

Quiver Laplacians,  
Feature Selection,  
&  
Chromatin Accessibility

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based on [arxiv:2404.06993](https://arxiv.org/abs/2404.06993)

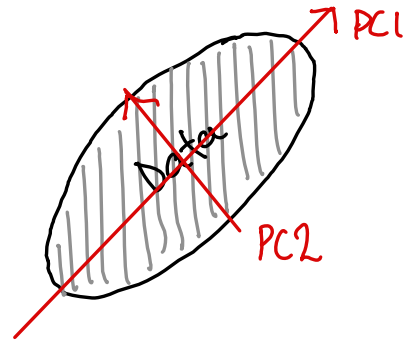
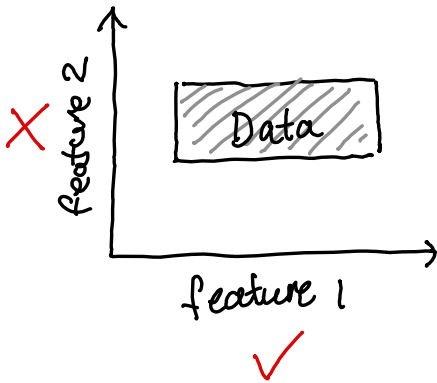
# Feature selection

- reduce dimensionality
- find features that best explain the data

e.g.

Most varying features

Principal Component Analysis



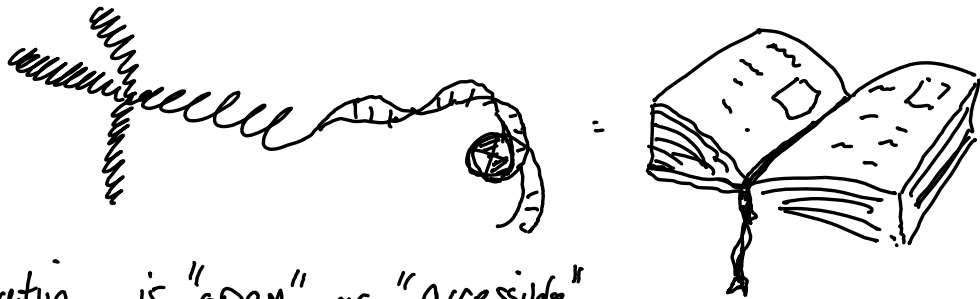
# Chromatin Accessibility

If genes are like recipes...

CAGCATG... = 

1 cup	Gly
1 cup	His
	⋮

... chromatin is like the recipe book

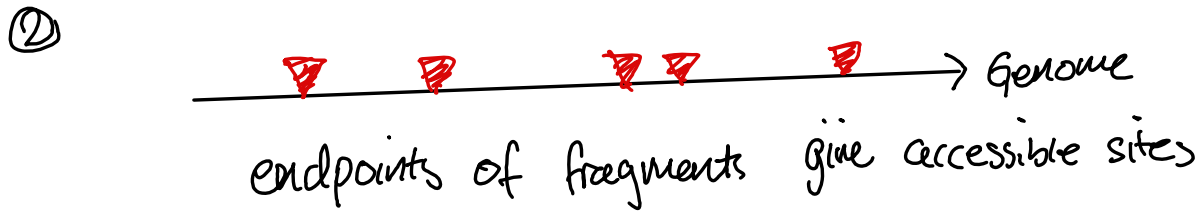
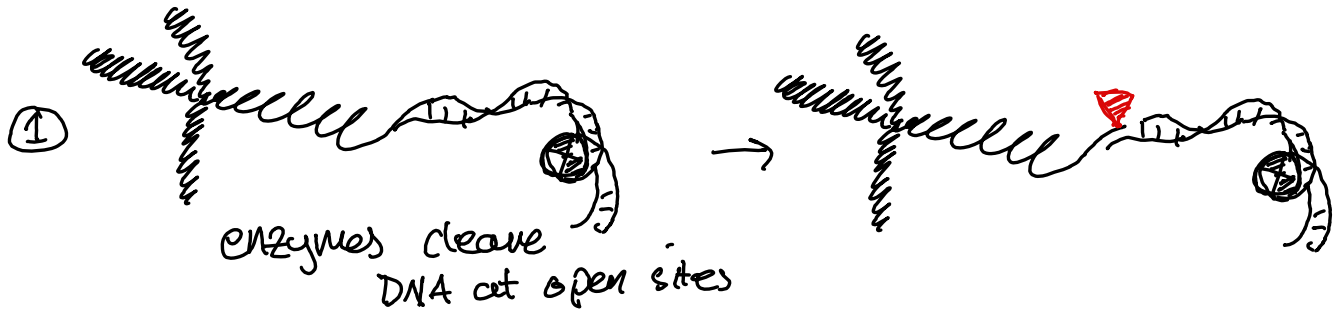


