

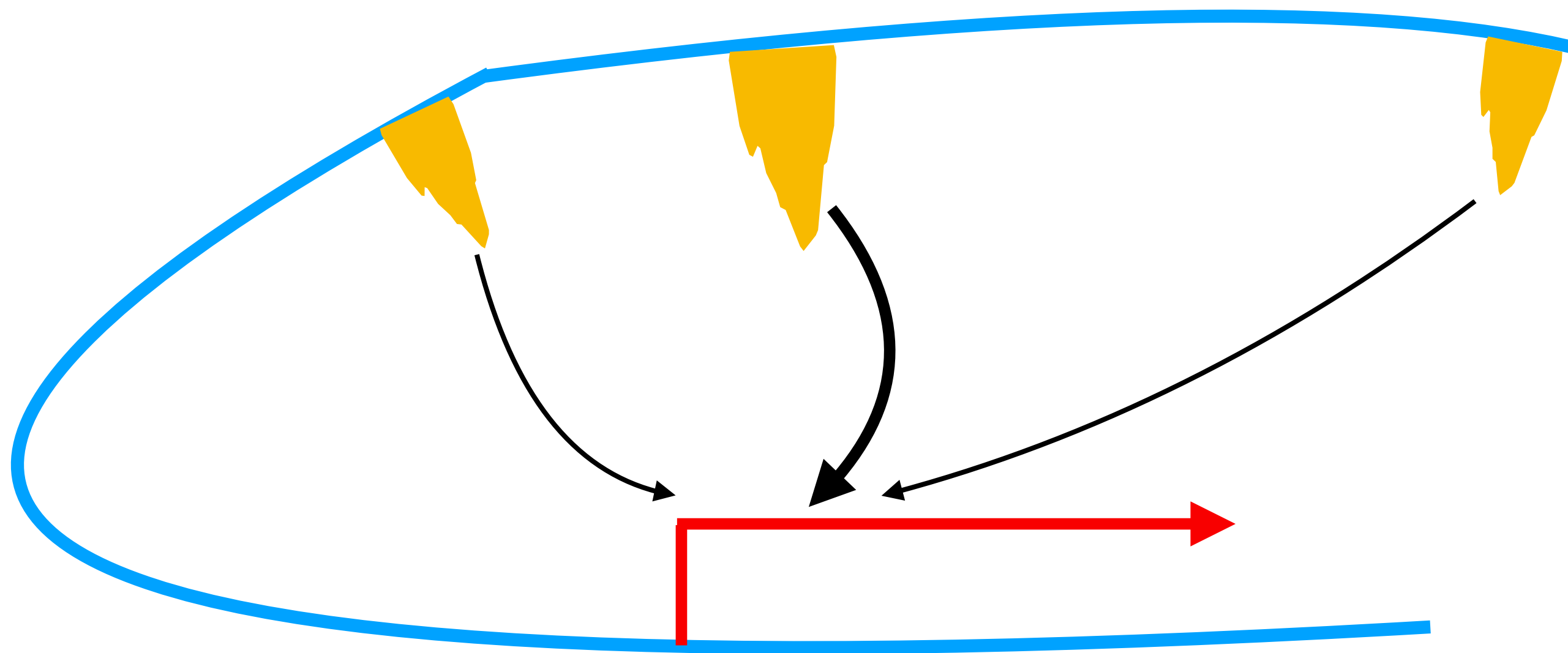
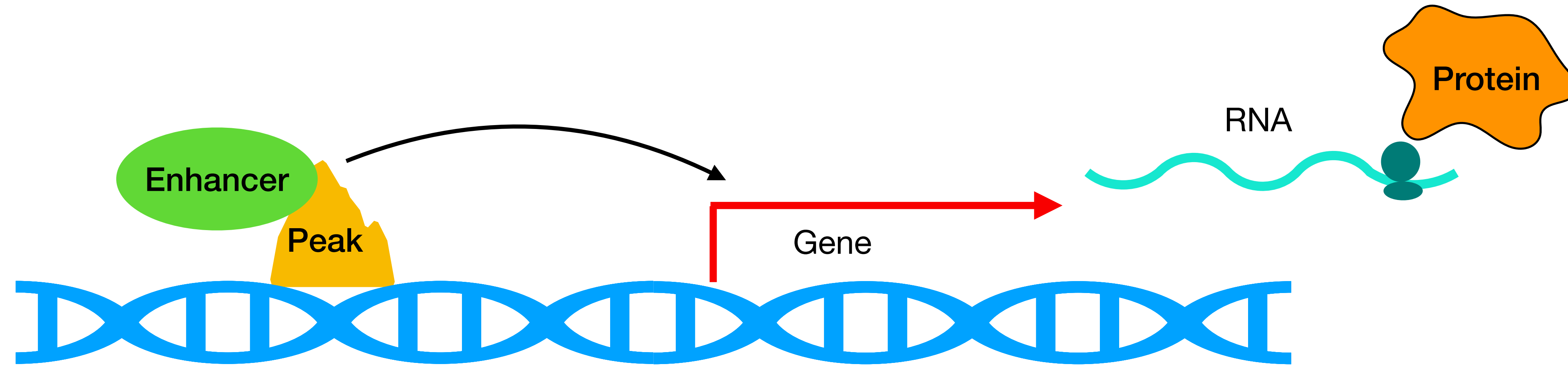
# Activity-by-Contact Model to Predict Enhancer-Gene Connections

Lillian Petersen

McVicker's Lab

Salk Institute for Biological Sciences

# Enhancers Control Gene Expression

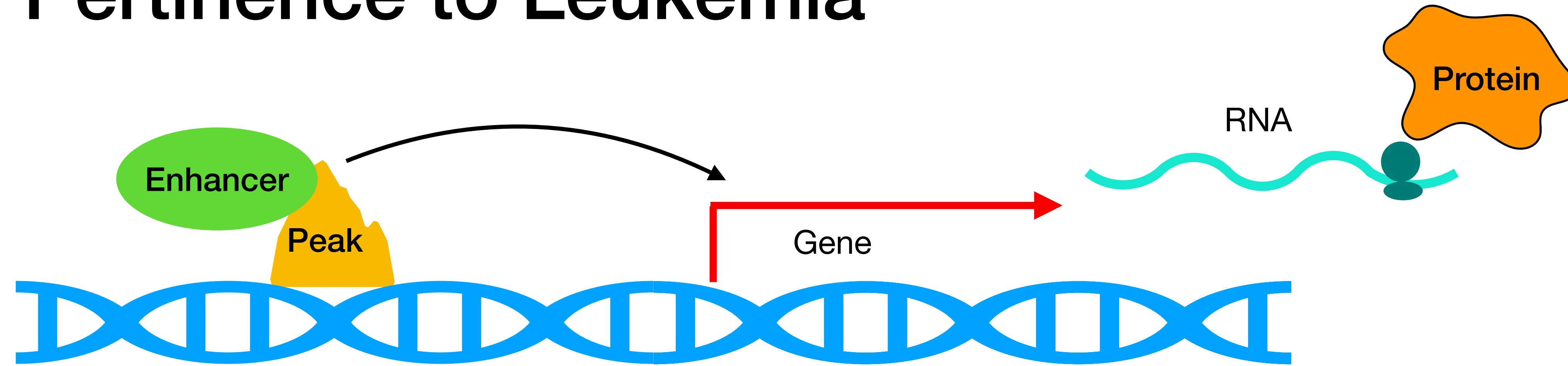


- Multiple enhancers control one gene
- An enhancer may control many genes
- Connections span large genomic distances

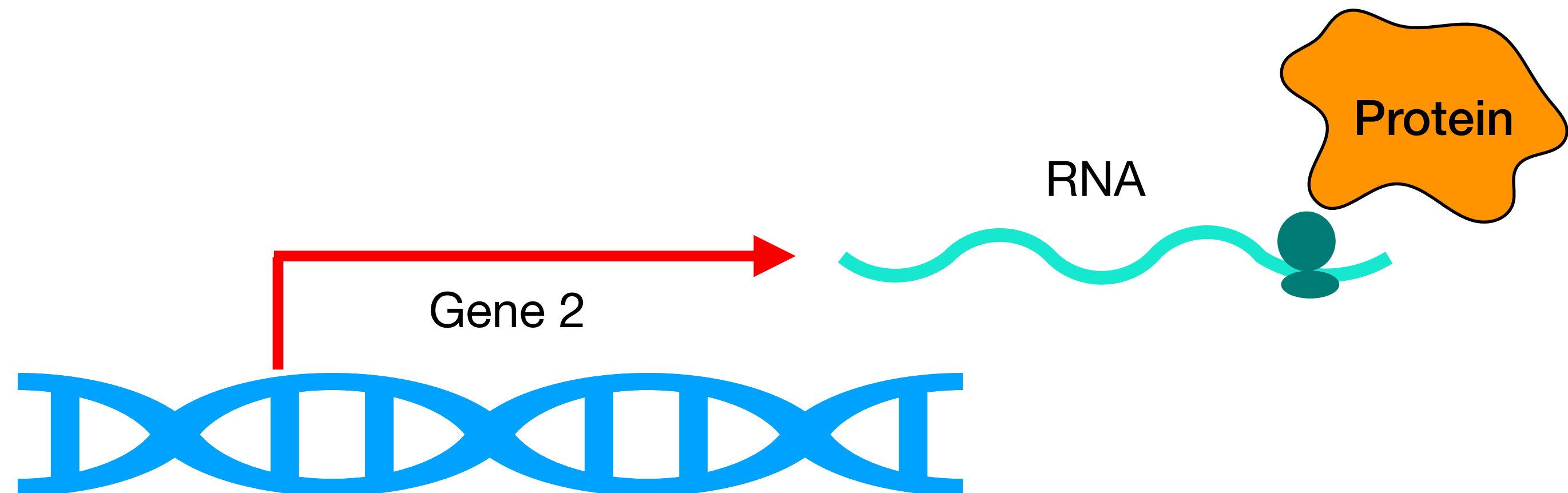
## Theories:

- Biochemical Specificity
- 3D Architecture (topological domains)

# Pertinence to Leukemia



- A mutation or translocation may change the expression of a gene and lead to the creation of an oncogene

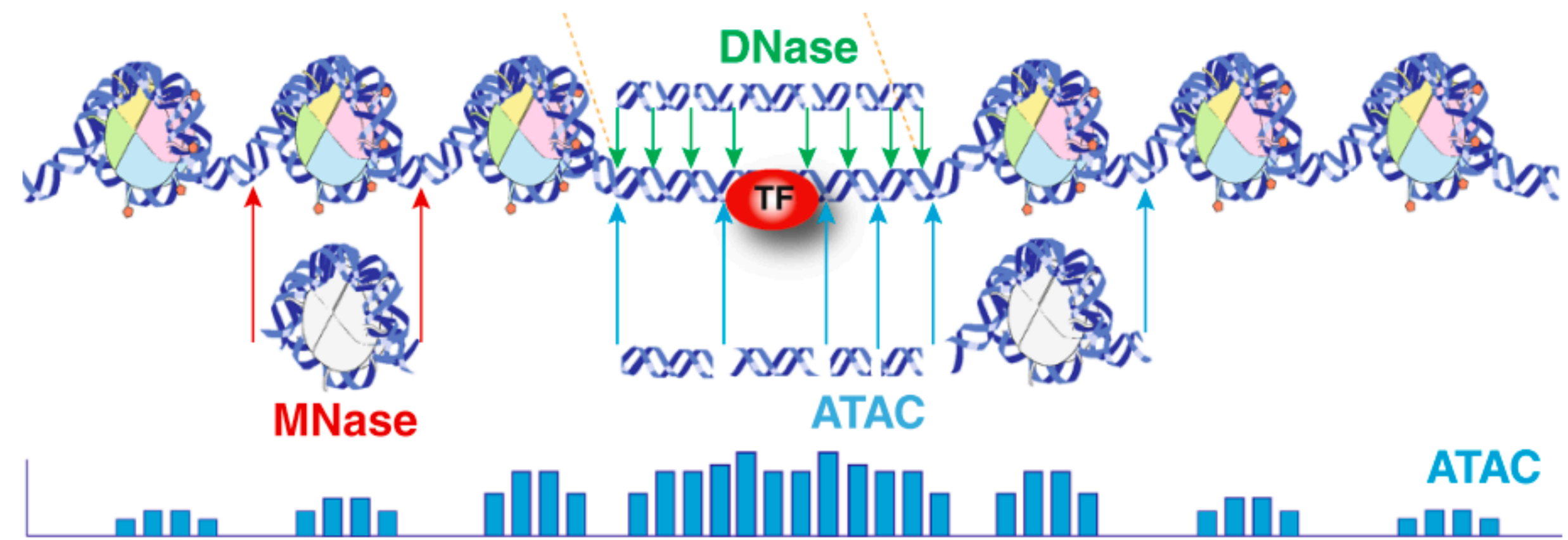


# Connecting Enhancers to Genes: Importance

- Better understanding of the activation of oncogenes
- Identify transcription factor binding sites
- Possibly identify kinases for drug targets

