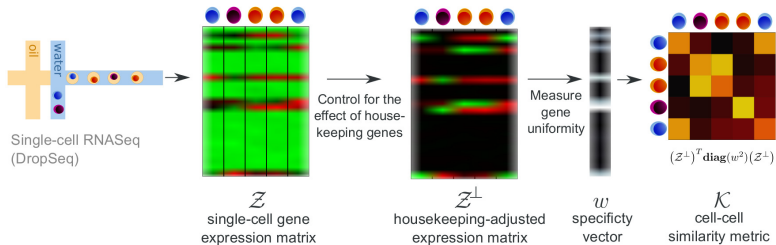


Figure: B-Cells

Component 1

Overall flow – cell similarity kernel



- The main steps involved in identifying similarity between cells

Component 1

Reducing the noise contributed by highly expressed but uninformative genes

Goal: Identify the shared subspace of genes

Low-rank decomposition

$$A = U_r \Sigma_r V_r = \sum_{i=1}^r \sigma_i u_i v_i^T,$$

Example decomposition choices:

- ▶ Mean vector
 - ▶ *Optimal in a least-square sense when the chance of observing a gene is uniform across all cells.*
- ▶ Singular Value Decomposition (SVD)
- ▶ Nonnegative Matrix Underapproximation (NMU)
- ▶ Sparse NMU

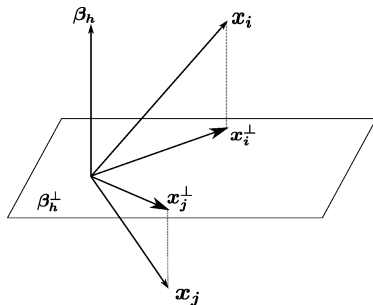
Component 1

Reducing the noise contributed by highly expressed but uninformative genes

Goal: Remove the effect of common subspace

- ▶ \mathbf{x}_i and \mathbf{x}_j : tissues/cell types i and j
- ▶ z-score normalize \mathbf{x}_i to compute \mathbf{z}_i
- ▶ β_h : the common signature
- ▶ z-score normalize β_h to compute \mathbf{z}_h
- ▶ Project to the orthogonal subspace:

$$\mathbf{z}_i^\perp = \left(\mathbf{I} - \frac{\mathbf{z}_h \mathbf{z}_h^T}{\|\mathbf{z}_h\|_2^2} \right) \mathbf{z}_i.$$

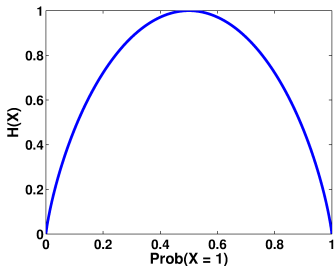


Similar in nature to the partial Pearson's correlation

Component 1

Enhancing the signal from preferentially-expressed genes

Goal: Estimate expression-specificity of genes across different cells



- ▶ Entropy as a measure of expression uniformity: $H(i) = -\sum_j p_{ij} \log(p_{ij})$
- ▶ How informative observing a gene is with respect to the cell type that it came from
- ▶ Maximum entropy when probability of a gene coming from all cell types is equal
- ▶ For each gene i , compute a specificity factor w_i .

Similar formulation have been previously used for marker detection.

Component 1

Putting pieces back together

ACTION-adjusted cell signatures

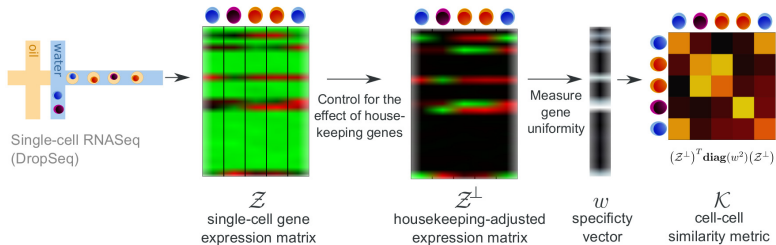
$$\mathbf{Y} = \text{diag}(\mathbf{w})\mathbf{Z}^\perp$$