The chromatin is "open" or "accessible"  
in certain regions to allow protein complexes to regulate gene expression

↓   ↓   ↓

enhancers   promoters   e.g. transcription factors

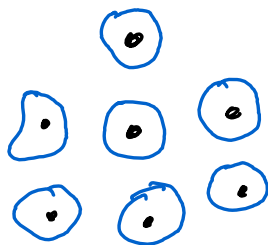
Chromatin accessibility can be measured (ATAC-seq)



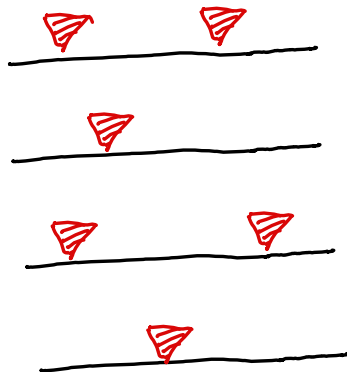
problem is... there are 3 billion genomic positions!  
and noisy, sparse etc...

# Feature selection: Peak calling

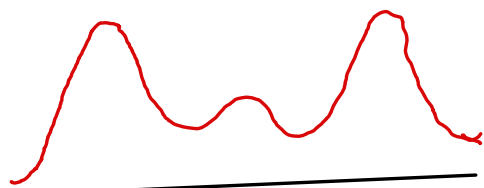
①



take many samples  
of cells

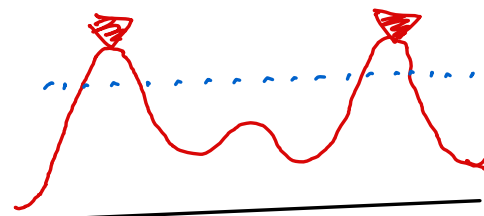


②



Aggregate sample density

③



Selected sites are peaks

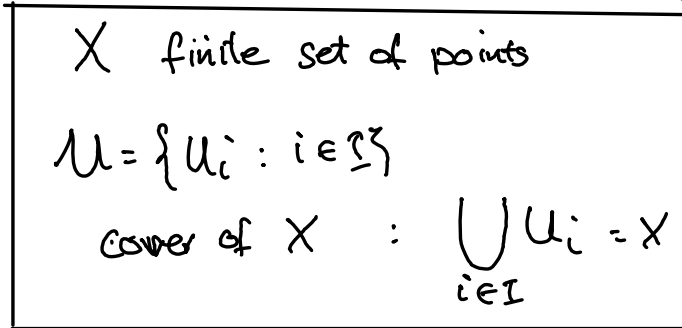
Now 100,000s of features

Often we're interested in subsets of the data

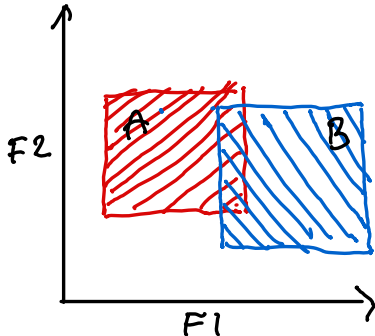
↓ e.g. cell types

e.g. in blood:

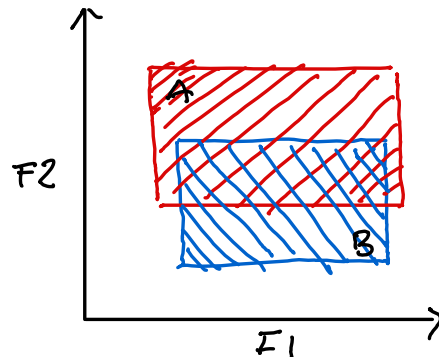
T cells  
B cells  
NK cells  
Monocyte cells.  
⋮



But features relevant for  $X$   
may not be relevant for each  $U_i$  (& vice versa)



F1 higher variance for  $A \cup B$   
but not A or B



F1 higher variance for A, B  
but not  $A \cup B$

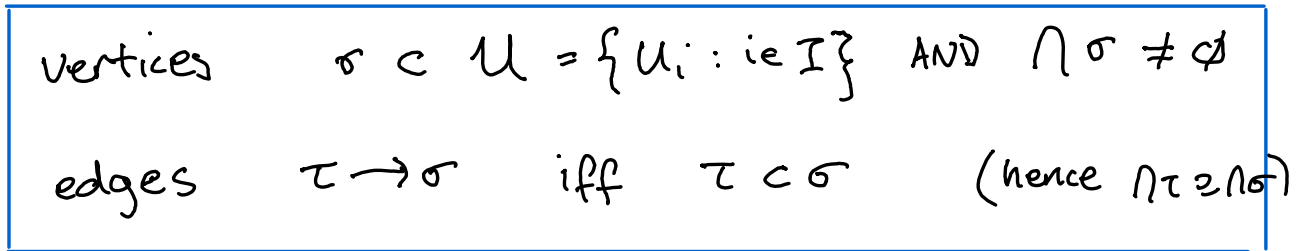
A cover of the data  
elements are  
distinguished subpopulations

A feature selection process  
Outputs subspace of  
features  
includes inner product  
(feature correlation)

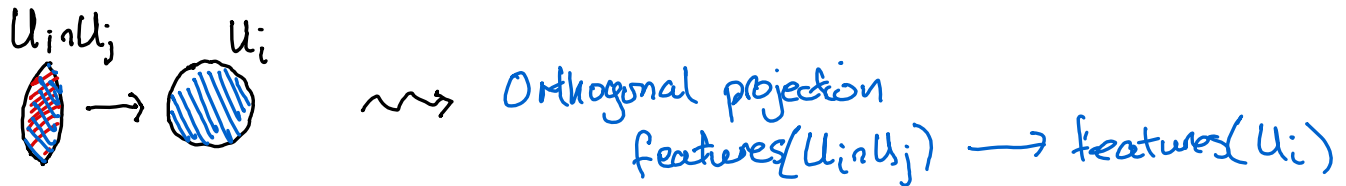
How to combine?

features consistent  
with the cover

A cover defines a directed graph



Feature selection attaches a f.i.d. vector space to each node





$\mathcal{Q}$  a finite quiver

finite sets

$V$  vertices

$E$  edges



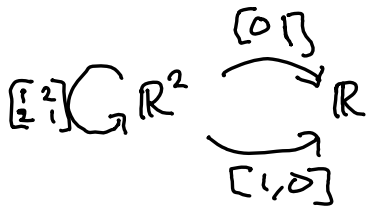
source & target maps

$$s, t: E \rightarrow V$$

A. FdHilb - representation of  $\mathcal{Q}$ .

$$A_v \in \text{FdHilb} \quad \forall v \in V$$

$$A_e: A_{s(e)} \rightarrow A_{t(e)} \quad \forall e \in E$$



space of global sections of  $(Q, A.)$

$$\Gamma(Q, A.) = \left\{ (x_v)_{v \in V} \in \prod_{v \in V} A_v : \forall e \in E \quad A_e(x_{s(e)}) = x_{t(e)} \right\}$$

e.g. for  $\begin{array}{ccc} \mathbb{R} & \xrightarrow{1} & \mathbb{R} \\ \bullet & & \bullet \end{array} \leftarrow -1 \mathbb{R}$