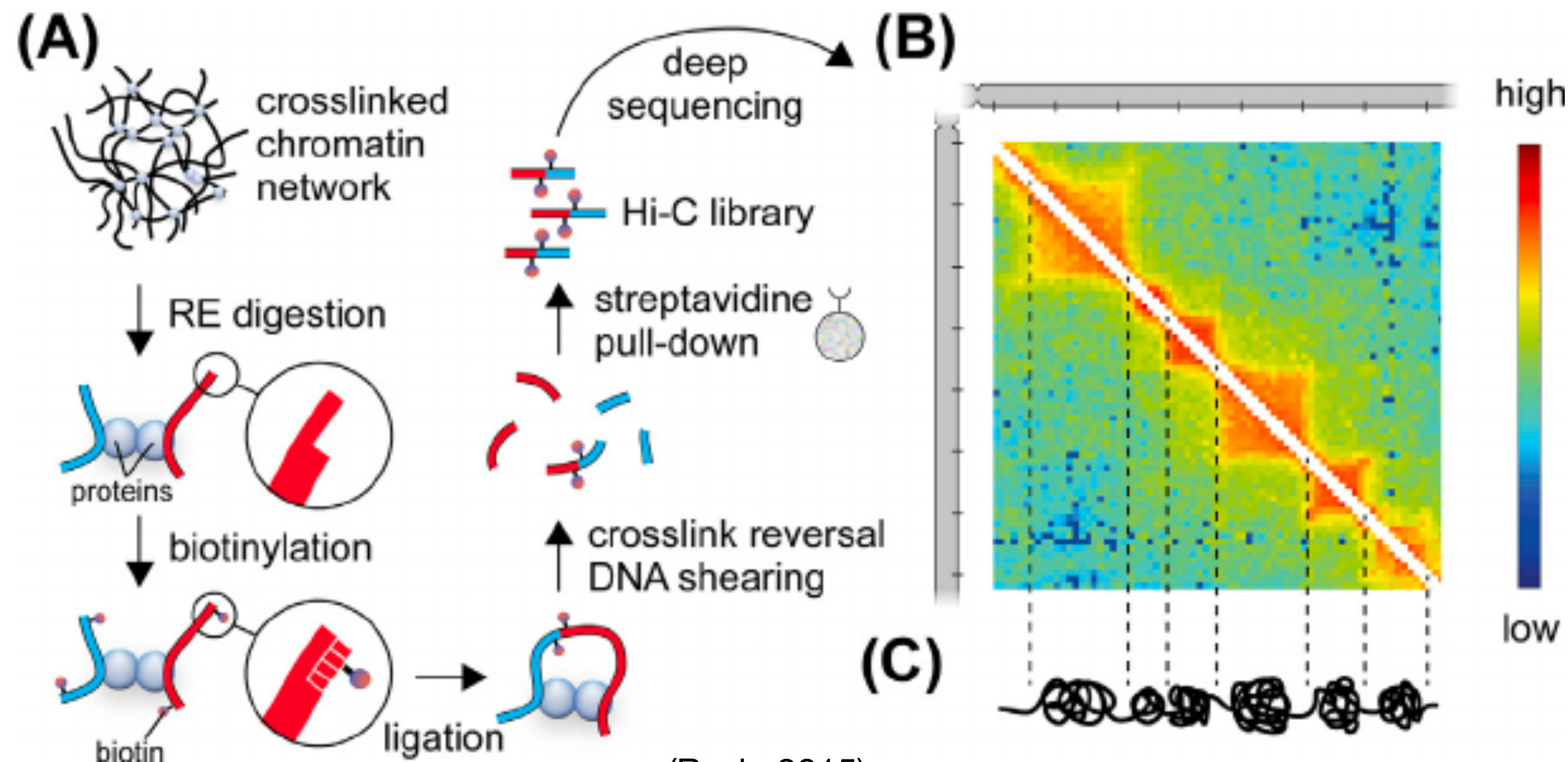
# Sequencing Methods

## ATAC-seq: Chromatin Accessibility



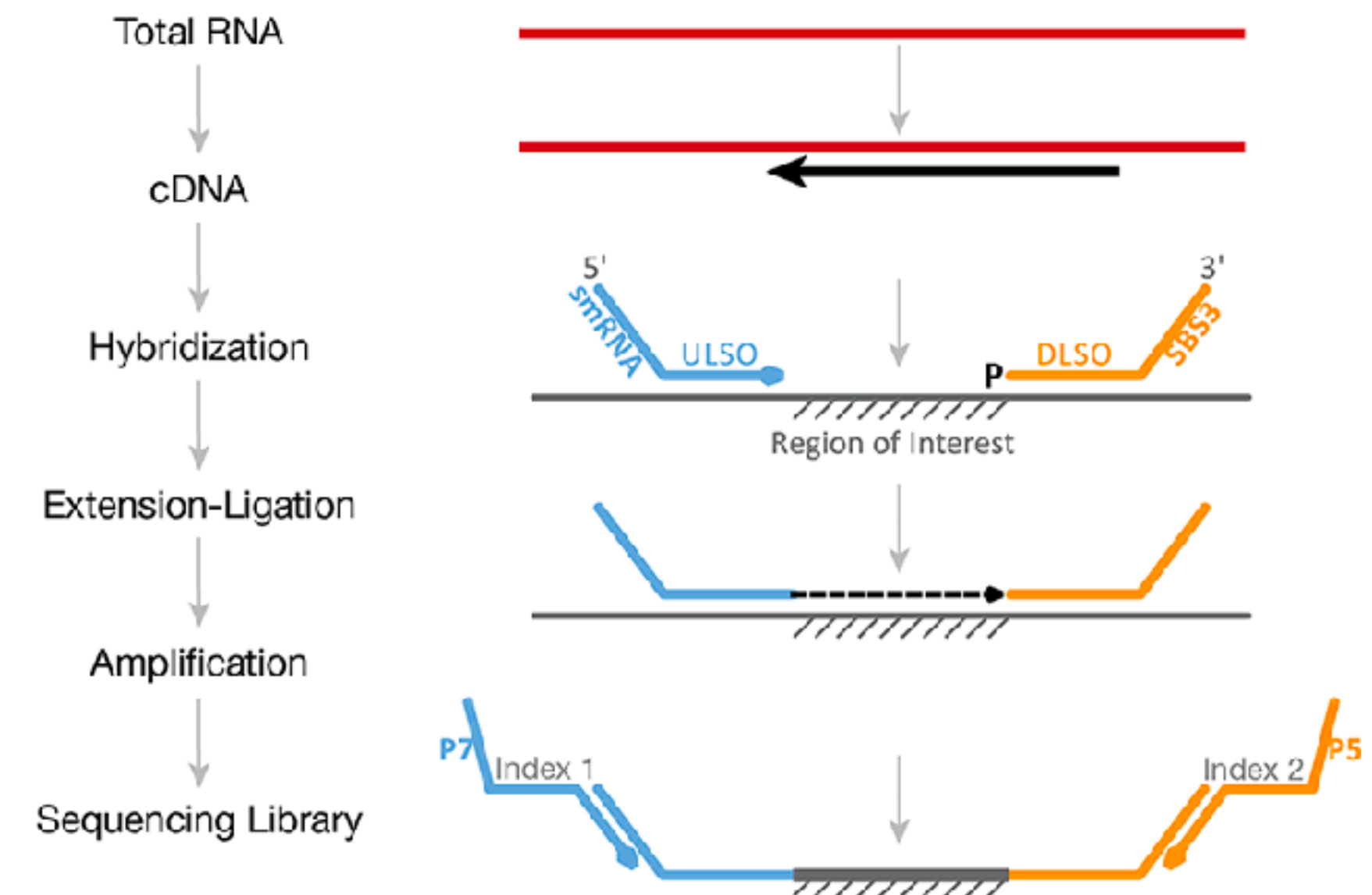
(Yiwei 2019)

## HiC: Contact Frequency



(Razin 2015)

## RNA-seq: Gene Expression



# Equation

**Activity-by-Contact (ABC) = Activity (ATAC) x Contact (HiC)**

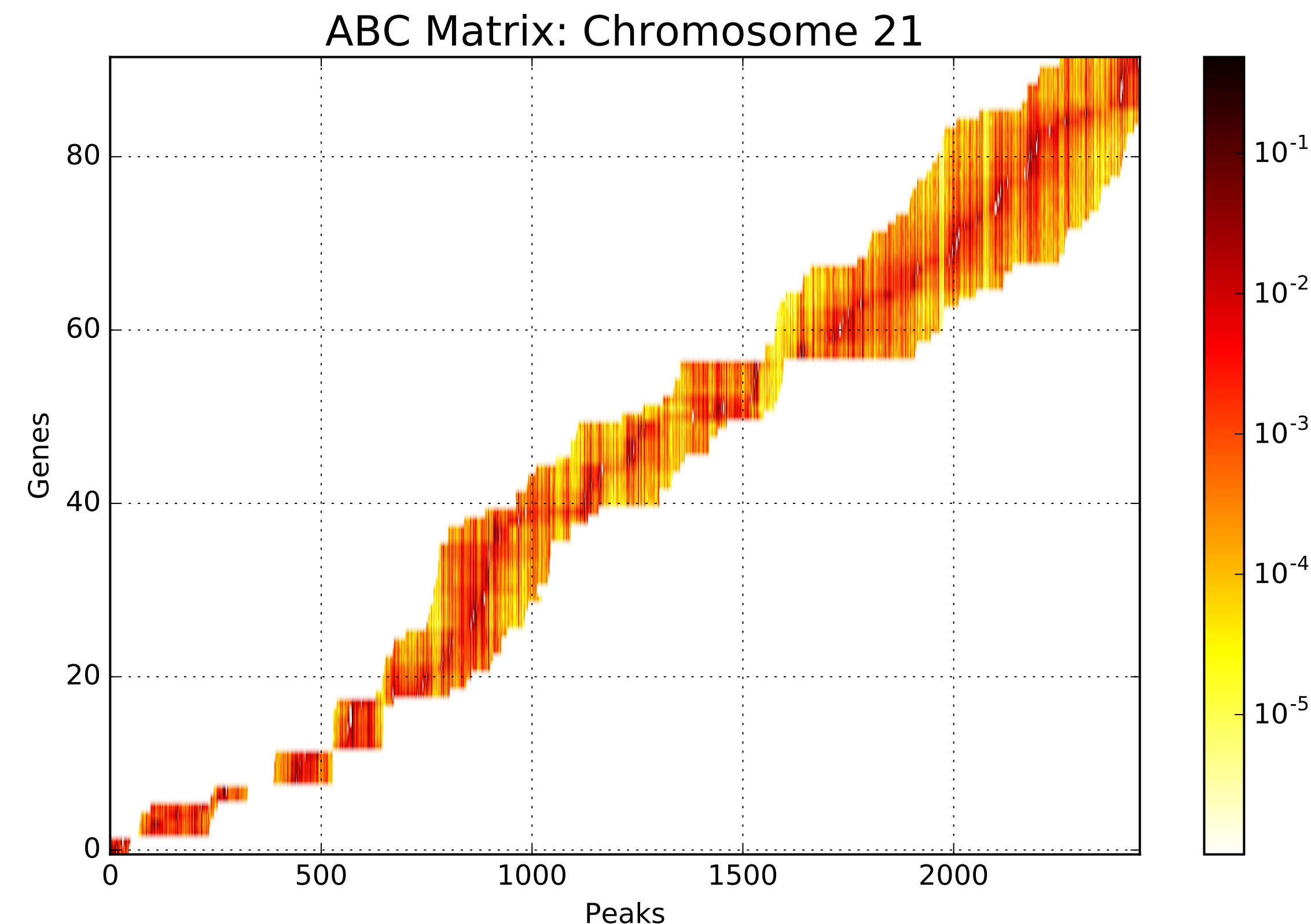
$$\text{ABC score}_{E-G} = \frac{A_E \times C_{E-G}}{\sum_{e \text{ within } 5 \text{ Mb}} A_e \times C_{e-G}}$$