ACTION metric (kernel)

$$\begin{aligned}\mathbf{K}_{ACTION} &= \mathbf{Y}^T \mathbf{Y} \\ &= (\mathbf{Z}^\perp)^T \text{diag}(\mathbf{w}^2) (\mathbf{Z}^\perp)\end{aligned}$$

Component 1

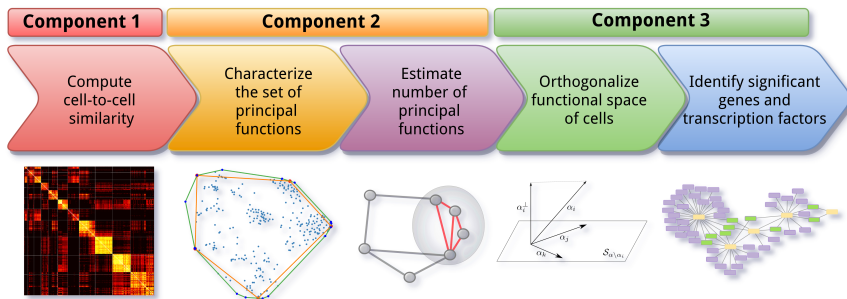
Cell similarity kernel – revisited



- Now we have computed the ACTION kernel

Overall Workflow

Component 2



General framework

$$\underset{\mathbf{C}, \mathbf{H}}{\operatorname{argmin}} \quad \left\| \mathbf{Y} - \underbrace{\mathbf{Y} \mathbf{C} \mathbf{H}}_{\mathbf{W}} \right\|$$

$$\text{subject to:} \quad \left\| \mathbf{C}(:, i) \right\|_1 = 1.$$

$$\left\| \mathbf{H}(:, i) \right\|_1 = 1.$$

$$0 \leq \mathbf{C}, 0 \leq \mathbf{H}$$

Various algorithms can be cast using this formulation

- ▶ **K-means:** $\mathbf{C} \in \mathbb{R}^+, \mathbf{H} \in \{0, 1\}$
- ▶ **K-medoids:** $\mathbf{C} \in \{0, 1\}, \mathbf{H} \in \{0, 1\}$

Component 2

Convex Nonnegative Matrix Factorization (NMF)

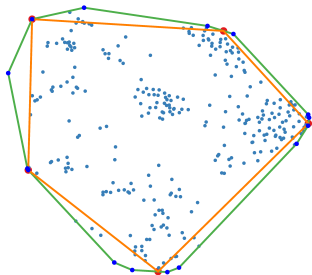
Convex NMF

$$\begin{aligned} & \underset{\mathcal{K}, \mathbf{H}}{\operatorname{argmin}} && \| \mathbf{Y} - \mathbf{Y}(:, \mathcal{S}) \mathbf{H} \| \\ & \text{subject to:} && \| \mathbf{H}(:, i) \|_1 = 1, \mathbf{H} \in \mathbb{R}^+. \end{aligned}$$

- ▶ It uses the same formulation as k-medoid, but relaxes the hard assignment of cells: $\mathbf{C} \in \{0, 1\}$, $\mathbf{H} \in \mathbb{R}^n$
- ▶ Unlike k-medoid and k-means, it has an **optimal global solution**.
 - ▶ Under **near-separability** assumption: there exists for each cell type an ideal example in the population.
- ▶ A modification of the *Gram Schmidt* process.

Component 2

Convex NMF– Geometric interpretation

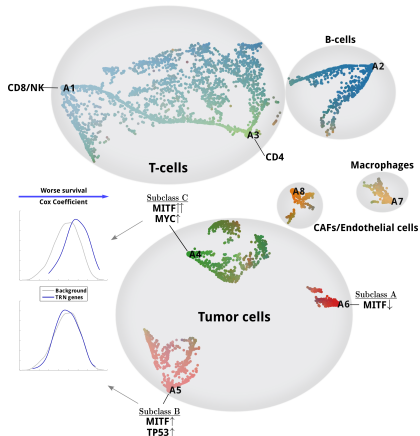


Geometry of functional space:
each point is a cell and red
points are the “pure cells”

- ▶ Picking k corner points/archetypes from the convex hull of the cells, such that they optimally “contain” the rest of cells.
- ▶ Each archetype is an ideal example of a cell type with a distinct set of **principal functions**.