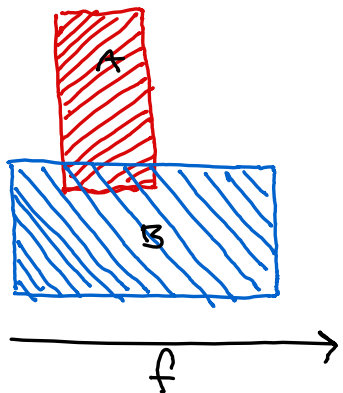
$(1, 1, 1)$  not a section

$(1, 1, -1)$  is a section

For a cover and feature selector

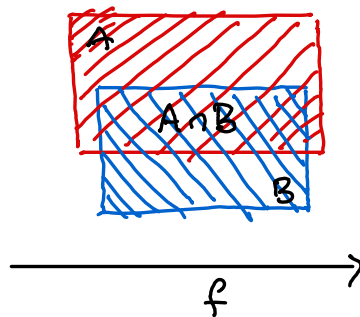
(globally) compatible features

are global sections of the corresponding quiver rep.



Not a globally compatible feature

relevant for B and  $A \cap B$   
but not for A!



Is a globally compatible feature

# Recap so far

Data

Cover

Feature  
selection

Gauver representation

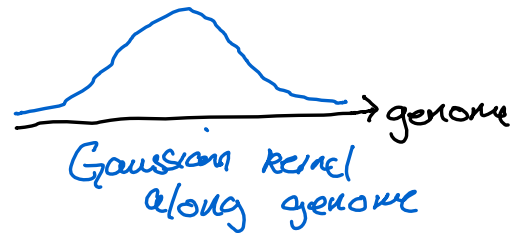
Global sections

chromatin accessibility profiles  
for thousands of single cells

different cell types

significantly accessible sites

Gauver from  $\subseteq$  relations of cover  
valued with space of selected features  
inner product



globally compatible features

How to compute sections?

One way: "boundary map"

$(\mathcal{G}, A_\bullet)$

$$B_A: \prod_{v \in V} A_v \rightarrow \prod_{e \in E} A_e$$

block form

$$(B_A)_{e,v}$$

$$\left\{ \begin{array}{ll} A_e - \text{Id}_v & \text{if } s(e) = t(e) = v \\ A_e & \text{or if } s(e) = v \\ -\text{Id}_v & \text{or if } t(e) = v \\ 0 & \text{o/w.} \end{array} \right.$$

$$\boxed{\text{ker } B_A = \prod (\mathcal{G}_j; A_\bullet)}$$

each (block row)

$$[0 \ 0 \ 0 \ \dots \ 0 \ A_e \ 0 \ 0 \ 0 \ \dots \ 0 \ -\text{Id} \ 0 \ 0 \ 0]$$

(other ways to compute, see Seiguel, Harrington, Nanda, 2021)

Data is noisy! want approximate sections

$$x \in \prod_{v \in V} A_v, \quad \|x\| = 1.$$

$$\|B_A x\|_2^2 \leq \epsilon \Leftrightarrow x^* B_A^* B_A x \leq \epsilon$$

Define the Laplacian of  $(\mathcal{Q}, A_\bullet)$

$$\text{as } L_A := B_A^* B_A.$$

$$\ker L_A = \Gamma(\mathcal{Q}, A_\bullet)$$

$$L_A \text{ is PSD: } 0 \leq \lambda_1(L_A) \leq \dots \leq \lambda_n(L_A)$$

$$\text{if } L_A x = \lambda_i x \Rightarrow x^* L_A x = \lambda_i$$

$$n = \sum_{v \in V} \dim A_v$$

$\Rightarrow$  eigenvectors for small eigenvalues are approx. sections

Stability

fix  $\mathcal{Q}$ .