- Identify peaks that are likely regulatory elements for specific genes

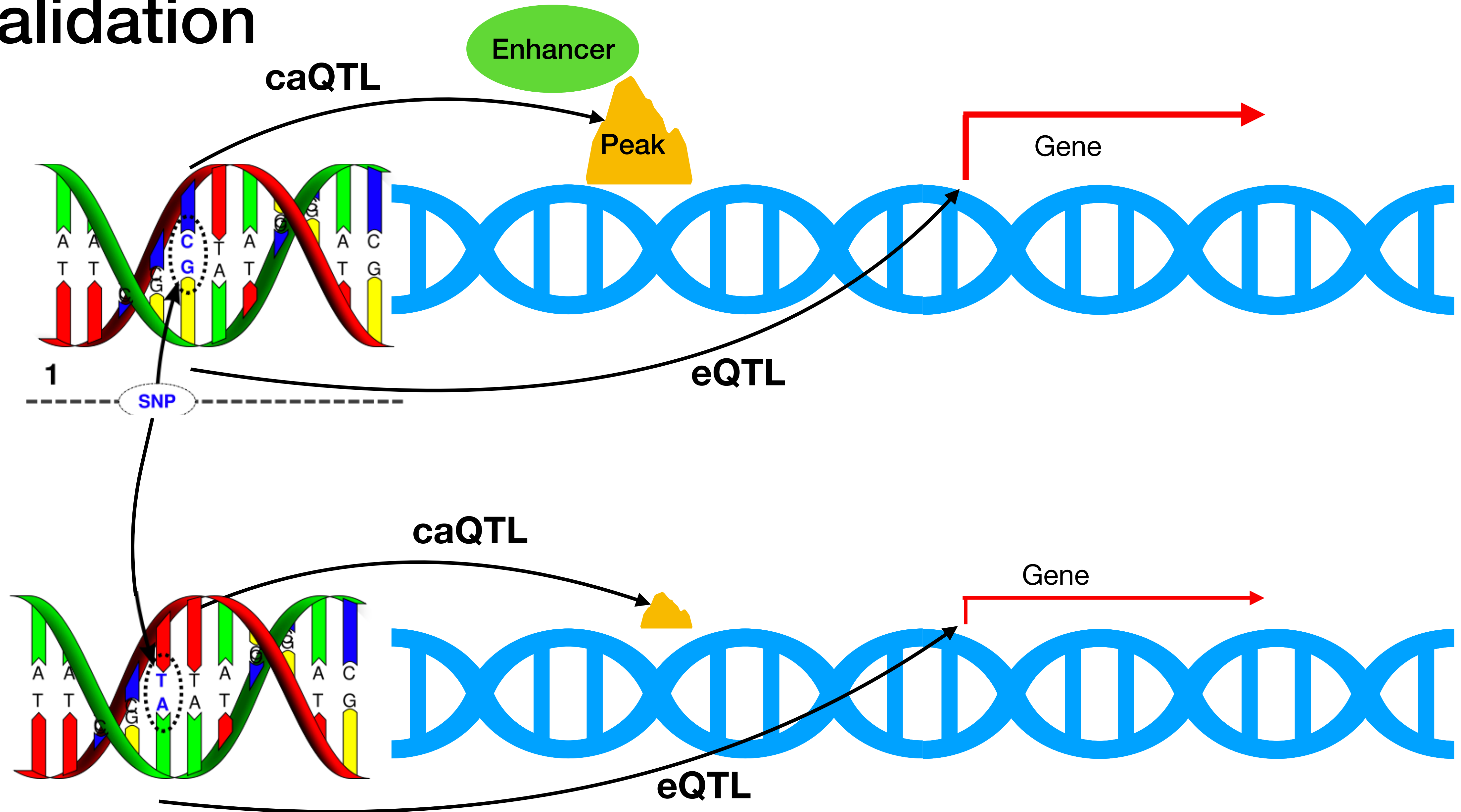


# Data and Computation

- 16 Leukemia B ALL samples with ATAC-seq, HiC, and RNA-seq
  - HiC matrices: merged to a single, high-resolution matrix
  - 10,000 protein-coding genes and 120,000 peaks
- Computed ABC score for every possible peak-gene connection within 1.5 Mb of TSS
- Computed other indices to predict connections
  - Distance from peak—gene
  - Correlation between peak intensity (ATAC) and gene expression



# Validation





# caQTL Publication

- Gate et al. (2018) identified caQTLs and eQTLs in T cells
- We can use this data to gain a list of known connections to examine the efficacy of the ABC model

## Genetic determinants of co-accessible chromatin regions in activated T cells across humans

Rachel E. Gate<sup>1,2,21</sup>, Christine S. Cheng<sup>3,4,21\*</sup>, Aviva P. Aiden<sup>5,6</sup>, Atsede Siba<sup>3</sup>, Marcin Tabaka<sup>3</sup>, Dmytro Lituiev<sup>1</sup>, Ido Machol<sup>5</sup>, M. Grace Gordon<sup>2</sup>, Meena Subramaniam<sup>1,2</sup>, Muhammad Shamim<sup>5,7</sup>, Kendrick L. Hougen<sup>8</sup>, Ivo Wortman<sup>3</sup>, Su-Chen Huang<sup>5</sup>, Neva C. Durand<sup>5</sup>, Ting Feng<sup>9</sup>, Philip L. De Jager<sup>3,10,11</sup>, Howard Y. Chang<sup>12</sup>, Erez Lieberman Aiden<sup>5,7,13,14,15</sup>, Christophe Benoist<sup>9</sup>, Michael A. Beer<sup>8,16</sup>, Chun J. Ye<sup>1,17,18,19\*</sup> and Aviv Regev<sup>3,20\*</sup>

Over 90% of genetic variants associated with complex human traits map to non-coding regions, but little is understood about how they modulate gene regulation in health and disease. One possible mechanism is that genetic variants affect the activity of one or more cis-regulatory elements leading to gene expression variation in specific cell types. To identify such cases, we analyzed ATAC-seq and RNA-seq profiles from stimulated primary CD4<sup>+</sup> T cells in up to 105 healthy donors. We found that regions of accessible chromatin (ATAC-peaks) are co-accessible at kilobase and megabase resolution, consistent with the three-dimensional chromatin organization measured by in situ Hi-C in T cells. Fifteen percent of genetic variants located within ATAC-peaks affected the accessibility of the corresponding peak (local-ATAC-QTLs). Local-ATAC-QTLs have the largest effects on co-accessible peaks, are associated with gene expression and are enriched for autoimmune disease variants. Our results provide insights into how natural genetic variants modulate cis-regulatory elements, in isolation or in concert, to influence gene expression.

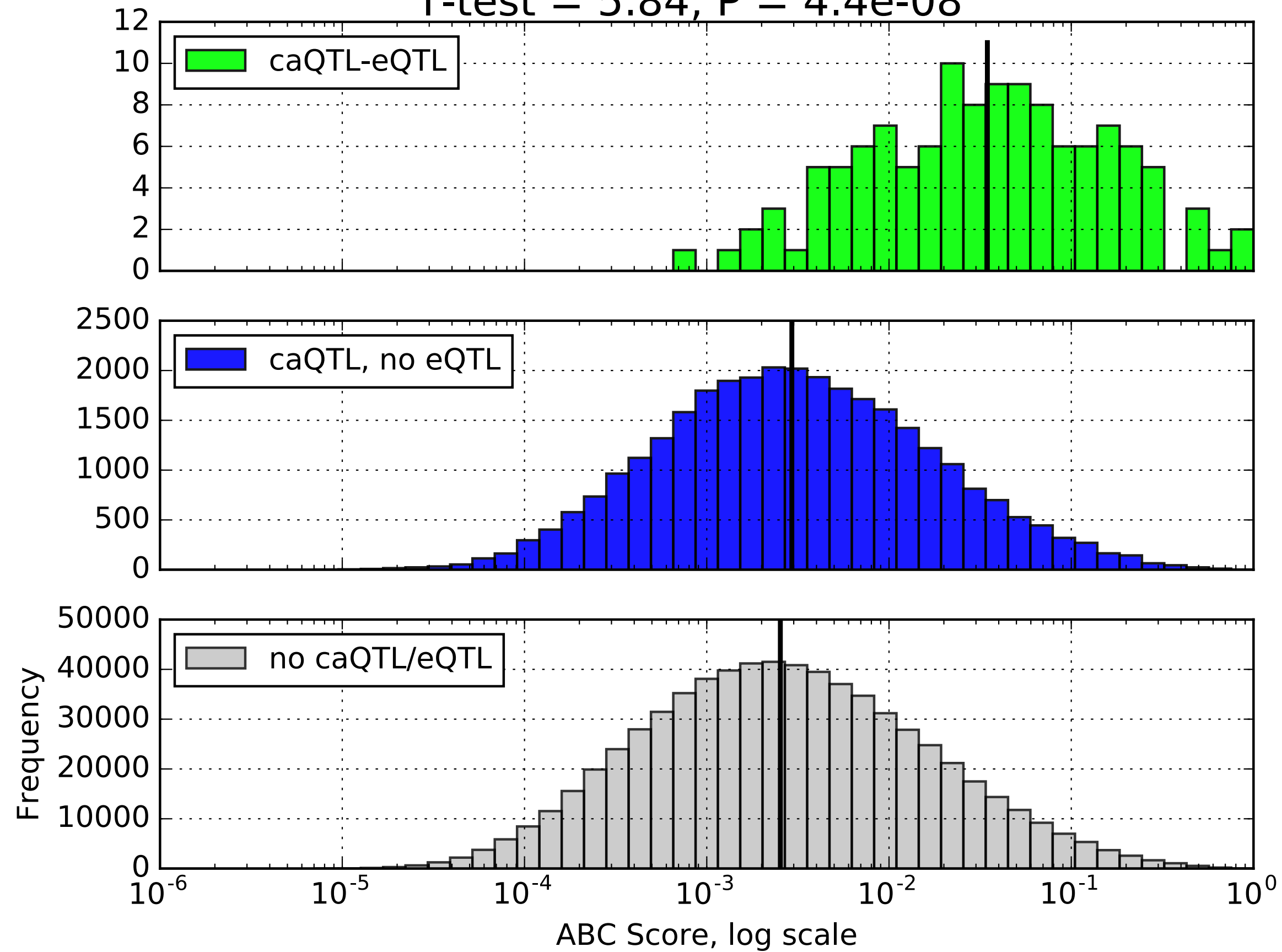
# Validation: Process

- Downloaded ATACseq, RNAseq data from GEO for 95 individuals in their study
- Our merged HiC matrix
- Identified peak-gene connections from caQTLs and eQTLs
  - 130 connections in total
- Computed ABC score, correlation between ATAC peaks and expression, distance from peak to tss

# Distributions by ABC Score and Distance

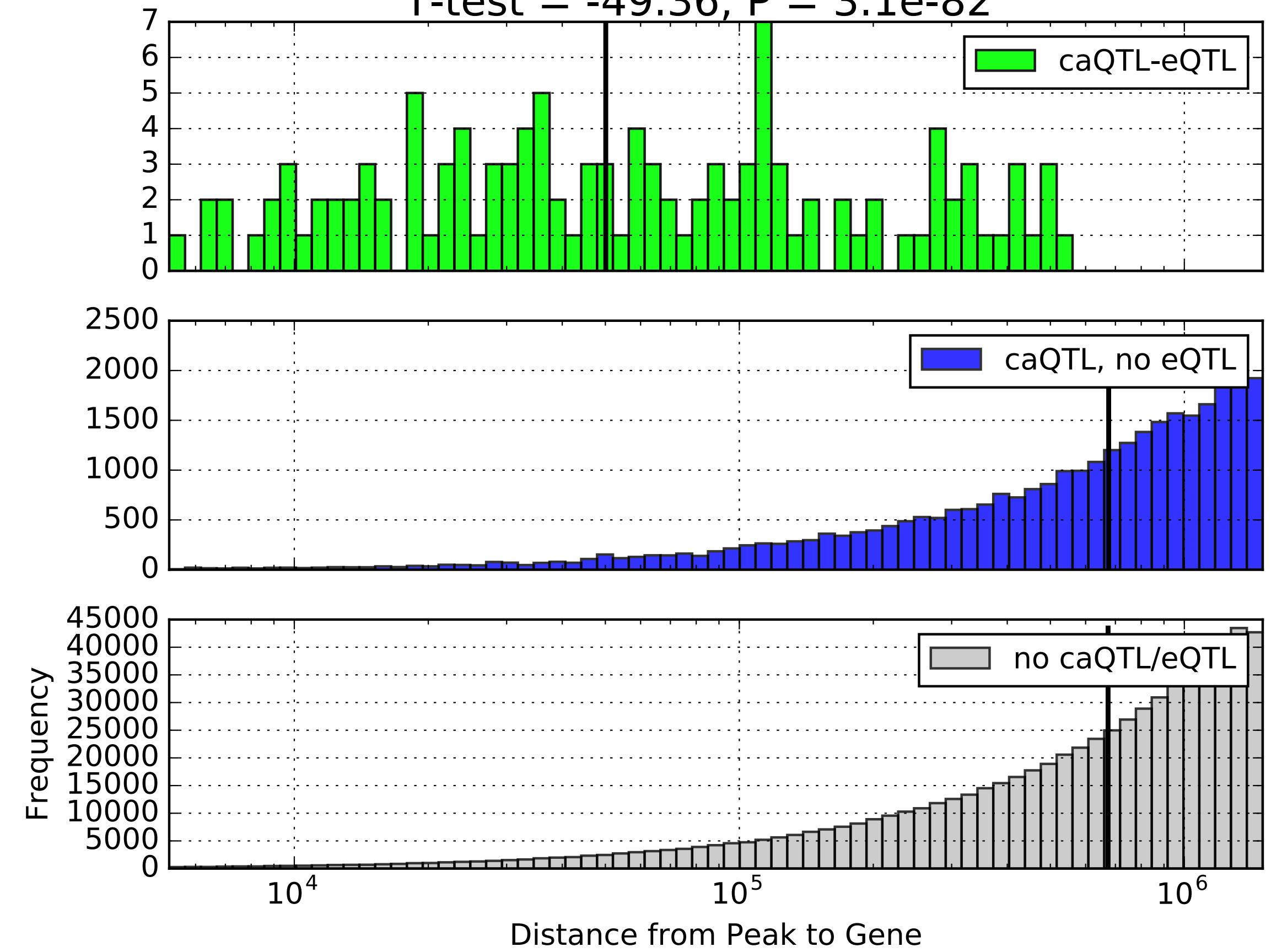
ABC Score of Known and Unknown Connections

