Recognizing Antigen Specificity and Functional Status of T cells by a Graph Deep Learning Model

Phi Le^{1,2}, Hai Yang², Tao He³, Aixin Tan⁴, Bridget P. Keenan^{1,2}, Li Zhang^{1,2,5}

¹Helen Diller Family Comprehensive Cancer Center, University of California, San Francisco, San Francisco; ²Department of Medicine, University of California San Francisco, San Francisco; ³Department of Mathematics, San Francisco State University, San Francisco; ⁴Department of Statistics, The University of Iowa, ⁵Department of Epidemiology & Biostatistics, University of California San Francisco, San Francisco;

BACKGROUND

- Immunotherapy has emerged as a promising approach in the treatment of cancer due to its ability to use the immune system to target cancer cells, and to combine with other treatment modalities, such as chemotherapy or targeted therapies, to enhance treatment effectiveness
- T cells are crucial components of the adaptive immune system, mediating antitumoral immunity and immune response to infections.
- T cell receptors (TCR) target specific antigens based on protein structure of nucleotide sequence. TCRs are highly varied and

adaptable to antigens.

Image from [6] Investigating which TCRs can effectively bind to antigens or cancer cells has become a significant area of interest in immunotherapy research.

 Gene expression is the process by which the information encoded in genes is converted into functional products, scRNA-seq gene expression presents the number of RNA sequence reads corresponding to each cell

• The integration of genomics, proteomics, and other omics technologies has provided invaluable insights into the underlying molecular mechanisms of the disease, paving the way for personalized and targeted approaches to patient care.

OBJECTIVE

 To build a model that seamlessly links gene expressions and TCR sequencing data to refine clusters of functional T cells and their associated gene list

Illustration Datasets

CD40 agonist clinical trial^{9,10}:

Esophageal/Gastroesophageal junction cancer patients received Sotigalimab (CD40 Agonist) treatments

• 10X Genomic datasets¹:

10X data set is a collection of CD8+ T cells from four healthy donors. For each cell, it has TCR sequence, cell surface protein expression, and antigen binding information.

METHODS

Deep Graph Learning Model

- Step 1: To capture the nonlinear relationships and differences in cell functions within the similarity network².
- Step 2: To learn the variations and matches in cell functions across different parts of the network through gene expressions³.

Levenshtein Distance

Pipeline of Integrating TCRs and Gene Expression

TCR network

Construct a TCR network based on TCR similarities.

Import gene expressions to graph as node features

Extract embedded gene expression values

Build an unsupervised graph neural network on the built

• Find clusters on embedded gene expression by Leiden

Similarities of

TCR sequences:

CASSIHHQDTQYF

CASSIHHQATQYF CATSIHHQDTQYF

CASSIHHQDTQYF CASSIHHQDTQYF

UMAP of clusters of

mbedded gene expression

graph

cluster method

CD40 agonist clinical trial^{9,10}

Treg

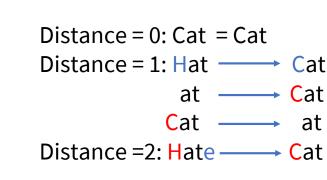
gd_Tcell

Node includes gene

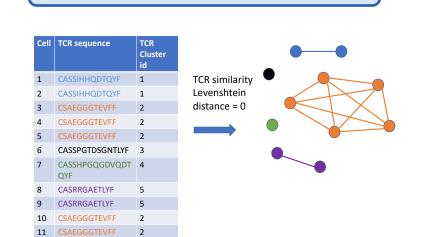
Deep graph learning

A0301 KLGGALQAK_IE-1_CMV_binder

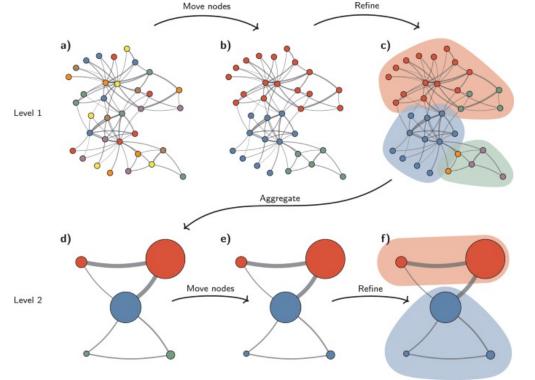
A0201_GILGFVFTL_Flu-MP_Influenza_binder



TCR Network Analysis⁴



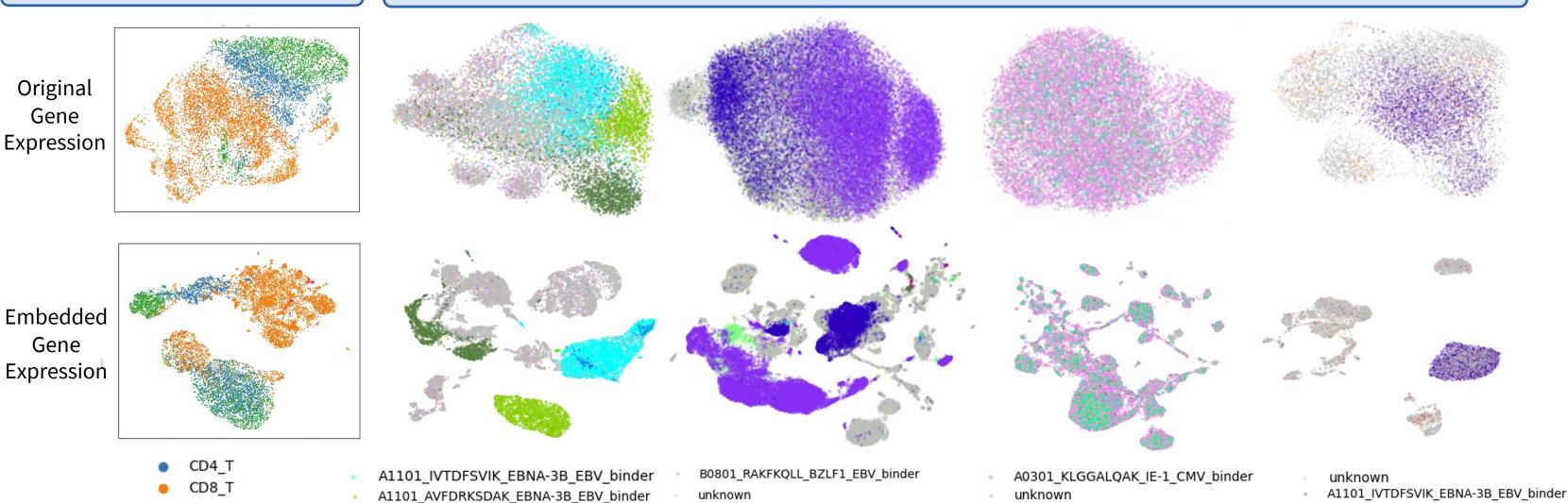
Leiden Cluster Algorithm⁵



- Construct a graph where edge connection is the correlation between embedded gene expression profiles.
- Apply community detection to identify clusters of cells within the
- Optimize cluster assignments by iteratively moving cells between
- Repeat optimization steps to find the optimal cluster assignments that maximize the within-cluster similarity and minimize the between-cluster similarity.

