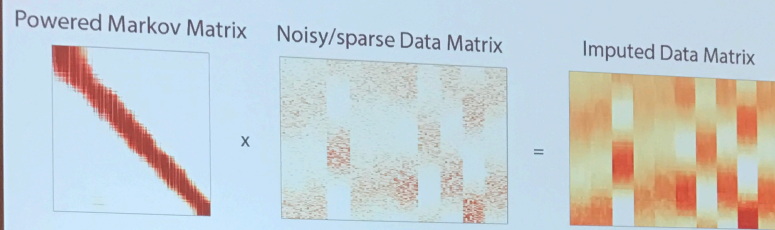


# RSGDREAM 17 debrief

JZ

## Markov Affinity-based Graph Imputation of Cells (MAGIC)



Cell values replaced by weighted average of extended neighborhood

## Dana Pe'er Lab of Computational Systems Biology

the organization, function and evolution of molecular networks. Cells sense multiple signals from the environment, robustly process and orchestrate the regulation of hundreds of genes and proteins to enable cellular functionality. How and where cellular functionality occurs through diverse mechanisms including transcriptional changes, translation, degradation, post-translational modification. The integration of high throughput genomic and proteomic technologies is a major challenge. The Dana Pe'er Lab is focused on the integration of new experimental data, quantitatively measuring the changes at the genome-wide scale.

Methods to integrate diverse high throughput data and unravel a cell's response to environmental stimuli. We elucidate the principles by which a cell robustly responds to environmental stimuli. Some of the questions we ask are: How does the response to stimuli change between cell-type, individual and species? How does the response to stimuli change over the course of evolution? How do small changes in gene expression propagate and manifest in phenotypic diversity and changes to cellular regulation lead to disease such as cancer?



Phone:  
(212) 854-4397

Email:  
dpeer@biology.columbia.edu

## MAGIC: A diffusion-based imputation method reveals gene-gene interactions in single-cell RNA-sequencing data

David van Dijk, Juozas Nainys, Roshan Sharma, Pooja Kathail, Ambrose J Carr, Kevin R Moon, Linas Mazutis, Guy Wolf, Smita Krishnaswamy, Dana Pe'er

**doi:** <https://doi.org/10.1101/111591>

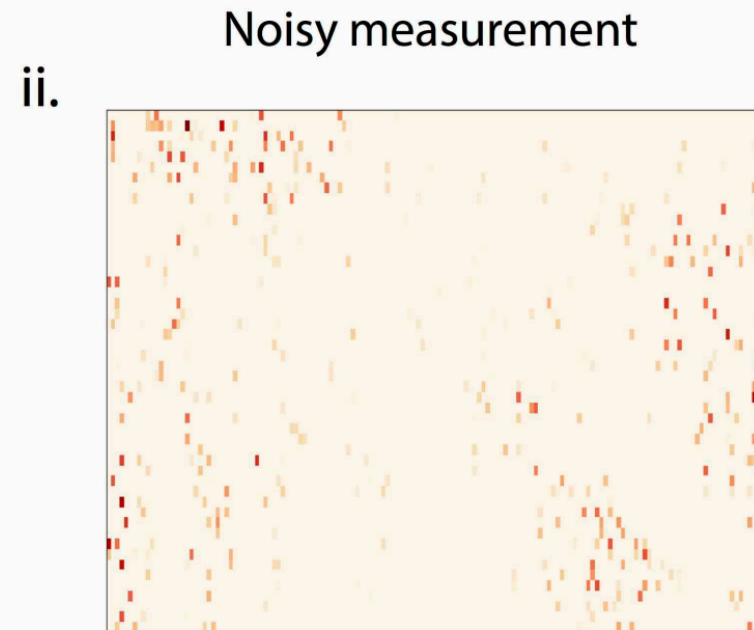
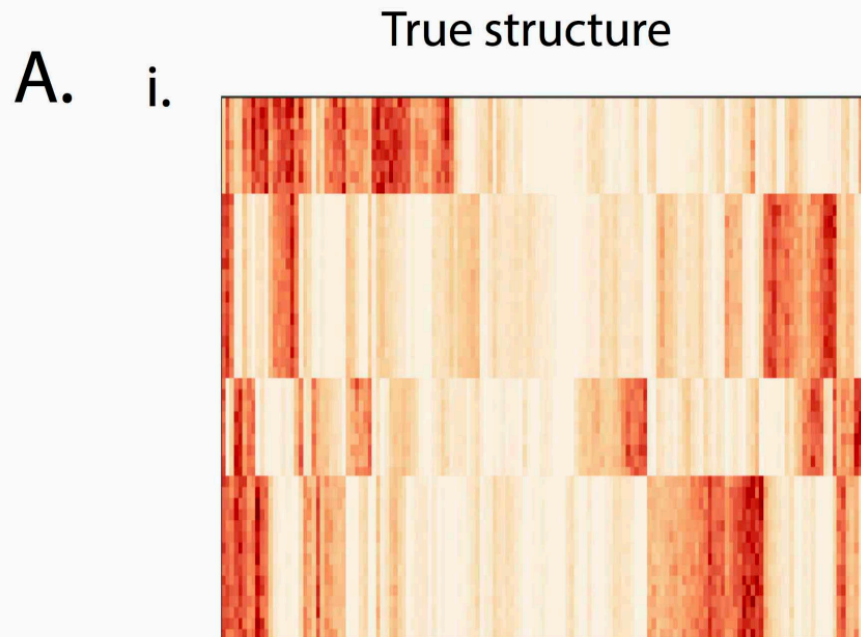
This article is a preprint and has not been peer-reviewed [what does this mean?].

**Abstract**

[Info/History](#)

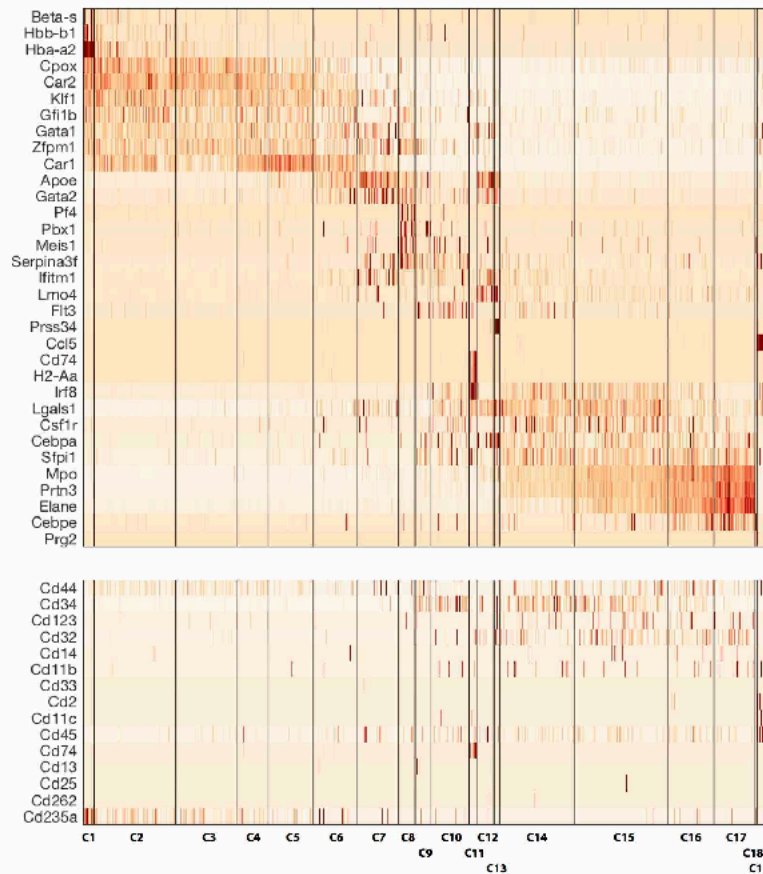
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[Preview PDF](#)