T-test = 5.84, P = 4.4e-08



Distance of Known and Unknown Connections

T-test = -49.36, P = 3.1e-82

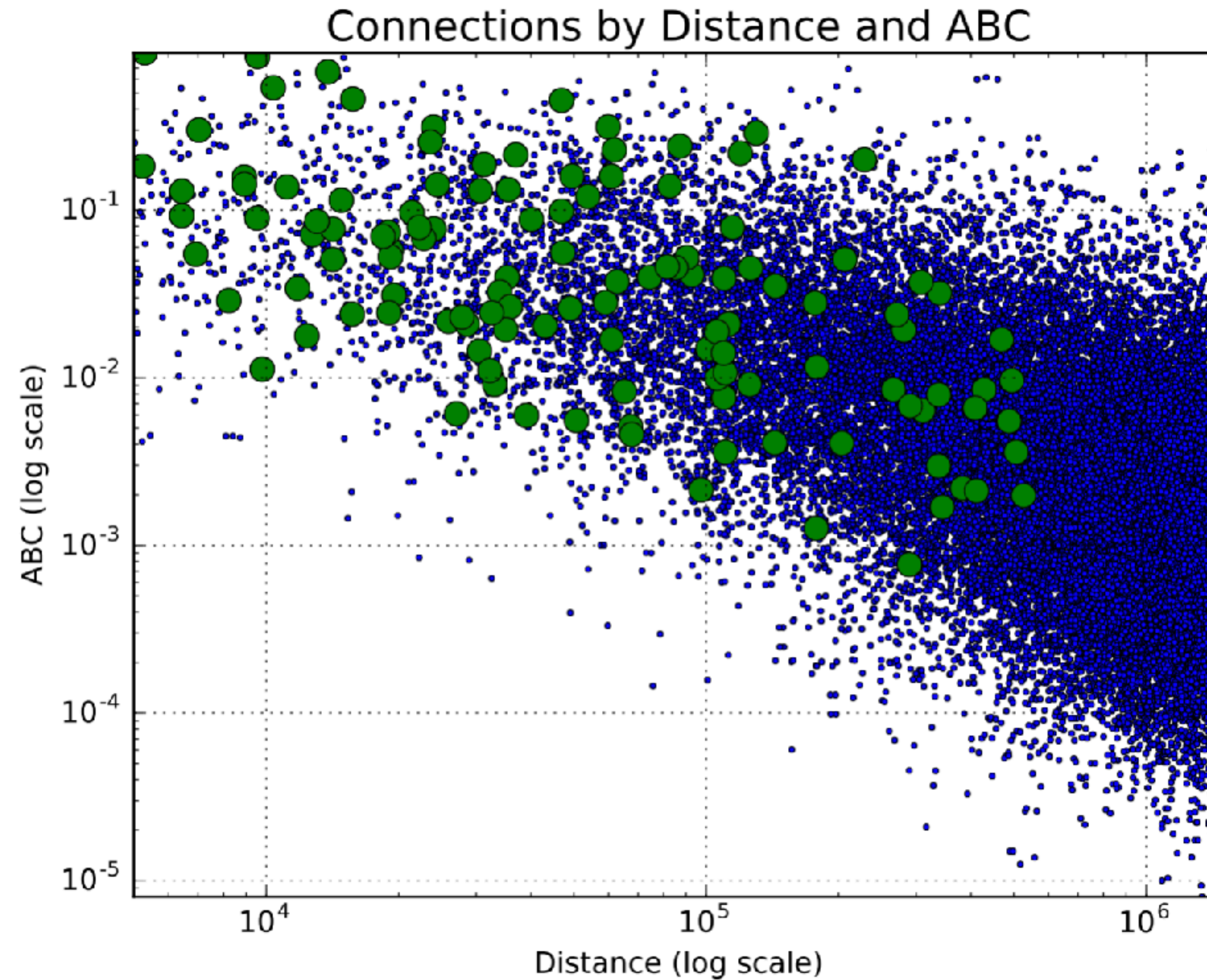


# Limitations of the Validation Dataset

- No *known negatives*
- Cannot detect connections with peaks or genes unaffected by SNPs
- caQTL-eQTL may be independent
- We don't have access to their entire dataset
- They likely cannot detect connections with small expression / peak intensity / low connectivity

