Interpretable Deep Learning for Chromatin-Informed Inference of Transcriptional Programs Driven by **Somatic Alterations Across Cancers**

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Signaling and transcriptional response

• Cancers are caused by the perturbations of multiple pathways and transcriptional regulatory programs





Pan-cancer modeling of regulatory programs



- Similar TFs may be dysregulated across cancers
- Similarities between cancer types can inform new therapies
- Extensive training data from more common tumor types also compensates for smaller sample sizes in similar but rarer cancers (e.g. pheochromocytoma and paraganglioma; PCPG)

Modeling non-linear relationships

ACVR2A PPP6C AXIN1 PPP2R1ACDH11 RBM10 FGFR2 FAM135B AMER1 MAP2K1 TCF7L2 DDX3X AKT1 CDH10STK11 BIRC6 MTOR ESR1 AP3K1 ELF3 MYH11 FAM46C CREBBP KDM6AIDH2 SETD2 TBX3NFE2L2 PBRM1 CHI RAC1 ZFHX3KEAP1 LRP1B FAT1 GNA11 SPENARID2 RB1 KMT2D ERCC2 CDKN1B CTCFVHL ATM KRAS BRAF PIM1ERBB2 CICARID1A IDH1 AR RUNX1 GFR3 A SMAD4 PTPN11 MYH9NOTCH1 FBXW F3B1 EGFR SMARCA4NOTCH2 TGFBR2BRCA2PIK3R1NBEAFOXA HRAS_{TSC1} BTG1 RNF43 MED12 GNAS RHOA CARD11 CDKN1A ARID1B PRKCE CUL3

https://www.intogen.org

- Effects of upstream alterations not equal, e.g., cancer drivers vs. passengers
- Complex interactions between genes, e.g., mutual exclusivity
- Role of genomic alterations is context specific
- Attention mechanism!



Attention mechanism

- A deep learning method to assign importance weights to input features
 - Widely used in Computer Vision/Natural Language Processing
 - Computed in a contextual manner



S Woo et al. ECCV. 2018.

The FBI is chasing a criminal on the run.		
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J Cheng et al. EMNLP. 2016.



Datasets/Approach: Modeling impact of somatic alterations on gene expression programs





Patients-specific regulatory networks



Approach: interpretable deep learning

- CITRUS
 - Chromatin-informed Inference of Transcriptional Regulators Using Self-attention mechanism
 - Self-attention mechanism
 - Sparse connections constrained by ATAC-seq prior



Sparse

Pan-cancer data sources



MR Corces et al. Science. 2018.

Datasets	Summary
ATAC-seq	410 tumors
Bladder (BLCA)	371 tumors
Breast (BRCA)	719 tumors
Cervical and endocervical (CESC)	267 tumors
Colon (COAD)	271 tumors
Esophageal (ESCA)	170 tumors
Glioblastoma (GBM)	143 tumors
Head and Neck (HNSC)	475 tumors
Kidney renal clear cell (KIRC)	357 tumors
Kidney renal papillary cell (KIRP)	272 tumors
Liver hepatocellular (LIHC)	336 tumors
Lung adenocarcinoma (LUAD)	459 tumors
Lung squamous (LUSC)	430 tumors
Pheochromocytoma and Paraganglioma (PCPG)	109 tumors
Prostate (PRAD)	449 tumors
Stomach (STAD)	373 tumors
Thyroid (THCA)	216 tumors
Uterine corpus endometrial (UCEC)	361 tumors

The Cancer Genome Atlas Research Network (TCGA)



ATAC-seq identifies shared and unique epigenetic landscape across cancers



TF motif prediction in ATAC-seq peak regions





CITRUS better predicts gene expression in held-out tumors compared to bilinear models

• Affinity regression (bilinear) vs. CITRUS (deep learning)



R Pelossof et al. *Nature Biotech*. 2015. HU Osmanbeyoglu et al. *Nature Comm*. 2017.



Overall attention weights

• Impacts of somatic alterations





Clustering based on inferred TF activity largely recovered the distinction between the major tumor types





Landscape of mutations and inferred TF activities





Impact of mutations on TFs in breast cancer

• Knock out in silico: different from t-test, simulates the knockout of mutations







Impact of PIK3CA mutation on TFs in breast cancer





Impact of TP53 mutation across cancers



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Conclusion and future work

- CITRUS: deep learning approach modeling transcriptional programs in pan-cancer
- Utilize self-attention mechanism to capture non-linear effects of mutations
- Integrate ATAC-seq as knowledge base
- Further explore potential clinical relevance



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Looking for students and postdocs! Please reach out at <u>osmanbeyogluhu@pitt.edu</u>



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