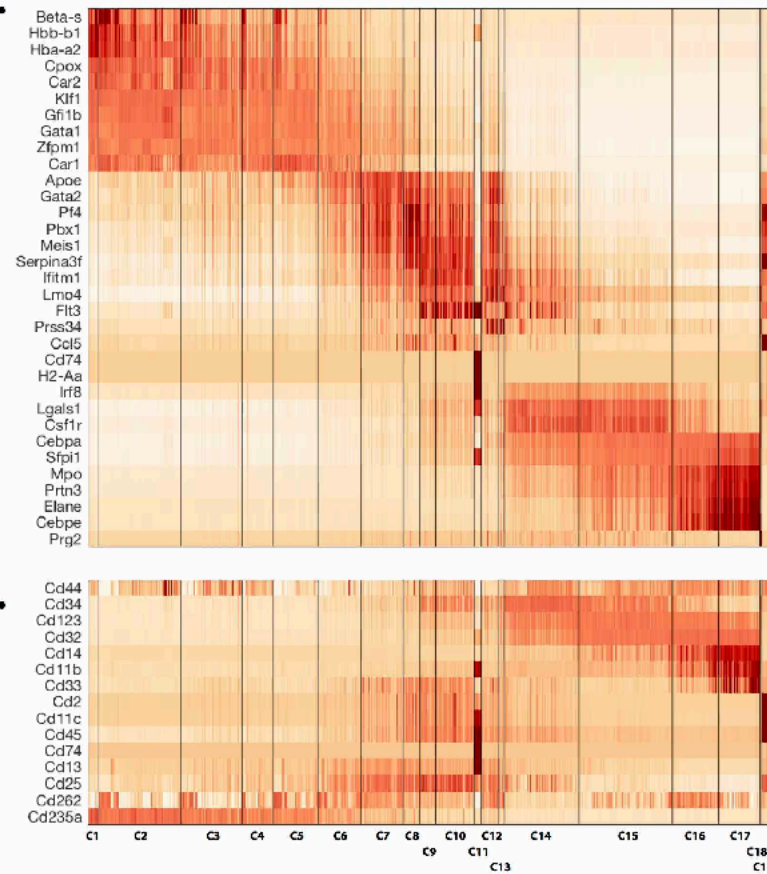
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i.

Before MAGIC

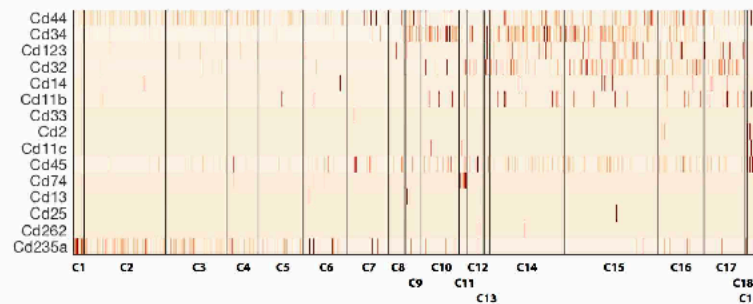


ii.

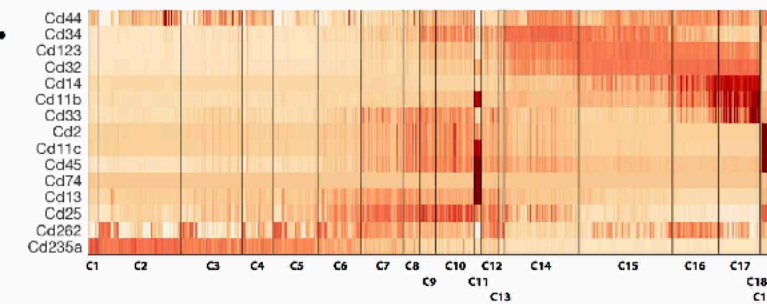
After MAGIC



B.  
i.



ii.





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*Res Comput Mol Biol.* 2017 May ; 10229: 336–352. doi:10.1007/978-3-319-56970-3\_21.

# Quantifying the Impact of Non-coding Variants on Transcription Factor-DNA Binding

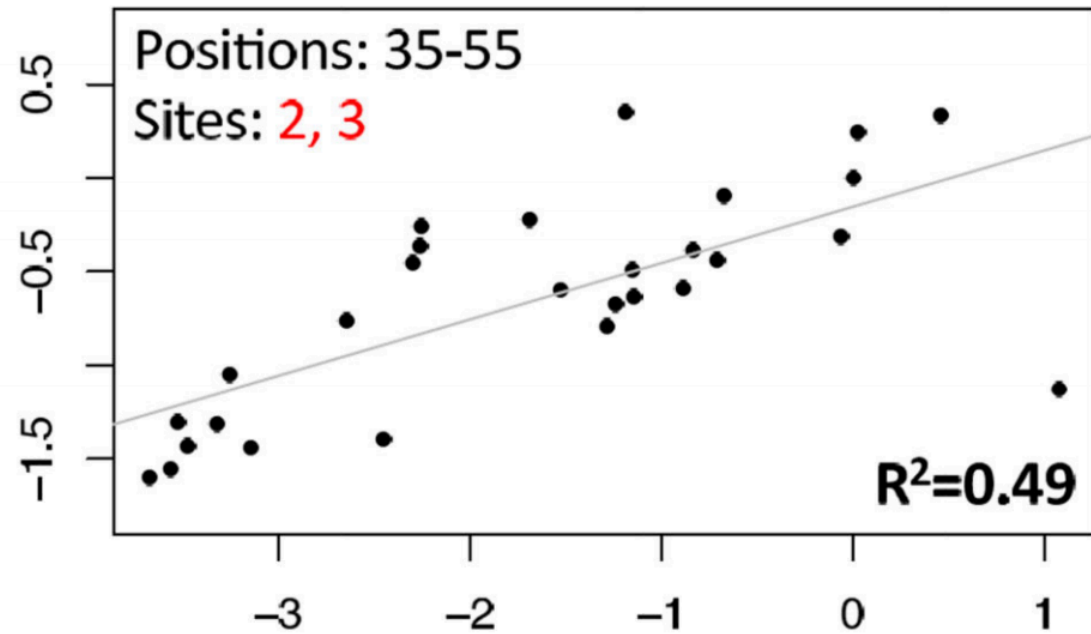
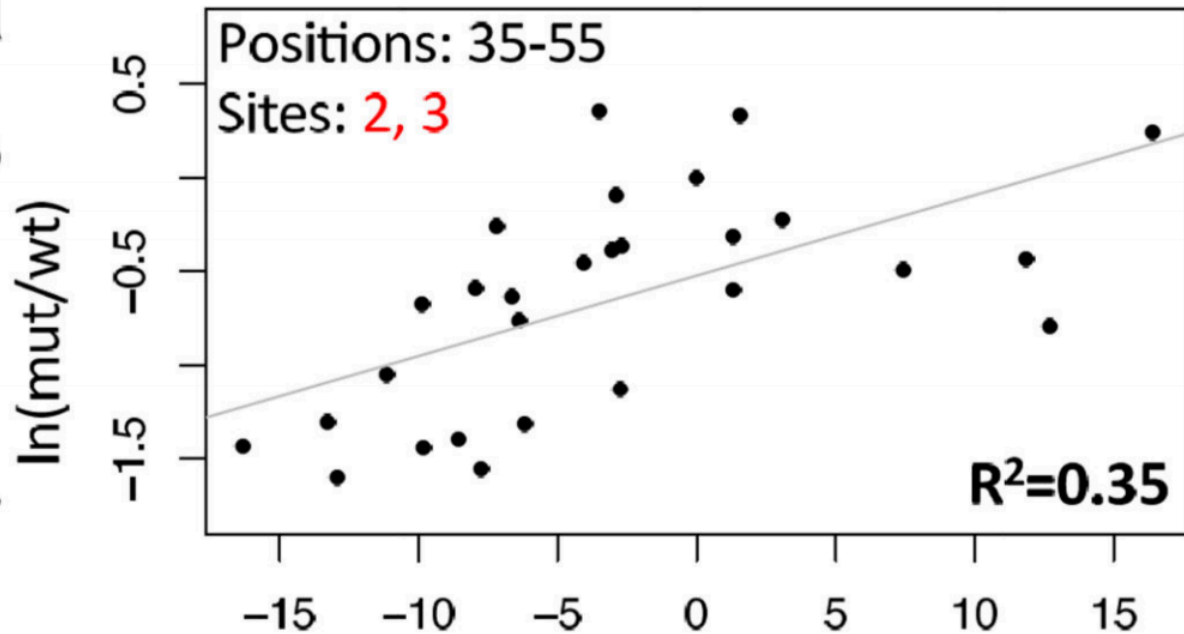
**Jingkang Zhao**<sup>1,2,†</sup>, **Dongshunyi Li**<sup>3,†</sup>, **Jungkyun Seo**<sup>2</sup>, **Andrew S. Allen**<sup>1,3</sup>, and **Raluca Gordân**<sup>1,3,4</sup>

<sup>1</sup>Center for Genomic and Computational Biology, Duke University, Durham NC 27708, USA