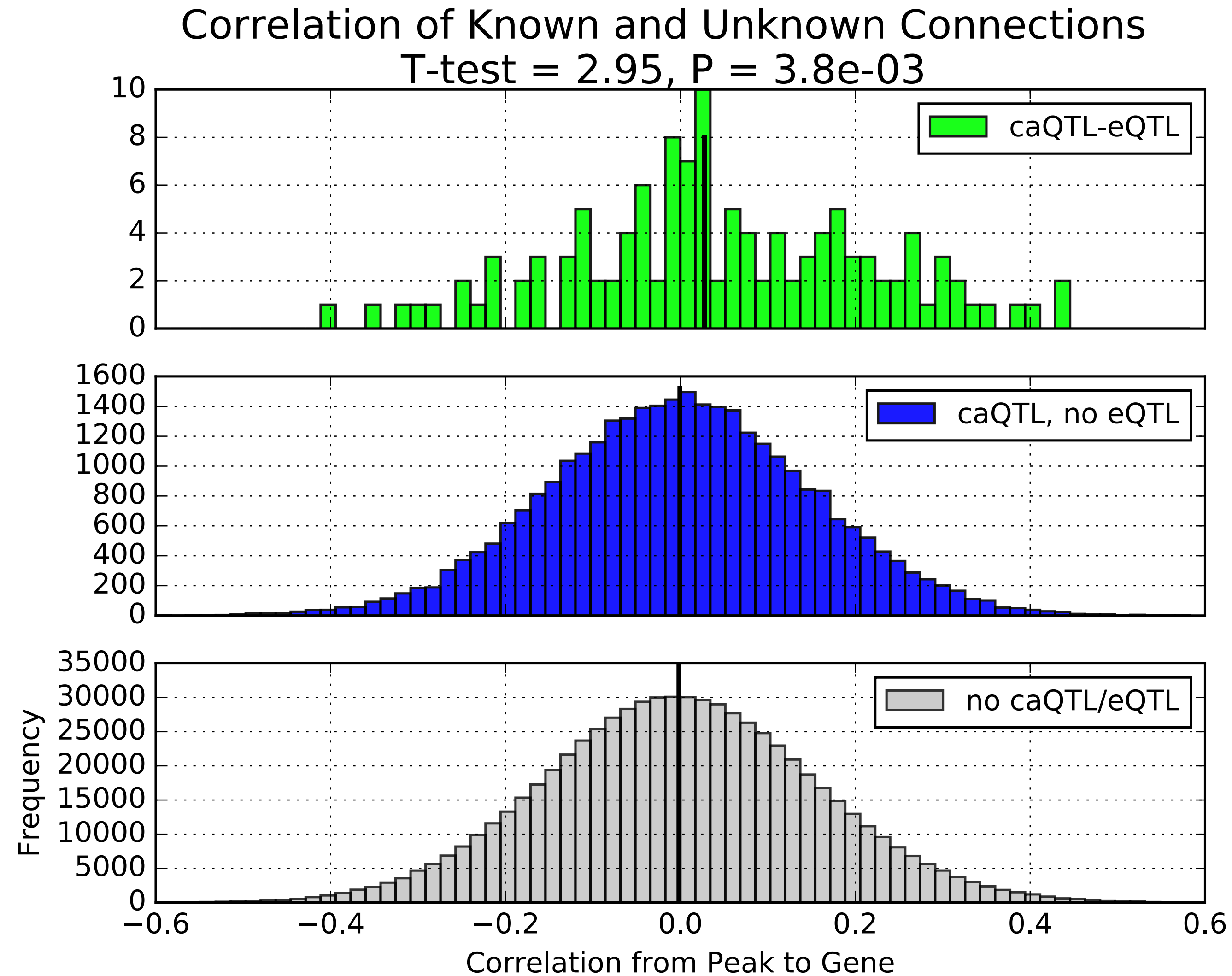


# ABC and Distance Log-Log Plot

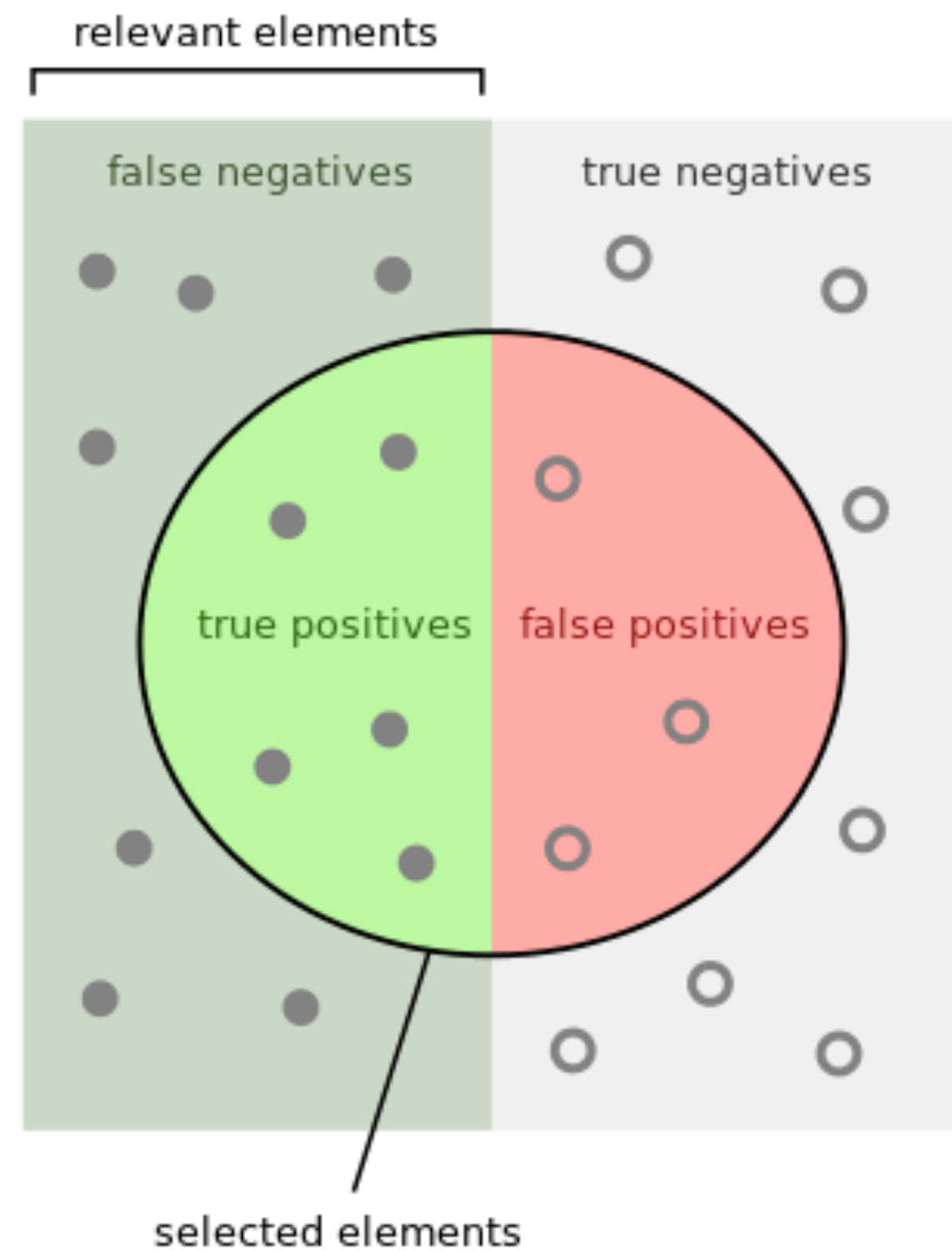




# Distributions by Correlation



# Precision Recall Curve

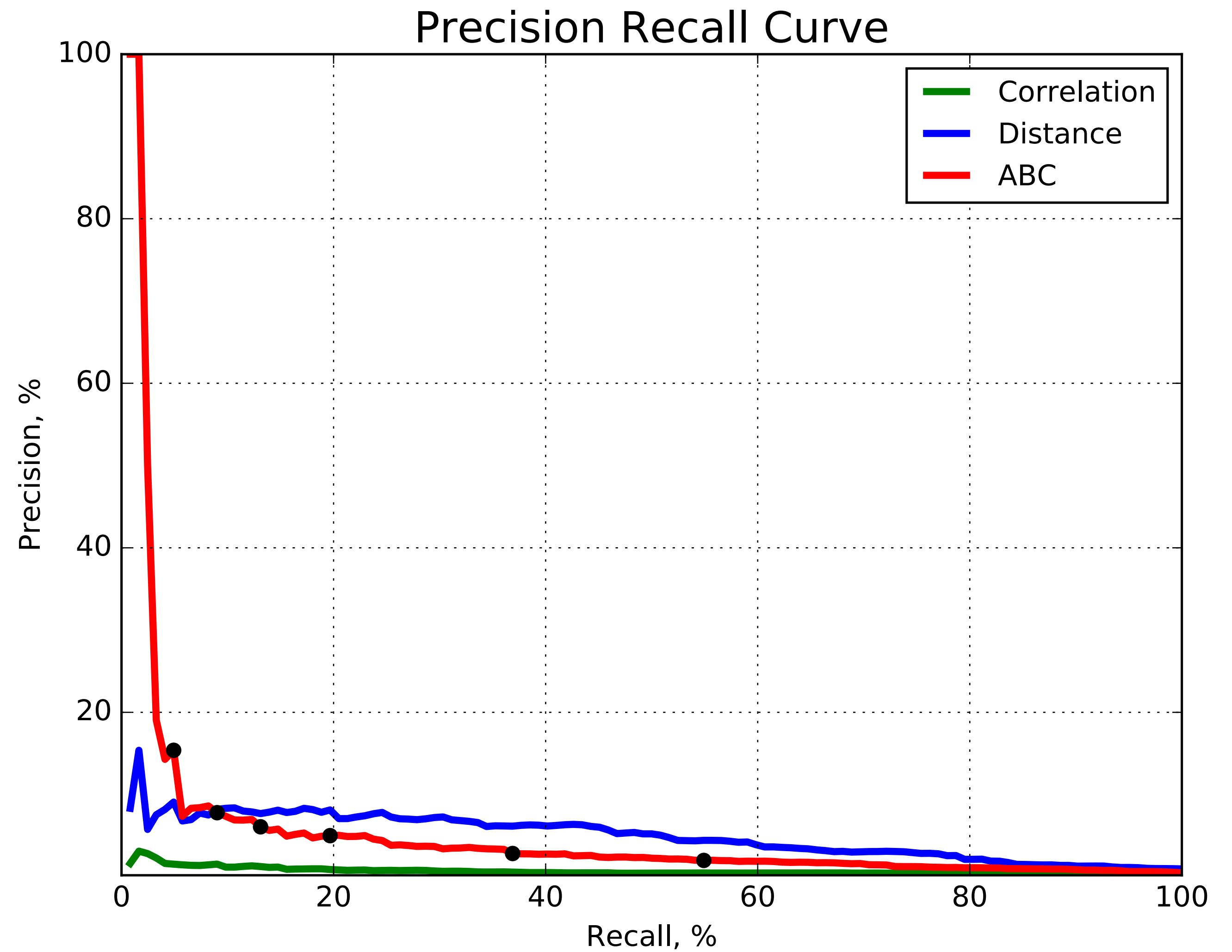


How many selected items are relevant?

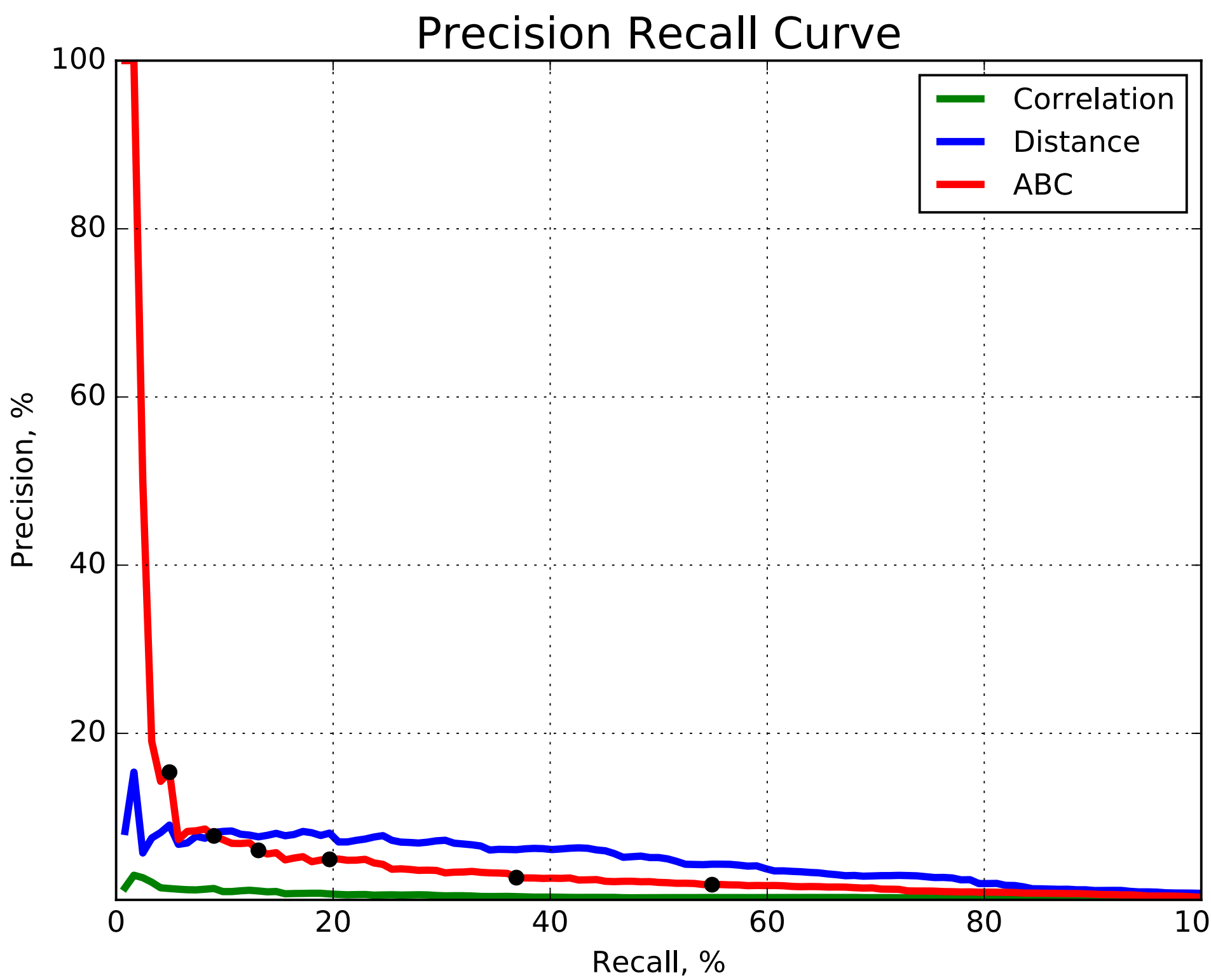
$$\text{Precision} = \frac{\text{true positives}}{\text{true positives} + \text{false positives}}$$

How many relevant items are selected?

$$\text{Recall} = \frac{\text{true positives}}{\text{true positives} + \text{false negatives}}$$



# Applying Validation To Leukemia Data

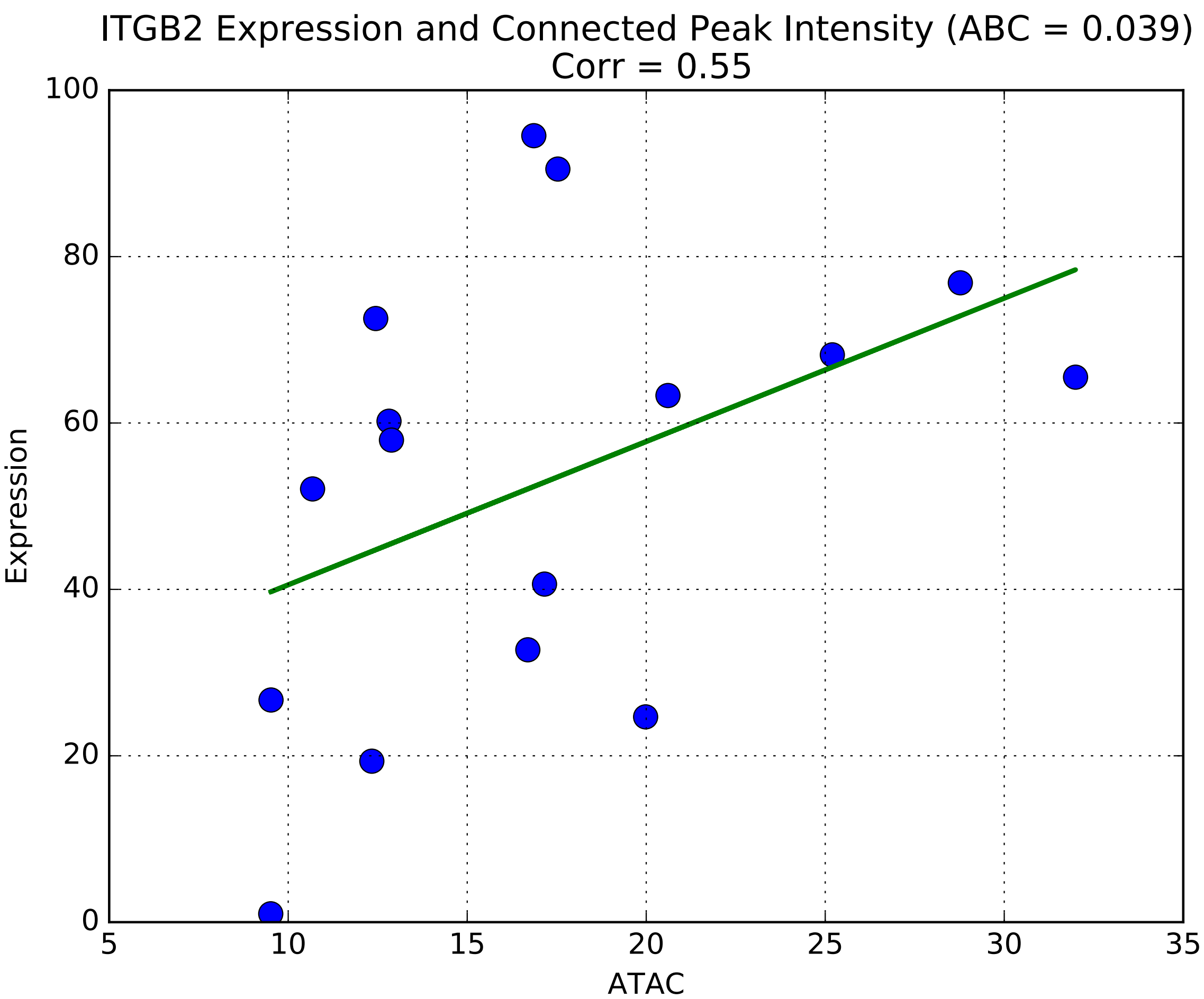
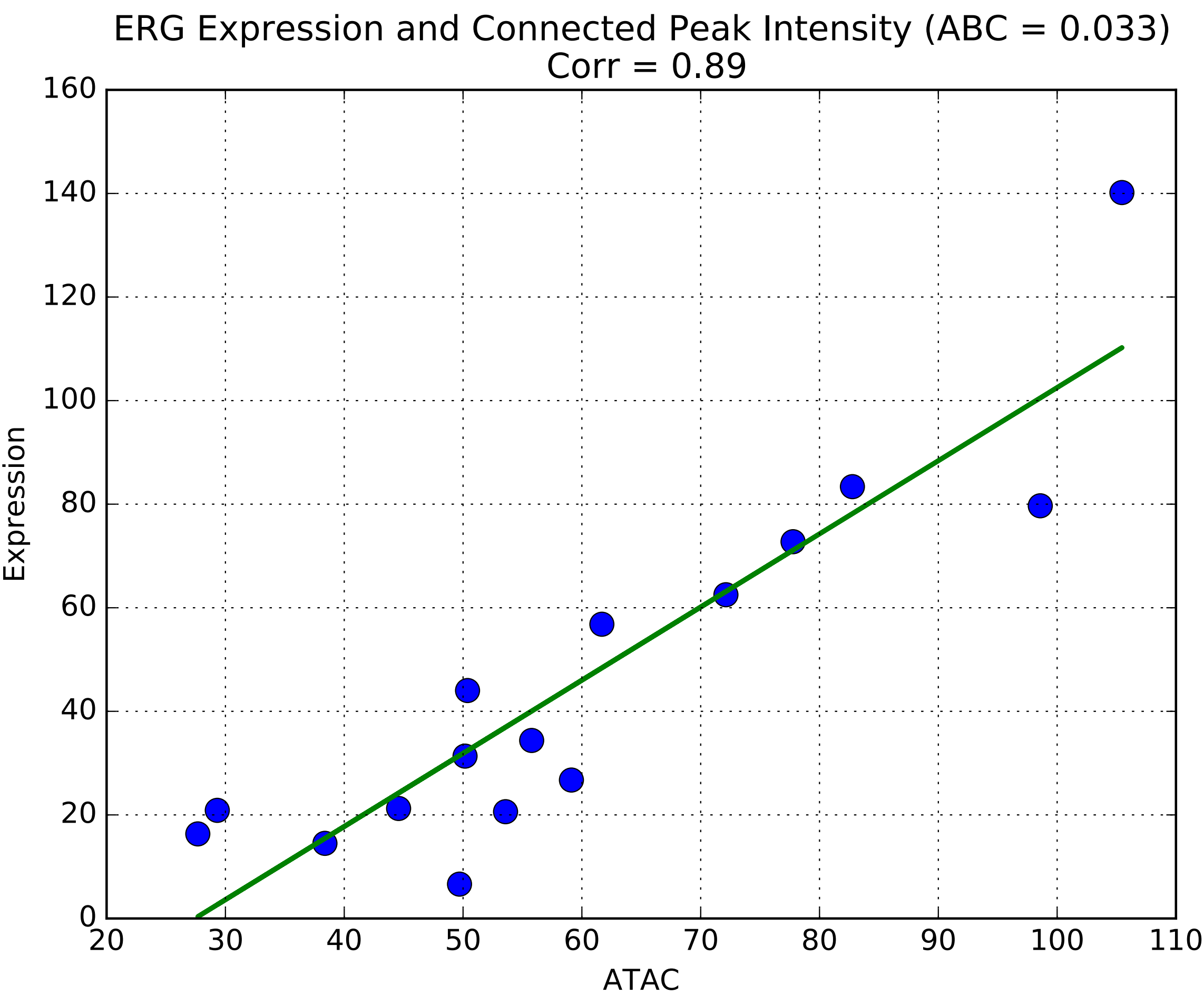