RESULTS

10x Genomics Data¹ with Antigen Binding Information*



A0201_GILGFVFTL_Flu-MP_Influenza_binder

A0301_KLGGALQAK_IE-1_CMV_binder

A0201_GLCTLVAML_BMLF1_EBV_binder

*We only list the top 5 detected antigens by cardinality. Unknown color code (silver) is for cells with unknown antigen binding

A1101_AVFDRKSDAK_EBNA-3B_EBV_binder

A0301_RLRAEAQVK_EMNA-3A_EBV_binder

A1101_IVTDFSVIK_EBNA-3B_EBV_binder

A0301_KLGGALQAK_IE-1_CMV_binder

A1101_AVFDRKSDAK_EBNA-3B_EBV_binder

A0201_RTLNAWVKV_Gag-protein_HIV_binder

Summary of Findings

- The embedded gene expression preserves the clusters of cell type calling for expanded TCRs similarity clusters
- The embedded gene expression can refine and separate different types of antigens clearly better then just using gene expression data
- The clusters obtained by the proposed pipeline outperforms than only using TCR clusters or gene expression clusters
- Performance check by Adjusted Rand Index** (ARI)

Index		I C K	Embedded gene expression
Donor 1	0.562	0.508	0.76
Donor 2	0.159	0.163	0.242
Donor 3	-0.0003	-0.001	0.003
Donor 4	0.168	0.894	0.902

** ARI is a well-known index to measure cluster performance, its value is in [-1,1], larger is

CONCLUSIONS

We developed a deep learning model that can seamlessly integrate single-cell gene expressions and T cell receptors. Our approach can

- Preserve the cell type calling for expanded TCR clusters
- Cluster cells into groups to predict antigen binding better than TCR network analysis

Limitation

- We can get up to 50% improvement of finding antigen binding clusters comparing to TCR network from 10X data
- In rare situation, we do not see significant differences between our method and TCR network
- Limited available data to test our model

REFERENCES

- 1.10X genomics. A New Way of Exploring Immunity. https://pages.10xgenomics.com/rs/446-PBO-704/images/10x_AN047_IP_A_New_Way_of_Exploring_Immunity_
- 2. Hamilton WL, Ying R, Leskovec J. Inductive Representation Learning on Large Graphs. Published online September 10, 2018. Accessed June 3, 2023. http://arxiv.org/abs/1706.02216.
- 3. Veličković P, Fedus W, et al. Deep Graph Infomax. Published online 2018. doi:10.48550/ARXIV.1809.10341.
- 4. Yang H, Cham J, Fan Z, et al. NAIR: *Network Analysis of Immune* Repertoire. Frontiers in Immunology (Accepted). https://github.com/mlizhangx/Network-Analysis-for-Repertoire-Sequencing-
- 5. Traag VA, Waltman L, Van Eck NJ. *From Louvain to Leiden:* guaranteeing well-connected communities. Sci Rep. 2019;9(1):5233. doi:10.1038/s41598-019-41695-z
- 6. CAR T-cell therapy, https://www.elicera.com/technology 7. Sun Y, Li F, Sonnemann H, et al. Evolution of CD8+ T Cell Receptor (TCR) Engineered Therapies for the Treatment of Cancer. Cells.
- 2021;10(9):2379. doi:10.3390/cells10092379 8. https://theaisummer.com/Graph_Neural_Networks/
- 9. Ko A NM, Chao J, Sohal DPS, et al. A Multicenter Phase 2 Study of Sotigalimab (CD40 Agonist) in Combination with Neoadjuvant Chemoradiation for Resectable Esophageal and Gastroesophageal Junction (GEJ) Cancers. 2022 September 9-13, 2022.; Paris, France. ESMO Annual Conference.
- 10. Maira Soto, Erin L Filbert, et al. *Use of high-dimensional and* spatial immune profiling to explore sotigalimab (CD40 agonist) activation of antigen presenting cells and T cells in the tumor microenvironment in patients with esophageal/gastroesophageal junction cancer. Journal of Clinical Oncology 2023 41:4_suppl, 450-450

Acknowledgement

- PL, YH, TH, BK and LZ are partially supported by NIH/NCI R21CA264381 and NIH/NLM R01LM013763-01A1.
- Bridget Keenan is supported by a UCSF Helen Diller Family Comprehensive Cancer Center Cancer Immunology and Immunotherapy grant and 1K12CA260225-01.

Corresponding author: philong.le@ucsf.edu