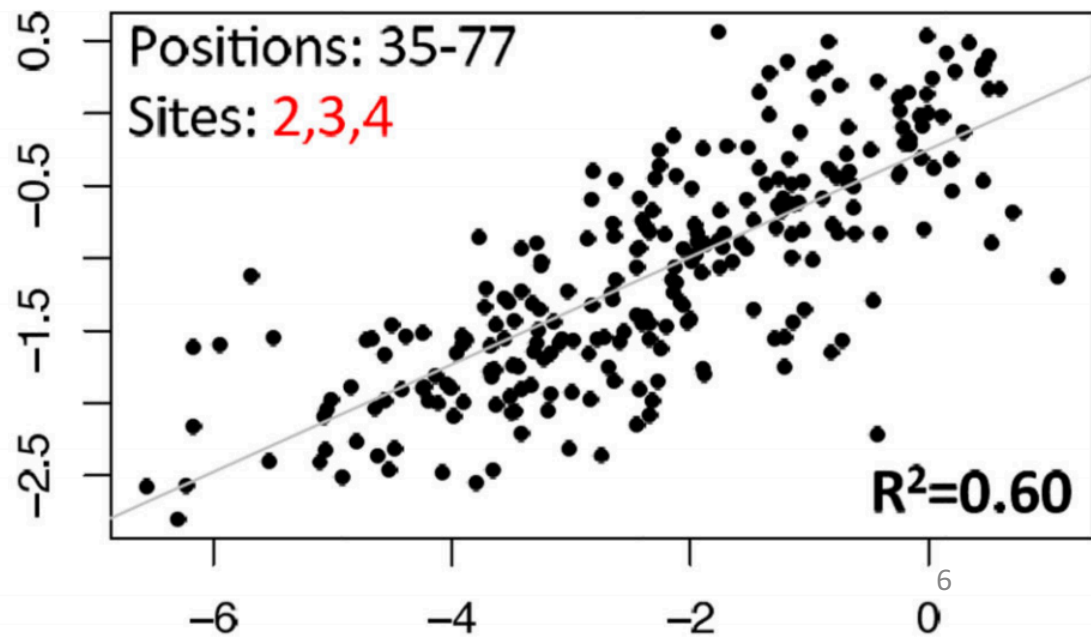
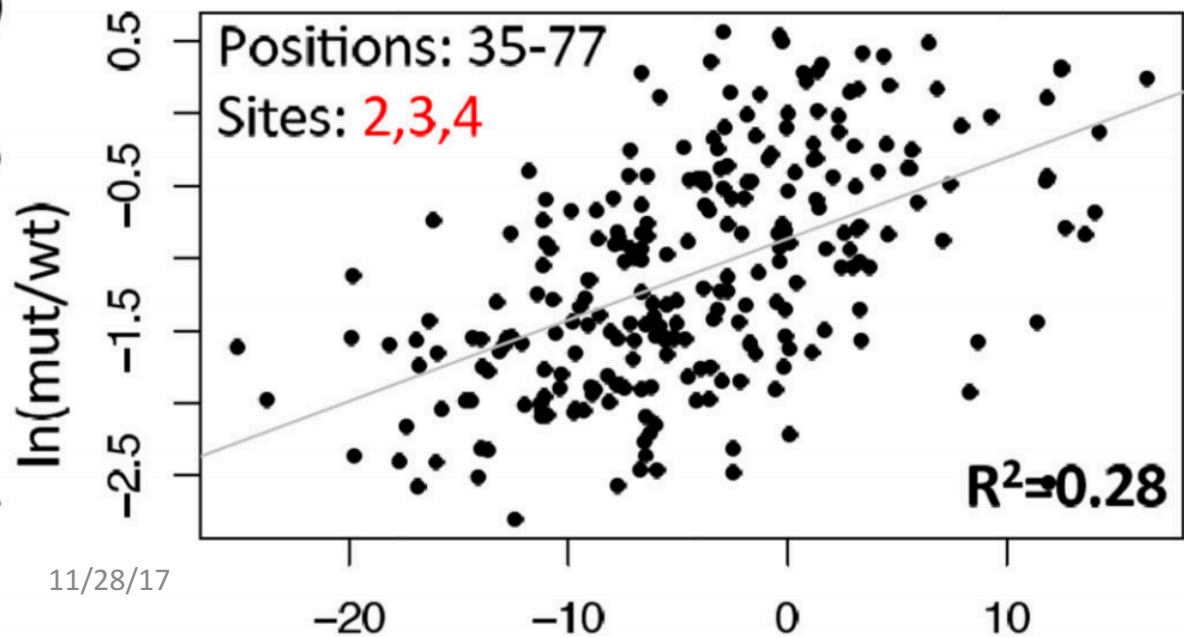
We use ordinary least squares (OLS) to estimate the parameters of the binding model for each TF, and we show that our predictions of TF-binding changes due to DNA mutations correlate well with measured changes in gene expression.

**a**

Expression change

**b**

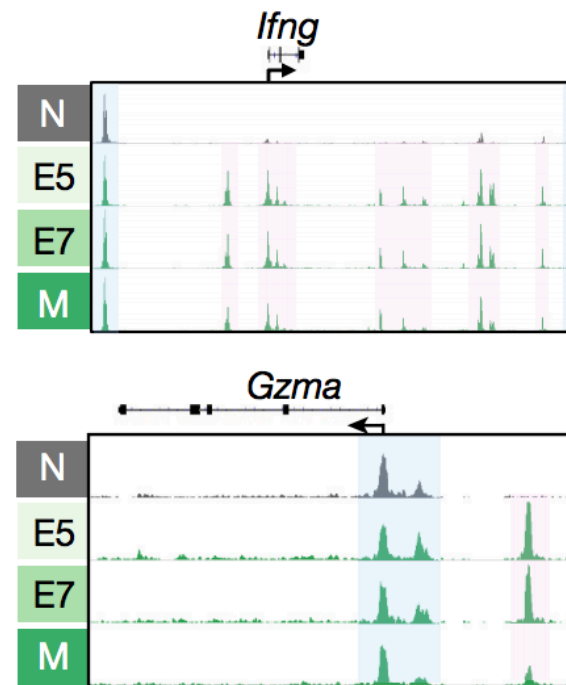
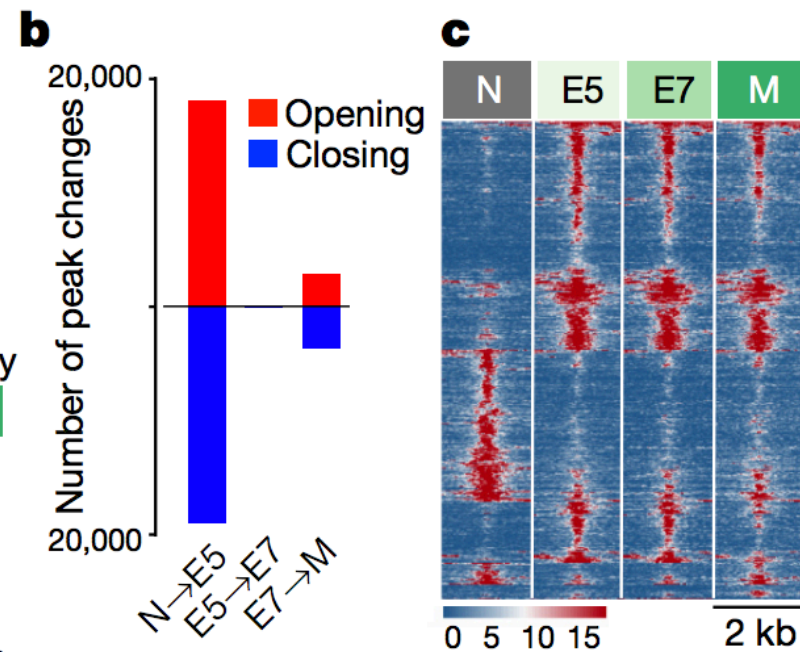
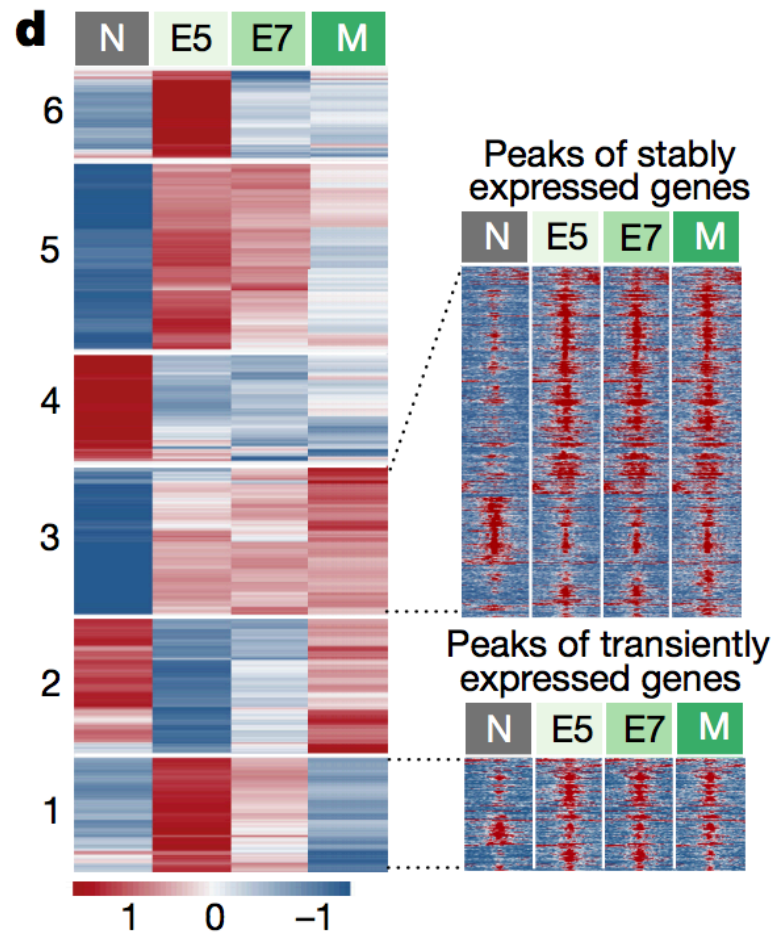
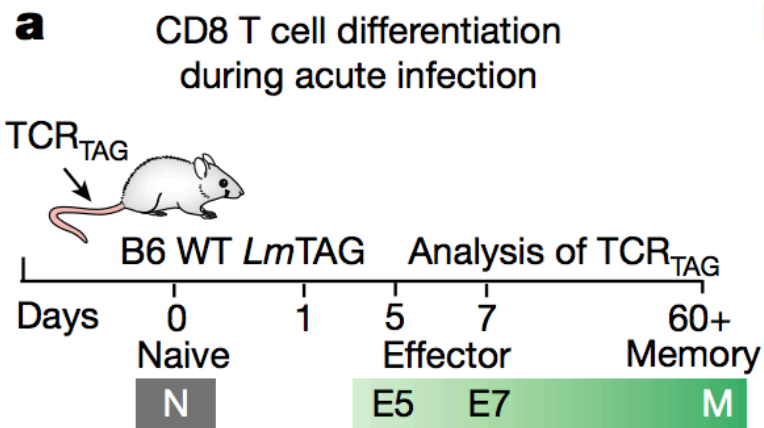
Expression change