ABC	0.45	0.25	0.2	0.14	0.06	0.03
Precision	15%	8%	6%	5%	3%	2%
Recall	5%	9%	13%	20%	37%	55%

# Leukemia Data: Process

- Calculated ABC Score for every possible peak-gene connection (within 1.5Mb)
- Also computed computed:
  - Distance
  - Correlation
  - Slope
- Identified peak-gene connections by ABC cutoffs identified in validation (6 groups)

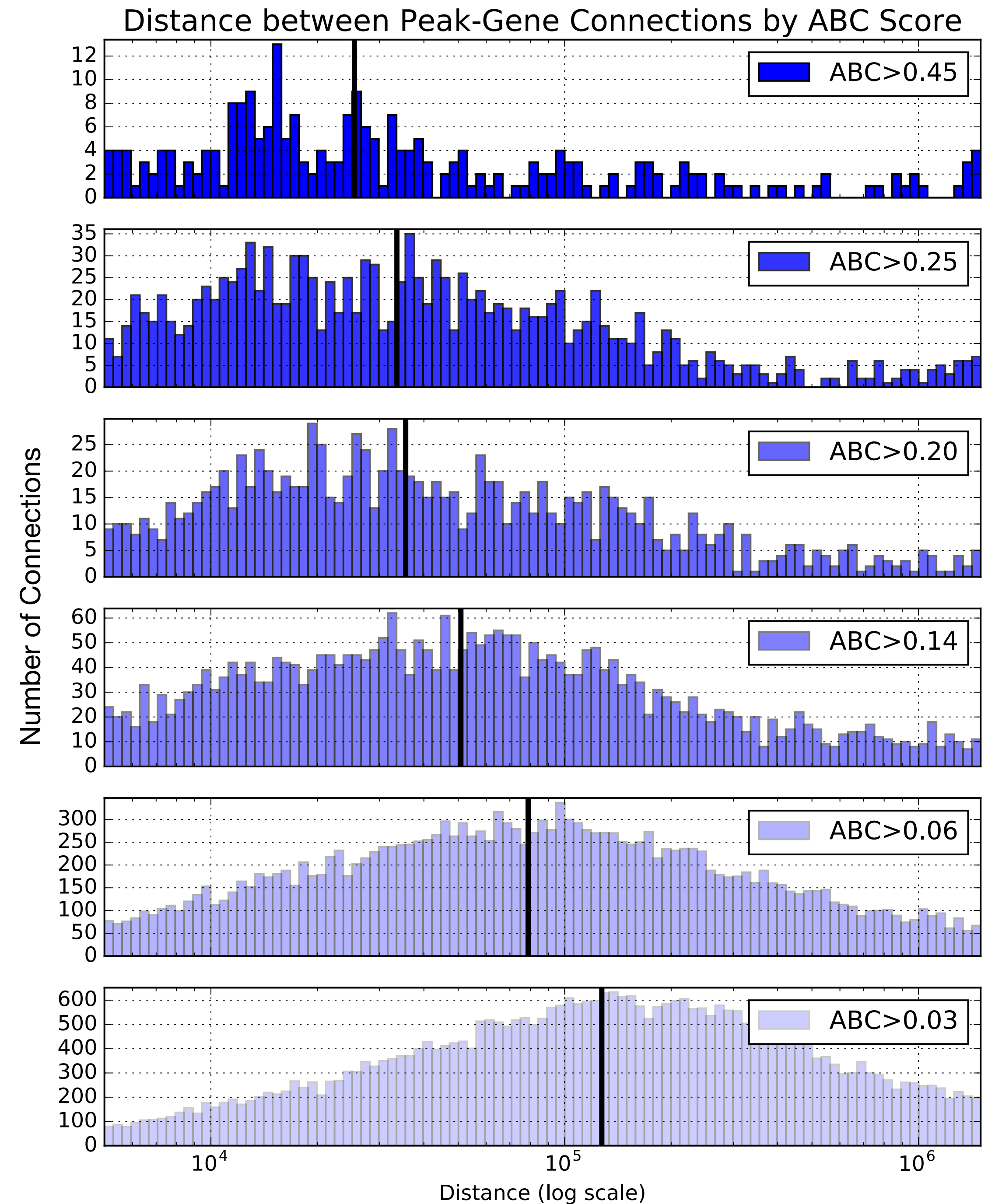
# Genes in Leukemia Dataset



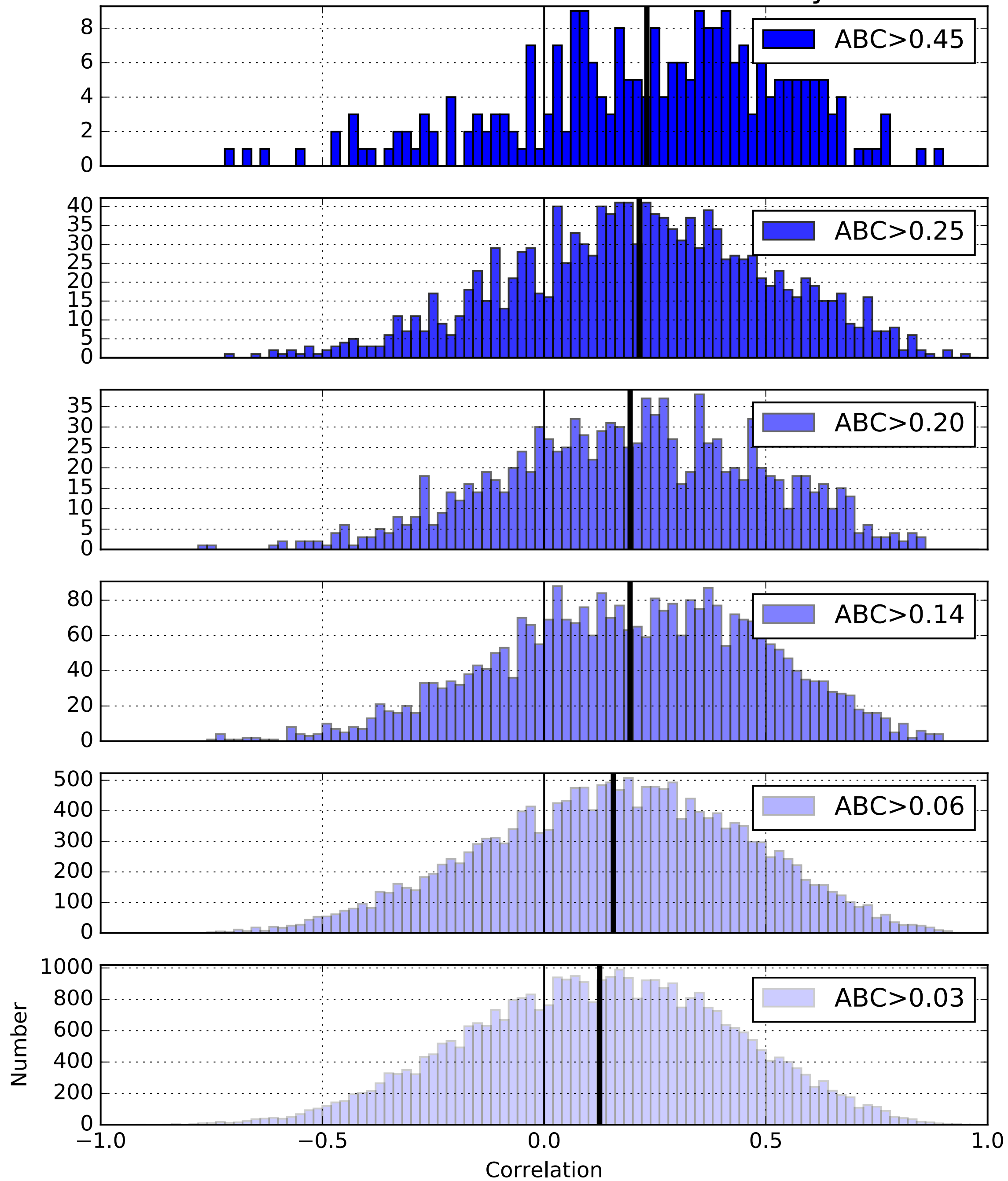


# Leukemia Data

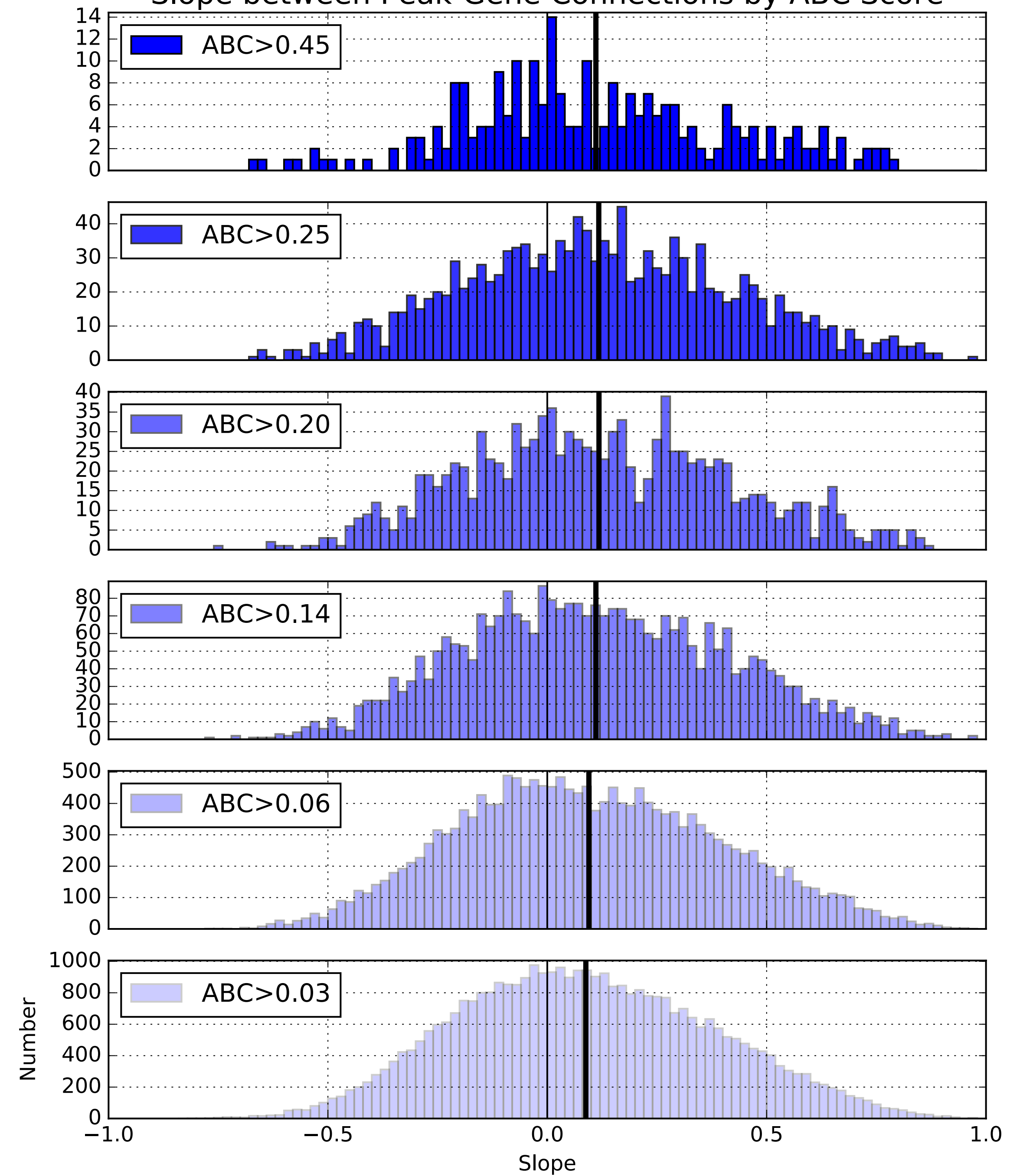
- Trends by ABC score:
  - Distance
  - Correlation
  - Slope
  - Peaks per gene
  - Genes per peak