Continuous view

Case study in the Melanoma dataset

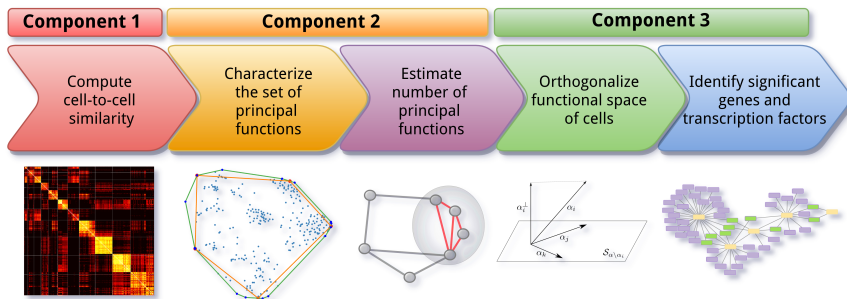


- ▶ T-cells reside in a continuum of states (*Thogerson et al.*).
- ▶ Tumor cells form compact groups.
- ▶ Two subclasses of MITF-associated tumors significantly differ in terms of their survival.

▶ ACTION sheds light on the underlying topology of cell types

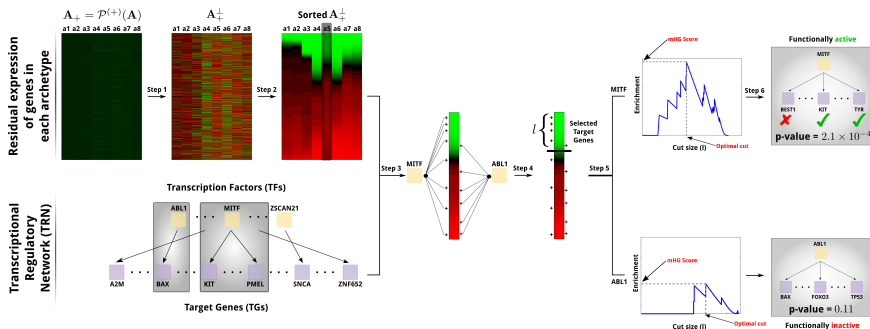
Overall Workflow

Component 3



Component 3

Constructing TRN



Component 3

Constructing TRN

Continued **Goal:** Identifying key regulatory elements that drive each cell type

1. Archetype Orthogonalization (\rightarrow Only over positive projection)

$$\mathbf{a}_i^\perp = \left(\mathbf{I} - \mathbf{A}_{-i}(\mathbf{A}_{-i}^T \mathbf{A}_{-i})^{-1} \mathbf{A}_{-i}^T \right) \mathbf{a}_i$$

2. Assessing significance of TFs/TGs

$$\begin{aligned} p\text{-value}(Z = b_l(\lambda)) &= \text{Prob}(b_l(\lambda) \leq Z) \\ &= \sum_{x=b_l(\lambda)}^{\min(T,l)} \frac{\binom{T}{x} \binom{m-T}{l-x}}{\binom{m}{l}} \end{aligned}$$

Use Dynamic Programming to compute exact p -value.

Functional activity of transcription factors (TFs)

Key point!

We identify “functional activity” of transcription factors (TFs) by aggregating transcriptional activity of their downstream targets, not the transcriptional level of TFs themselves. TFs can, and typically do, get regulated through post-translational mechanisms.