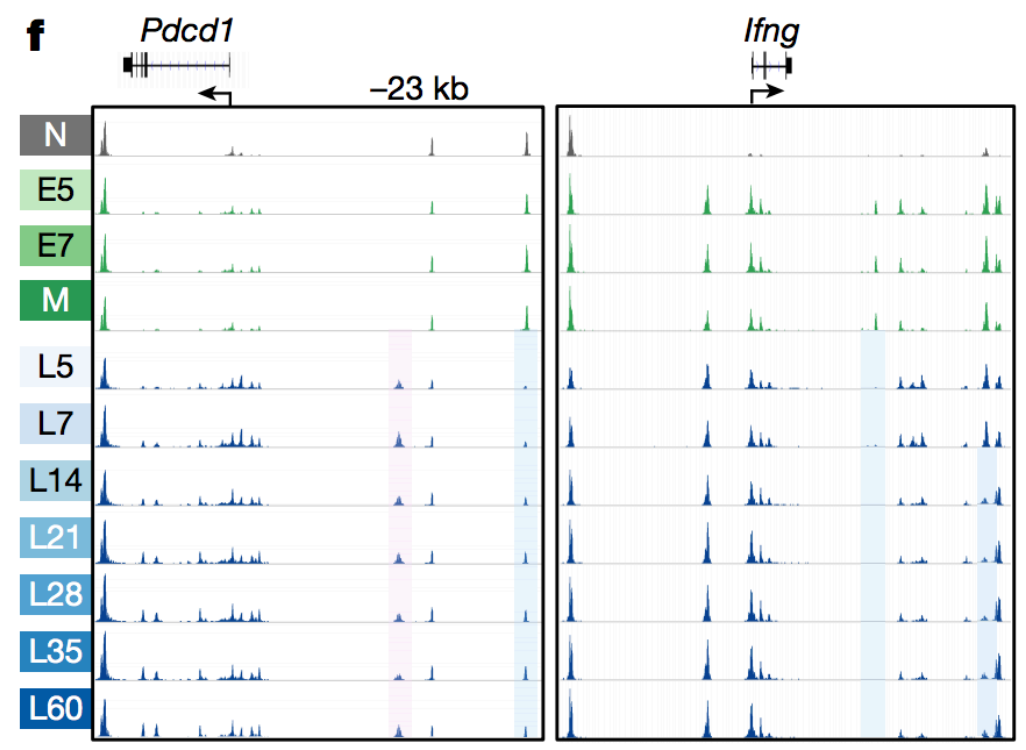
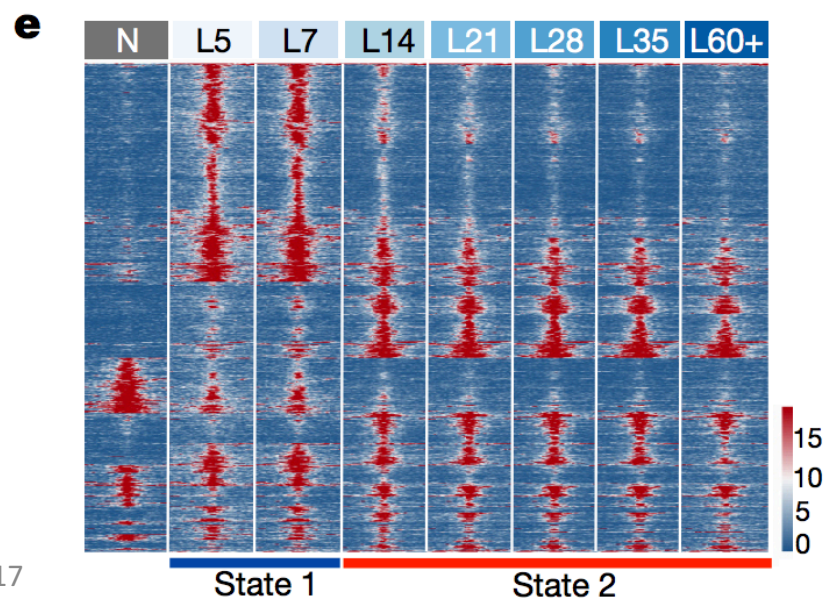
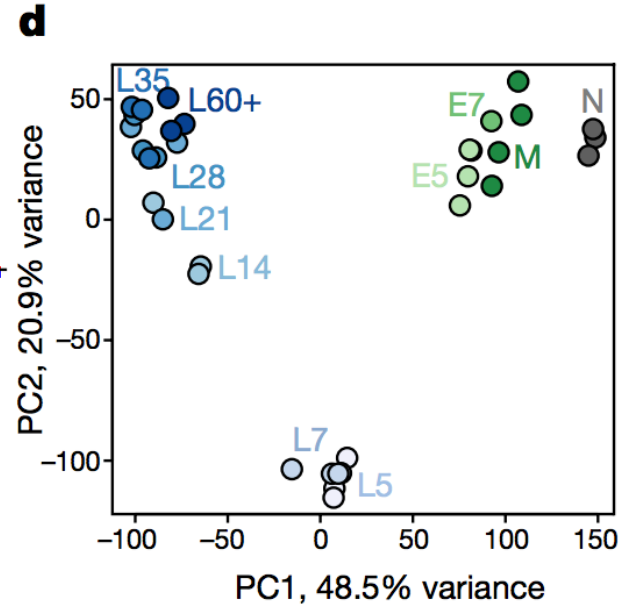
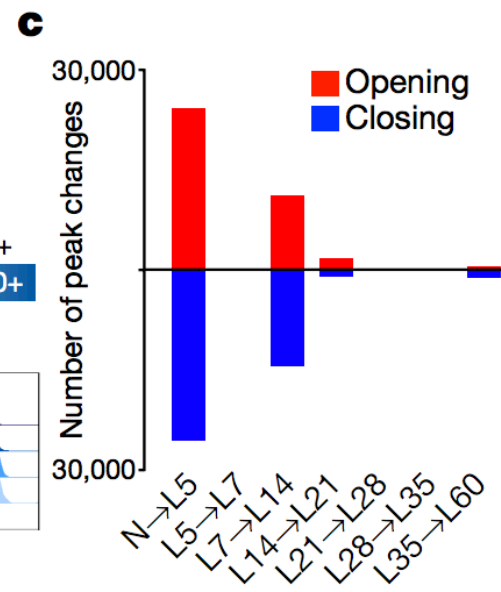
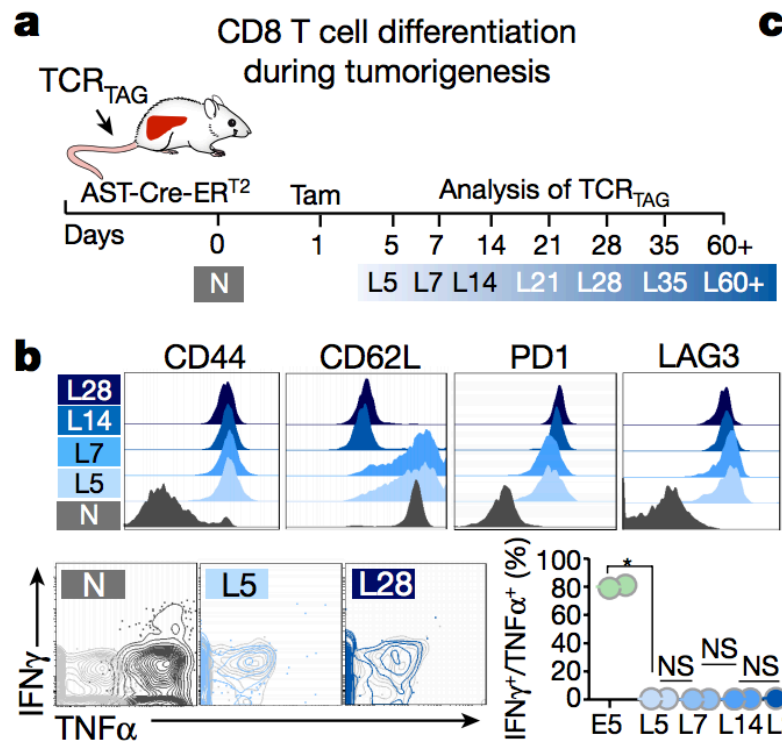