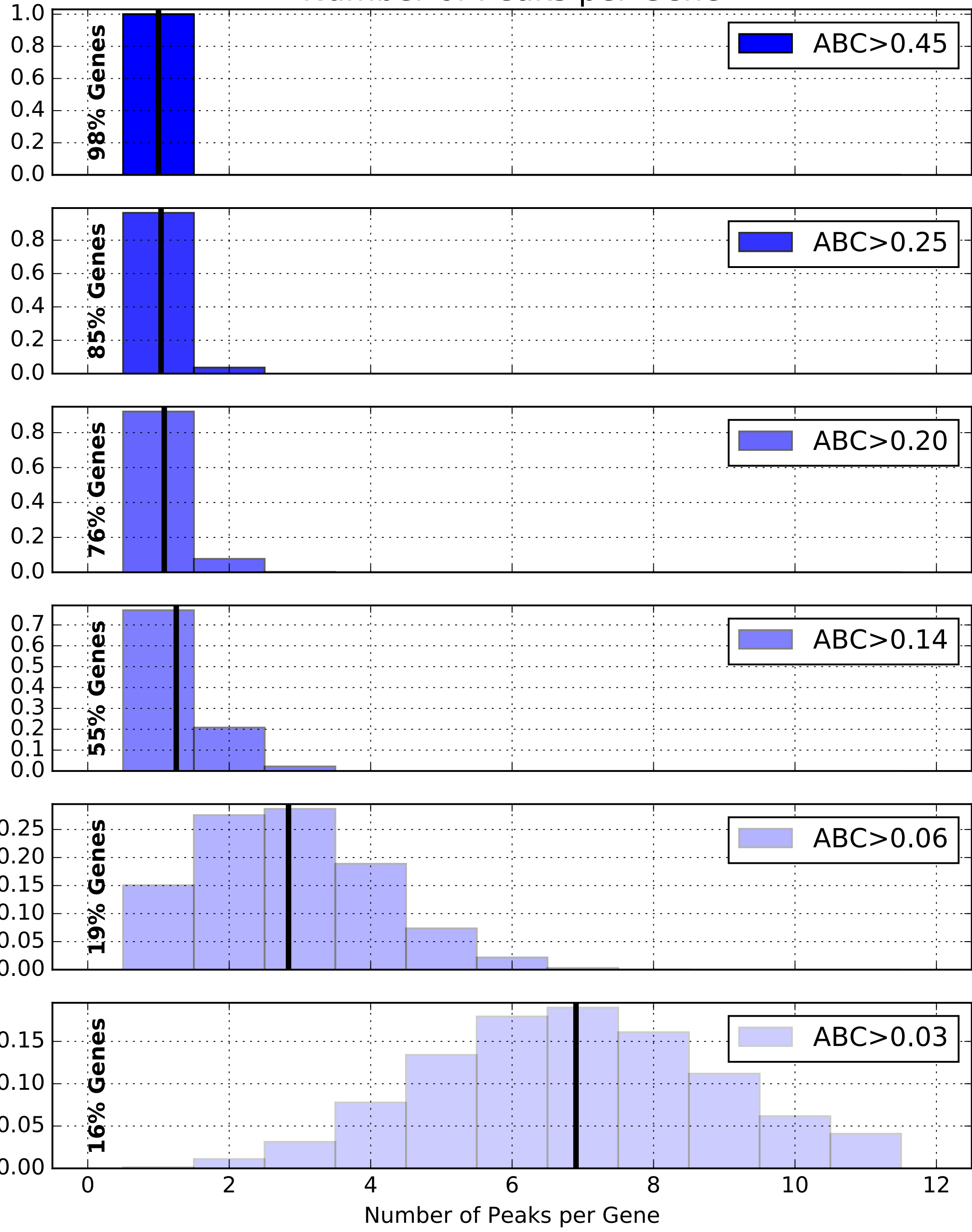
Correlations between Peak-Gene Connections by ABC Score



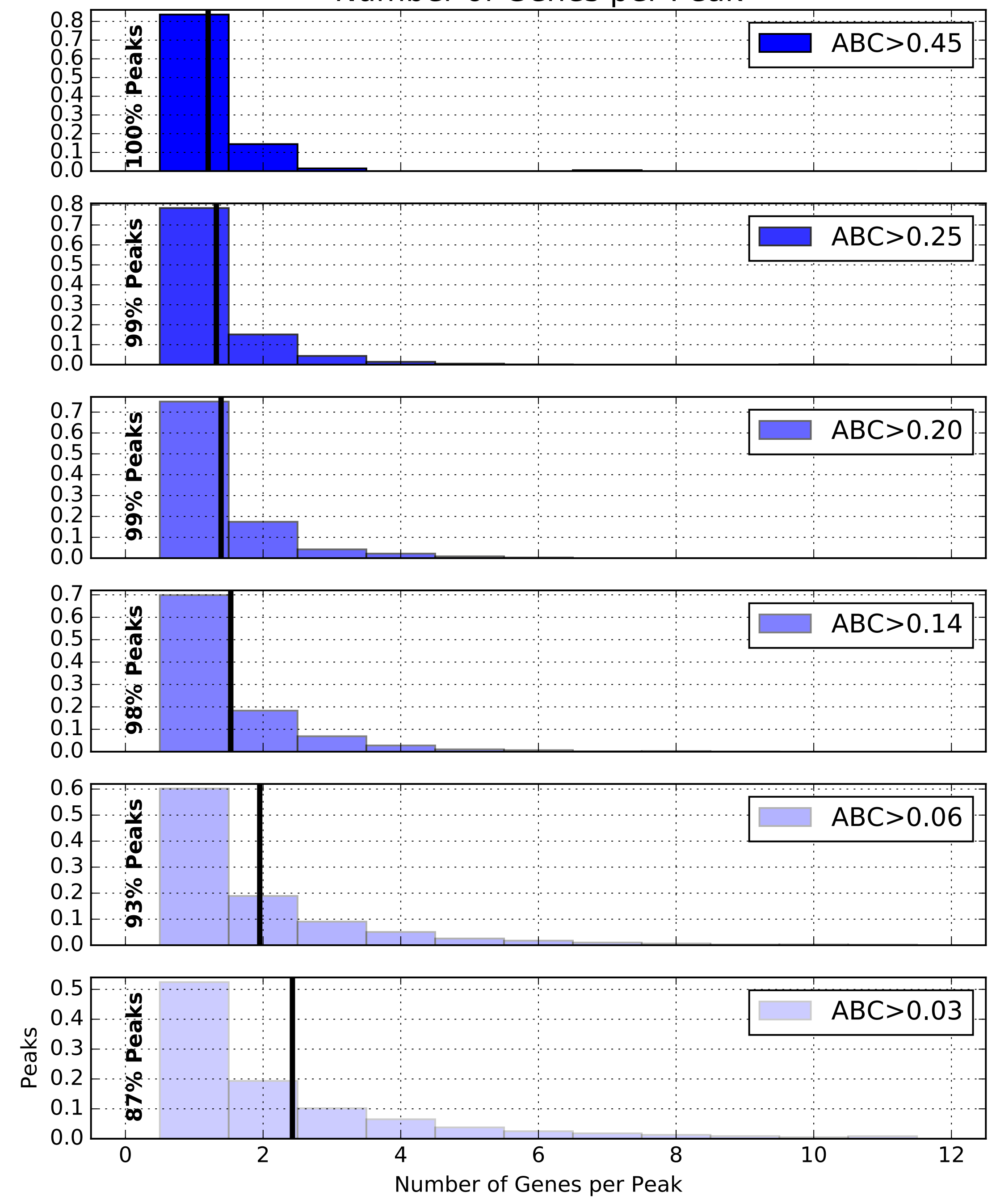
Slope between Peak-Gene Connections by ABC Score



Number of Peaks per Gene



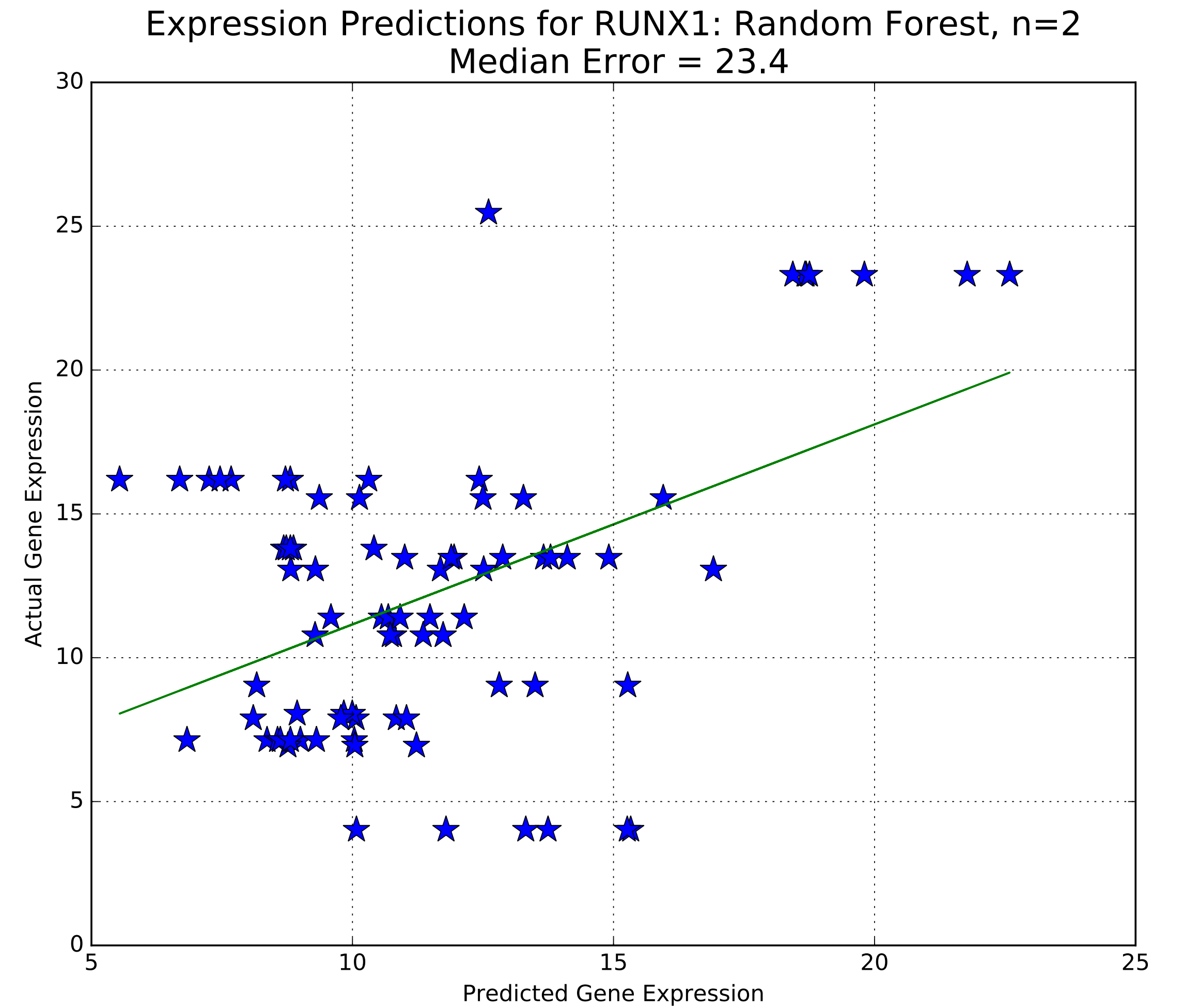
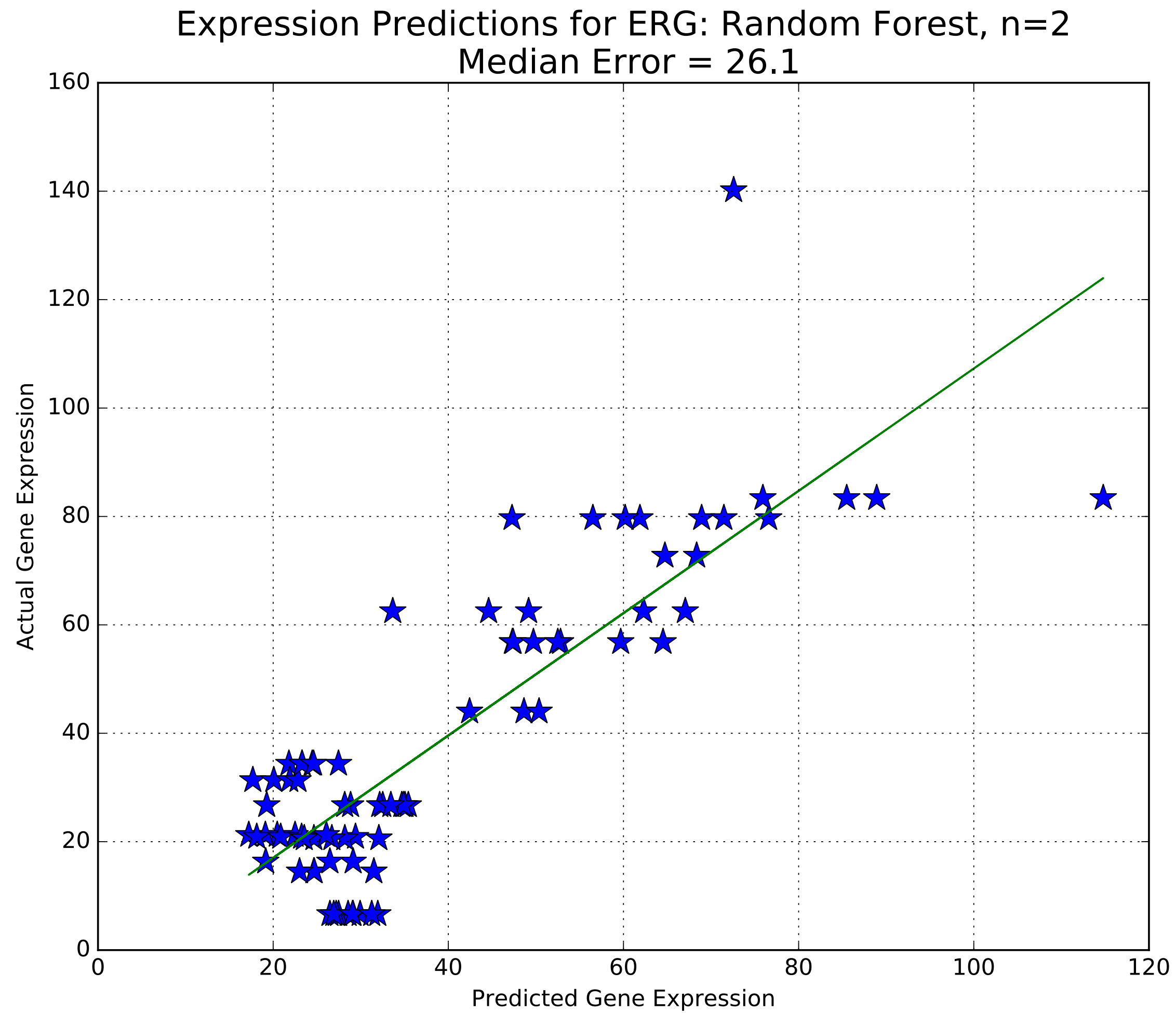
Number of Genes per Peak