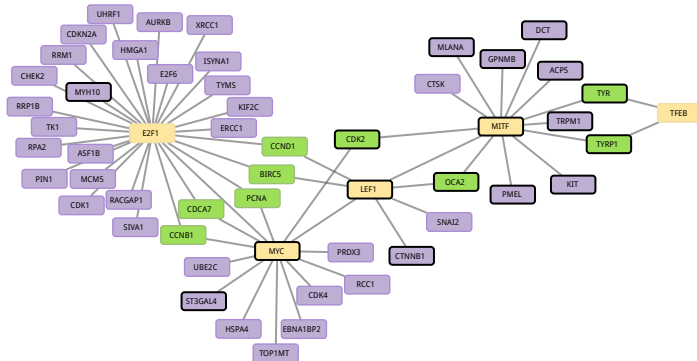
Dissecting transcriptional controls of Melanoma subtypes

Proliferative versus invasive status

- ▶ Both *Subtype A* and *Subtype C* exhibit high activity of *MITF* and *Sox10* transcription factors, which are canonical markers for melanoma cells in the “proliferative” (as opposed to “invasive”) state (*Verfaillie et al.*).
- ▶ These two subtypes are significantly enriched for marker genes in the proliferative state:
 - ▶ *Subtype A*: 9.3×10^{-14}
 - ▶ *Subtype B*: 7.9×10^{-11}
- ▶ Subtype A has higher *MITF* activity (according to its activated targets):
 - ▶ *GPMB, M1ANA, PMEL*, and *TYR* are shared between two subtypes.
 - ▶ *ACP5, CDK2, CTSK, DCT, KIT*, and *TRPM1/P1* are uniquely upregulated in subtype A.

Dissecting transcriptional controls of Melanoma subclasses

Case study in $MITF^{\uparrow\uparrow}/MYC^{\uparrow}$ subtype



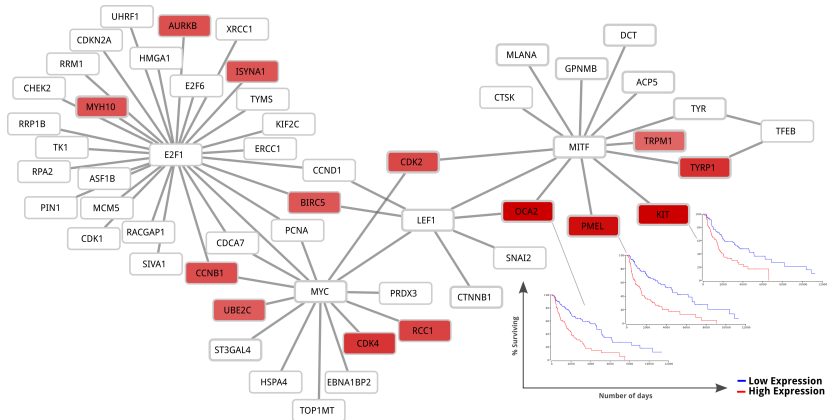
- ▶ 19 “functionally” active transcription factors in subtype A ($p\text{-value} \leq 0.05$)
- ▶ We focus on the five most significant TFs and their targets ($p\text{-value} \leq 10^{-3}$)

Case study in MITF^{↑↑}/MYC[↑] subtype

Core transcription factors

- ▶ MITF is one of the most well-known markers for classifying melanoma patients (**Hartman et al.**: MITF in melanoma: mechanisms behind its expression and activity).
- ▶ Overexpression of the E2F1 is common in high-grade tumors that are associated with poor survival in melanoma patients (**Alla et al.**: E2F1 in melanoma progression and metastasis).
- ▶ Melanoma cell phenotype switching, between proliferative and invasive states, is regulated by differential expression of LEF1/TCF4 (**Eichhoff et al.**: Differential LEF1 and TCF4 expression is involved in melanoma cell phenotype switching).
- ▶ Amplification and overexpression of the c-myc have been associated with poor outcome (**Kraehn et al.**: Extra c-myc oncogene copies in high risk cutaneous malignant melanoma and melanoma metastases).

Case study in MITF^{↑↑}/MYC[↑] subtype



1. Developed a novel cell similarity metric that is robust to biological noise, while at the same time is sensitive enough to identify weak cell type-specific signals
2. Characterized the functional identity of cells
 - ▶ Under the pure cell assumption, this metric induces a convex topology that embeds functional identity of cells
3. Utilized functional identity of cells to identify both discrete cell types and continuous cell states
4. Identified driving transcriptional controls that mediate the functional identity of cells

Clinical significance: Characterization of two MITF-associated subclasses of Melanoma patients, one of which has substantially worse outcomes, along with their underlying regulatory elements.

Questions?