# Chromatin states define tumour-specific T cell dysfunction and reprogramming

Mary Philip<sup>1</sup>, Lauren Fairchild<sup>2,3</sup>, Liping Sun<sup>4</sup>, Ellen L. Horste<sup>1</sup>, Steven Camara<sup>1</sup>, Mojdeh Shakiba<sup>1,5</sup>, Andrew C. Scott<sup>1,5</sup>, Agnes Viale<sup>4</sup>, Peter Lauer<sup>6</sup>, Taha Merghoub<sup>5,7</sup>, Matthew D. Hellmann<sup>5,8</sup>, Jedd D. Wolchok<sup>5,7,9</sup>, Christina S. Leslie<sup>2</sup> & Andrea Schietinger<sup>1,5</sup>

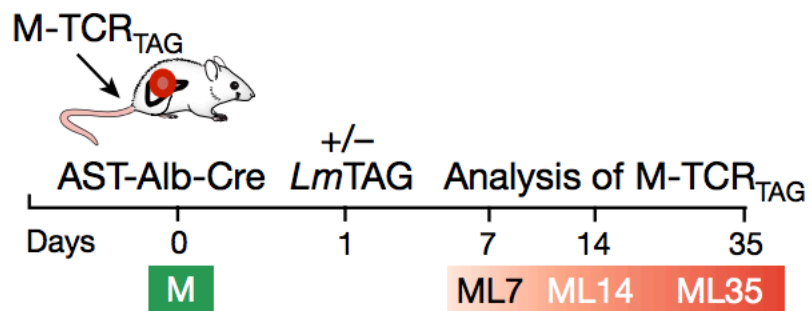
- *DNaseq 20m cells, attic-sea 50k cells, chromatin state to distinct the dysfunction state, 11.17 Nature*
- *changes of chromatin accessibility is corresponding to gene expression changes*
- *compare the changes of TF binding using the imputed network (ISMB?)*



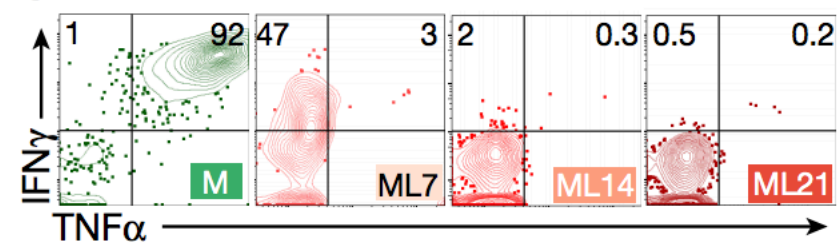




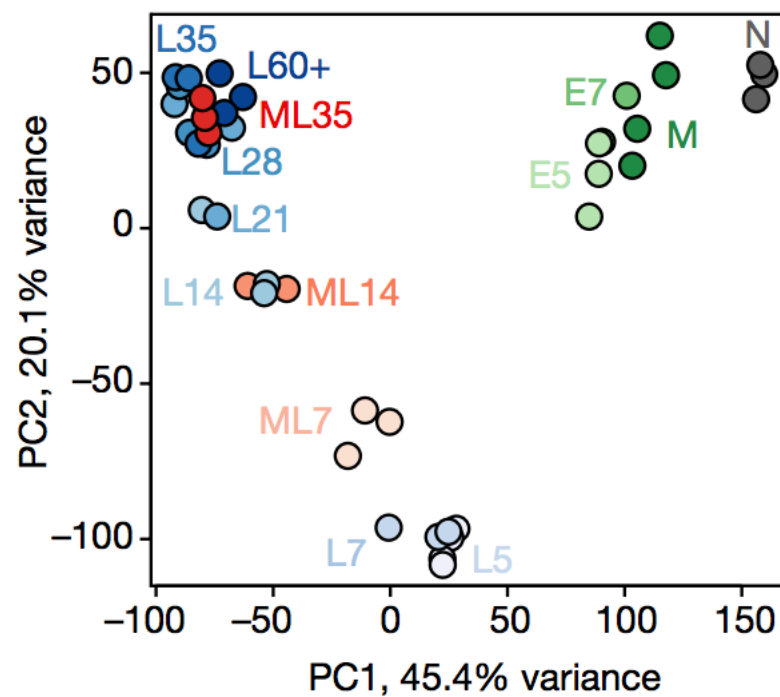
**a** Memory CD8 T cells in established tumours