# Predicting Gene Expression: Process

1. For every gene, identified peaks with  $ABC > 0.03$ 
  - Features: Peak intensities (16 samples  $\times$  n peaks)
  - Targets: Gene expression (16 samples)
2. Split targets and features into a training (80%) and testing (20%) set
3. Trained a Multivariate Regression and Random Forest Regression on the training set
4. Predicted the testing set
  - Computed Error and  $R^2$
5. Repeated steps 2 — 4 20 times for each gene

# Predicting Gene Expression





# Predicting Gene Expression

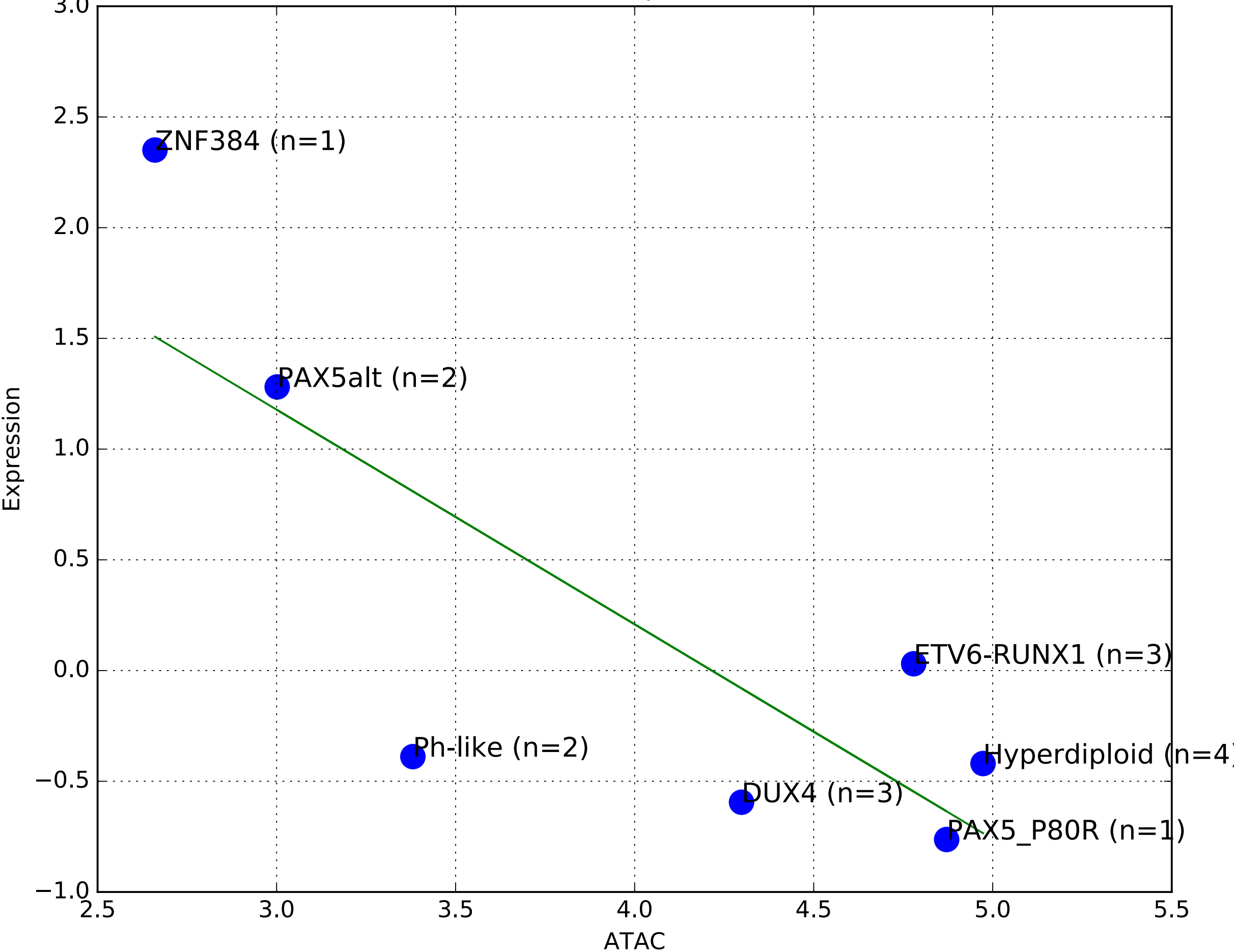
ABC	>0.45	>0.25	>0.2	>0.14	>0.06	>0.03
Median Error: Random Forest	31%	32%	35%	35%	35%	34%
Median Error: Multivariate Regression	50%	34%	32%	32%	32%	31%

# Subgroup Variability: Process

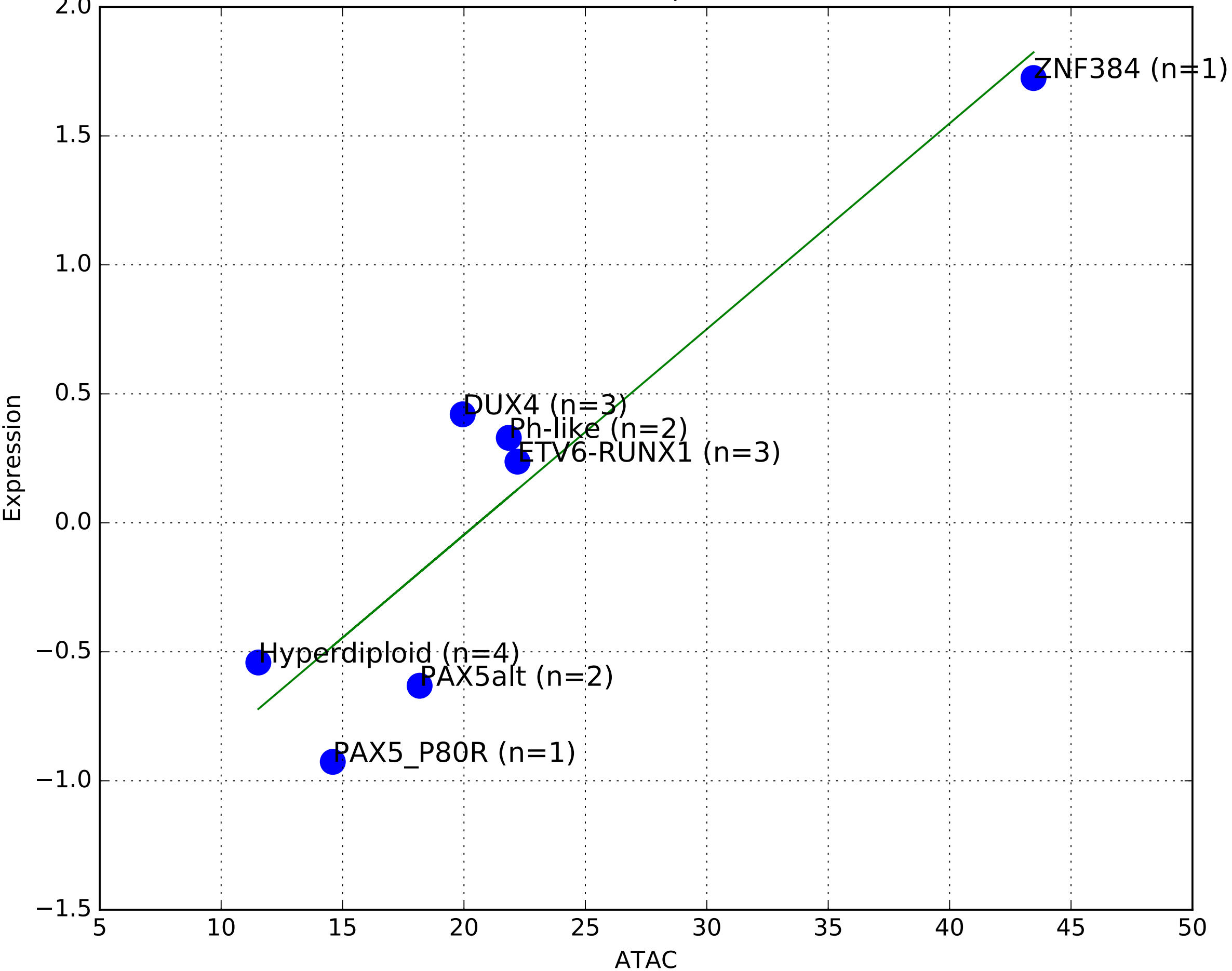
- Used the internet to identify a list of 70 leukemia-associated oncogenes
- Averaged gene expression and peak intensity within the 7 subgroups:
  - Hyperdiploid, DUX4, ETV6-RUNX1, PAX5alt, Ph-like, PAX5\_P80R, ZNF384
- Computed correlations and slopes between peaks and genes

# Subgroup Variability: RUNX1 and MYC

RUNX1 Expression Between Subgroups, by Connected Peak (ABC = 0.03)  
Corr = -0.8, P = 0.03



MYC Expression Between Subgroups, by Connected Peak (ABC = 0.06)  
Corr = 0.92, P = 0.004



# Conclusions

- ABC offers a promising way to identify regulatory elements of genes
  - Performs much better than correlation and is more complex than distance
- In agreement with Fulco et al (2019), we find that enhancers typically regulate multiple genes, and genes are regulated by multiple enhancers
- ABC is highly correlated with distance
  - Not clear whether using contact is better than distance
- ABC might offer a way to examine regulatory elements and interpret the functions of noncoding genetic mutations that influence risk for human diseases, such as Leukemia

# Next Steps

- Add components to ABC score
  - DHS or H3K27ac ChIP-Seq
- Motif calling at known connections
- Redo the validation with more types of data
  - CRISPR perturbation data
  - HiChip connections