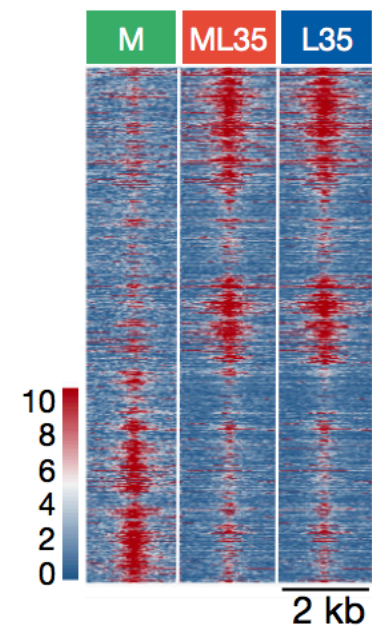
**b**

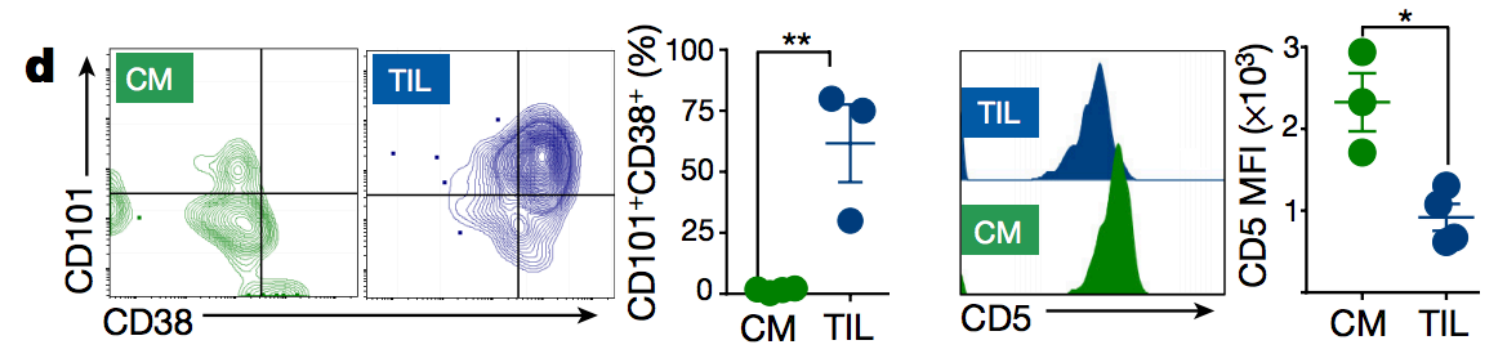
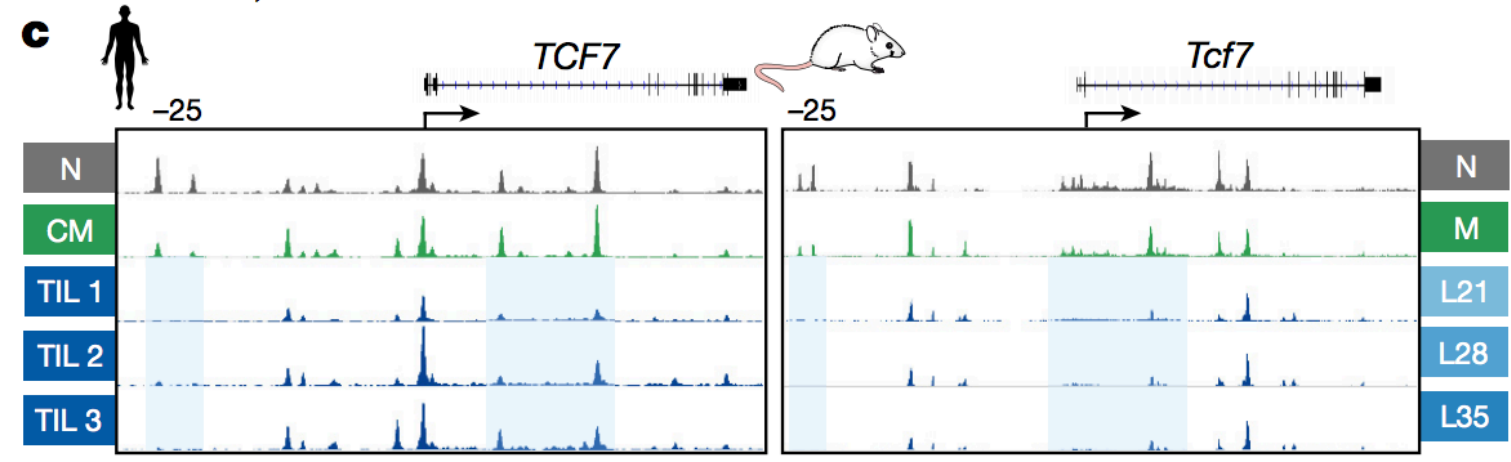
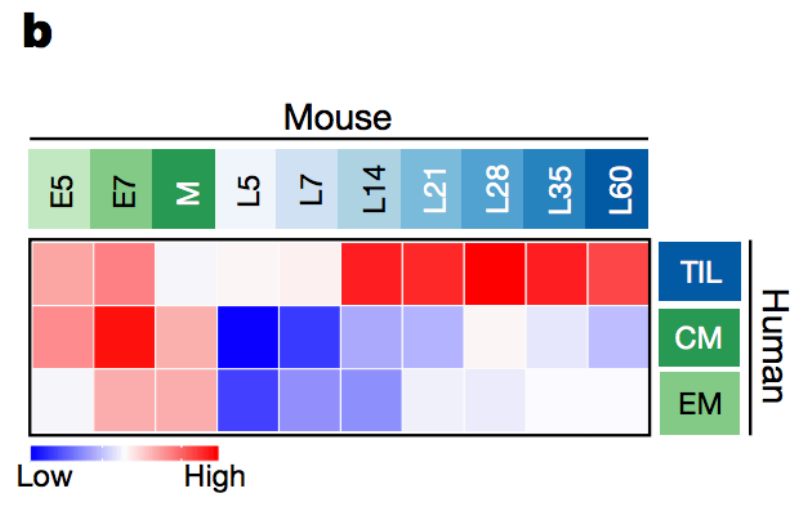
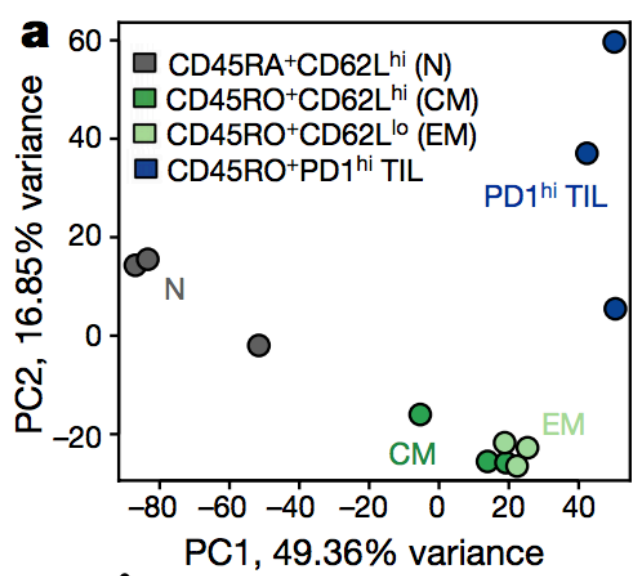


**c**

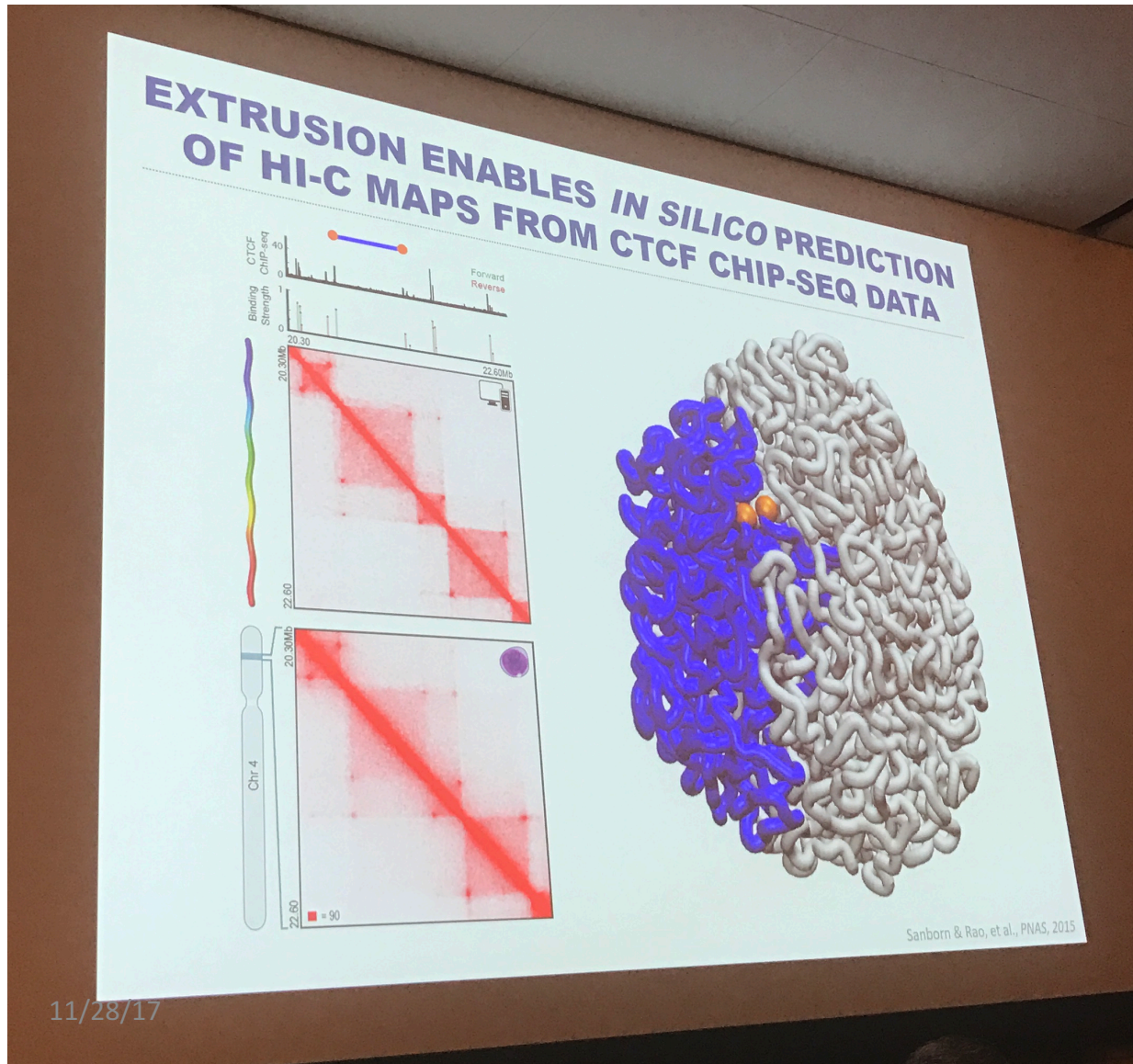


**d**





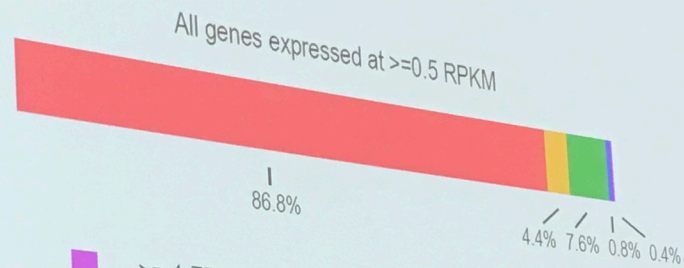
# A 3D Code in the Human Genome



CTCF and Hi-C



## SURPRISINGLY, FEW GENES ARE AFFECTED BY THE LOSS OF COHESIN!



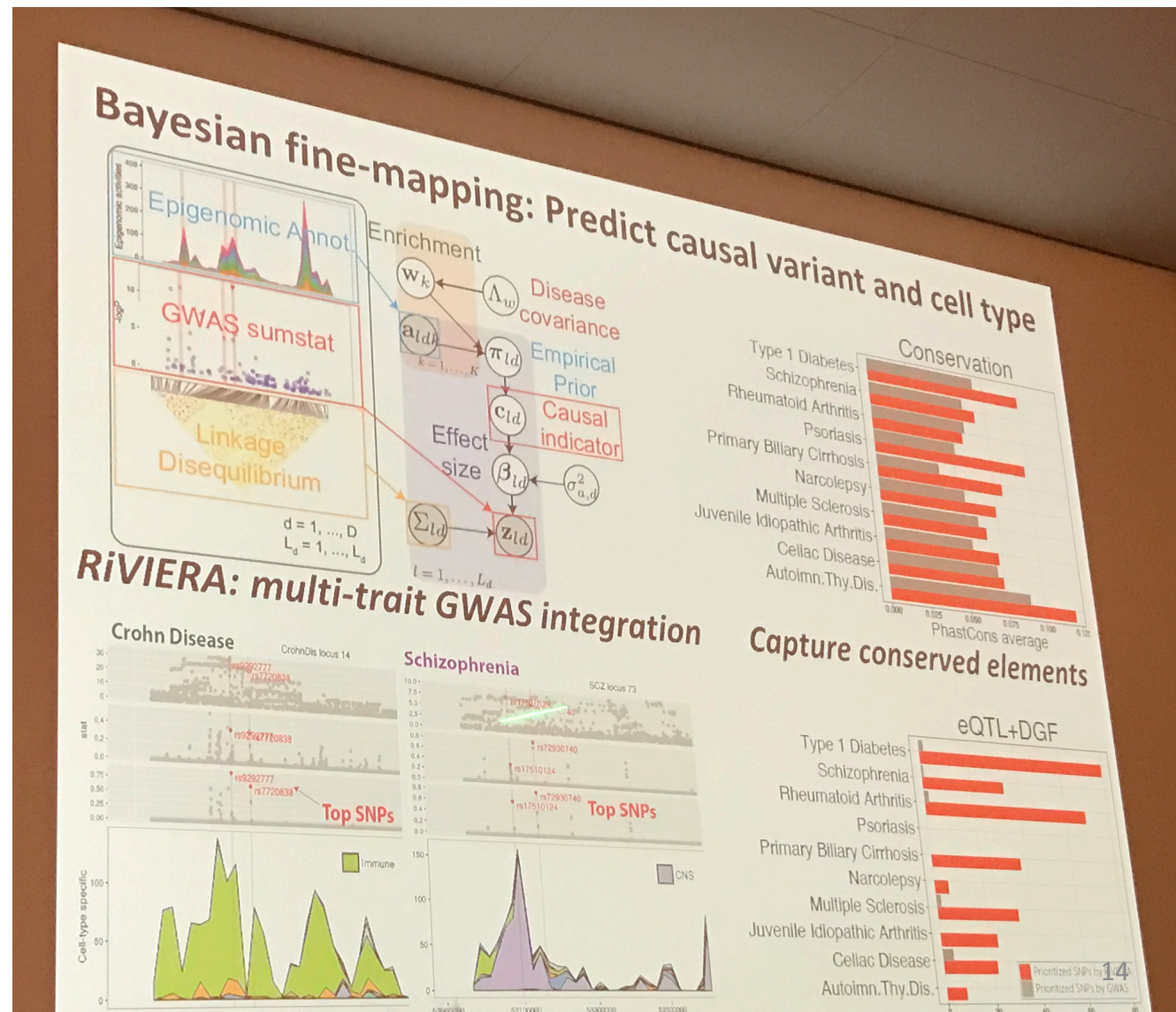
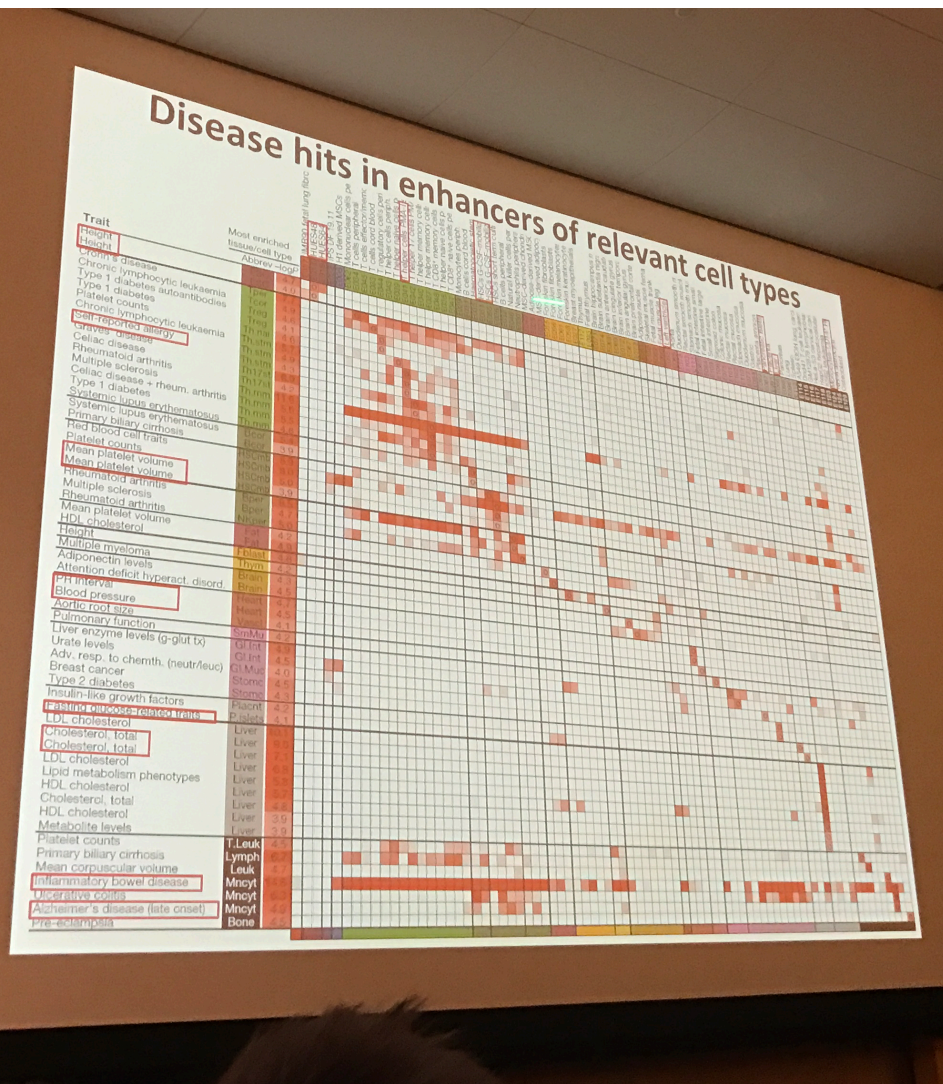
- $\geq 1.75$ -fold down-regulated (p<0.05, n = 49)
- $\geq 1.75$ -fold up-regulated (p<0.05, n = 97)
- $\geq 1.3$ -fold down-regulated (p<0.05, n=927)
- $\geq 1.3$ -fold up-regulated (p<0.05, n=534)
- Genes that are changed by less than 30% (n=10,615)

Rao et al., Cell, 2017

Hi-C is useless in predicting enhancer gene linkage?

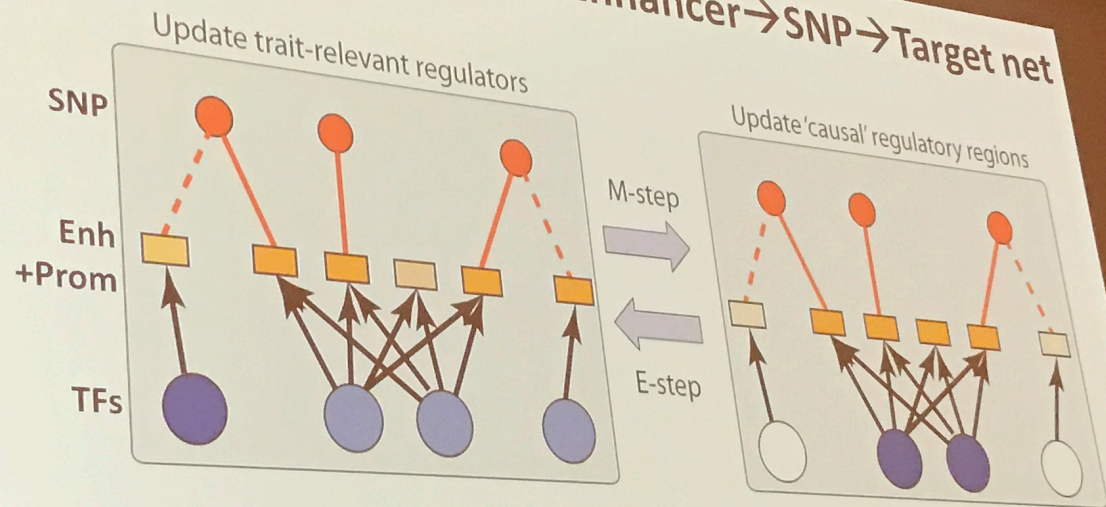


# From Genetics To Therapeutics: Uncovering And Manipulating The Circuitry Of Non-coding Disease Variants





# CONVERGE: Refine TFs → Enhancer → SNP → Target net



## Input:

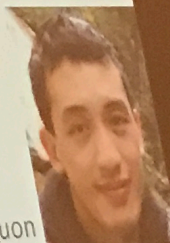
- GWAS P-values
- Regulatory network
- Region ↔ LD SNPs net

EM

## Output:

- Trait-relevant TFs
- Causal SNPs
- Target genes

Gerald Quon





# IMPROVED PREDICTIONS OF SEQUENCE SPECIFICITIES OF RNA-BINDING PROTEINS BY DEEP LEARNING

Peter K. Koo<sup>1,2</sup>, Praveen Anand<sup>2</sup>, and Sean R. Eddy<sup>1,2,3</sup>

<sup>1</sup>Howard Hughes Medical Institute, <sup>2</sup>Department of Molecular and Cellular Biology, <sup>3</sup>Department of Applied Mathematics, Harvard University, Cambridge, MA (USA)

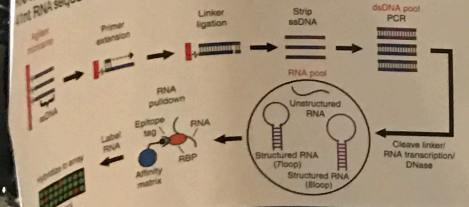


## Objective

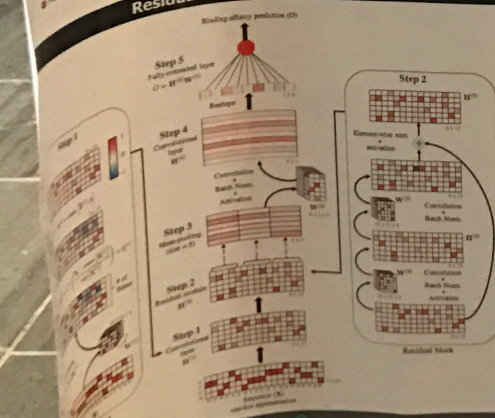
Understanding the recognition principles of RNA-binding proteins (RBPs) is essential to gain insight into the mechanisms of many biological processes. We introduce a computational method, we call ResidualBind, that aims to capture the relationships of the specificities between RBPs and RNA sequences using a deep learning approach. By using a diverse array of experimental datasets that spans many RBP families, we find that ResidualBind significantly outperforms previous state-of-the-art methods. Through a systematic *in silico* mutagenesis study, we demonstrate that ResidualBind captures robust recognition principles that correlate well with experimentally determined  $K_d$  values. We also employ saliency analysis on ResidualBind to visually visualize the important nucleotides that compose the learned recognition code. We then explore the generalization performance of a pre-trained ResidualBind model across various *in vivo* CLIP-based datasets.

## RNAcompete overview [1]

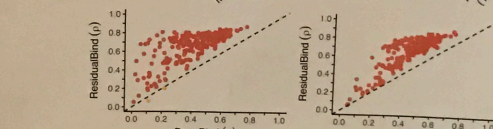
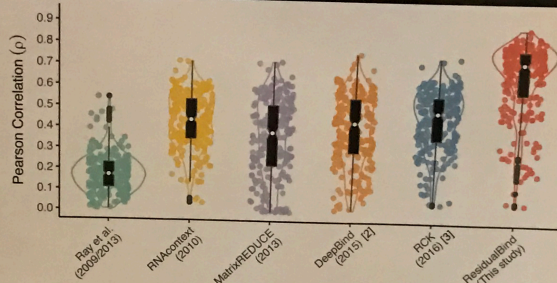
RNAcompete measures binding affinity scores for a given RBP across ~240K short RNA sequences



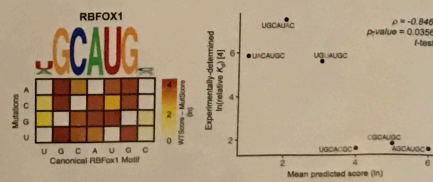
## ResidualBind architecture



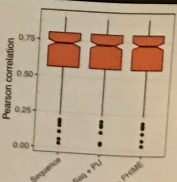
## ResidualBind performance is state-of-the-art



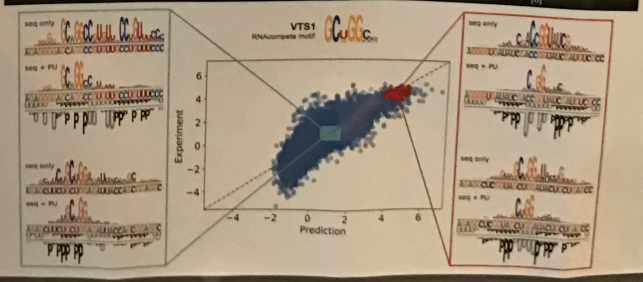
## Predictions correlate with experimental binding affinities



## Predictions with secondary structures



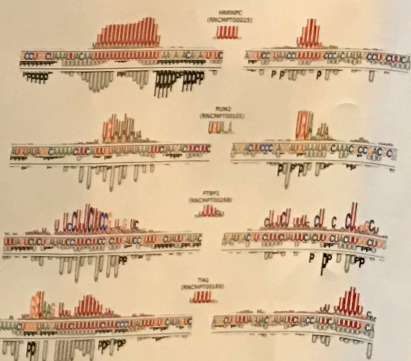
## Secondary structure simplifies learned representations



## In vivo generalization performance



- ResidualBind generalizes comparably to previous methods
- Biases in RNAcompete limits generalization - partial binding domains, sequence bias, limited structures, exp. conditions, etc...



- Limited sequence diversity of RNAcompete may not fully capture *in vivo* recognition principles

## Future

- Currently exploring large-scale eCLIP datasets (AUC: 0.936 ± 0.064 across 159 experiments)
- Applications: identify the potential function of a given transcript by detecting and correlating putative RBP binding sites

## References

[1] Ray, Debashish, et al. "A compendium of RNA-binding motifs for decoding gene regulation." *Nature* 499:767-772 (2013).  
[2] Alipanahi, Babak, et al. "Predicting the sequence specificities of DNA and RNA-binding proteins by deep learning." *Nature biotechnology* 33:10 (2015): 1011-1019.  
[3] Chen, Yan, Yuhao Wang, and Boris Berger. "RCK: accurate and efficient inference of sequence- and structure-based protein-RNA binding models from RNAcompete data." *Bioinformatics* 32:12 (2016): 1911-1919.  
[4] Aueler, Sigrid D., et al. "Molecular basis of RNA recognition by the human alternative splicing factor Fox-1." *The EMBO journal* 25:1 (2006): 163-173.  
[5] Bernhart, Stephan H., Ivan L. Hofacker, and Peter F. Stadler. "Local RNA base pairing probabilities in large sequences." *Bioinformatics* 22:5 (2006): 614-615.  
[6] Springenberg, Joel Tobias, et al. "Spawning for simplicity: The self-organizing net." *arXiv preprint arXiv:1412.8509* (2014).