$A_\nu, \hat{A}_\nu$   $\mathcal{Q}$ -reps

$$\tau = (\tau_\nu: A_\nu \rightarrow \hat{A}_\nu)_{\nu \in V}$$

Thm OS, Harrington, Nanda 24

$$1 \leq k \leq n - \text{Null}(\tau)$$

$$\lambda_{\cdot k}(\hat{A}_\bullet) \leq \kappa(\tau)^2 \lambda_{k + \text{Null}(\tau)}(A_\bullet) + \partial(\tau) \|\tau^+\| \left[ 2\kappa(\tau) \lambda_{k + \text{Null}(\tau)}(A_\bullet)^{1/2} + \partial(\tau) \|\tau^+\| \right]$$

generalized condition number  
 $\kappa(\tau) = \|\tau\| \cdot \|\tau^+\|$

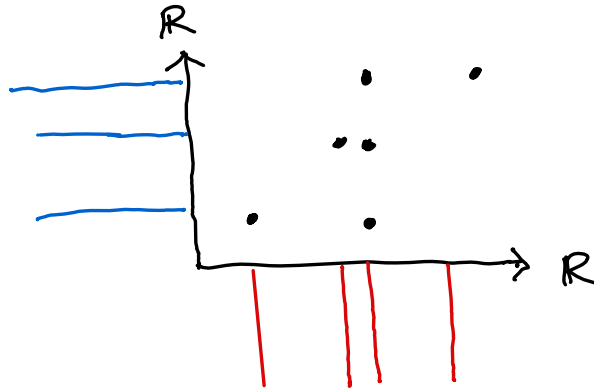
defect.

$$\partial(\tau) = \left[ \sum_{e \in E} \|A_e \tau_{\text{src}(e)} - \tau_{\text{targ}(e)} A_e\|^2 \right]^{1/2}$$

"how close to a morphism"  
of quiver reps

To compare  $\lambda_i(A_i)$  and  $\lambda_i(\hat{A}_i)$   
need Wasserstein metric  $W_p$

$$\mu_B = \sum \delta_{\lambda_i(\hat{A})}$$



joint distribution  
that minimizes  
 $L_p$ -cost.

$$\mu_A = \sum \delta_{\lambda_i(A)}$$



Corr.  $\mathcal{Q}$  quiver from cover

$A, \hat{A}$  reps from two different feature selectors

$$W_i(M_A, M_{\hat{A}}) \leq \frac{\# \text{edges } \mathcal{Q}}{m} \left[ f(\epsilon) \cdot c + g(\epsilon) \cdot (m - c) \right]$$

for  $f, g$  trigonometric polynomials

$$\epsilon = \max_v \text{dist}_{\text{Grass}}(A_v, \hat{A}_v)$$

$$m = \max \text{ total rank of } A, \hat{A}$$

$$c = \sum_v |\dim A_v - \dim \hat{A}_v|$$

# Eigenvalue bounds for changing the quiver $Q$ Thms OS, HATH, UN 24.

Does not preserve  $\Gamma(Q, A.)$

① Removing edges



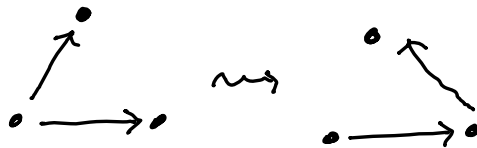
② Removing vertices  
(and assoc. edges)



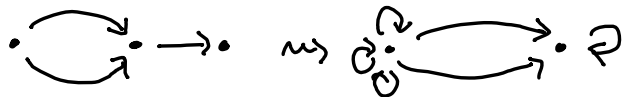
Does preserve  $\Gamma(A.)$

[for certain  $A.$ ]

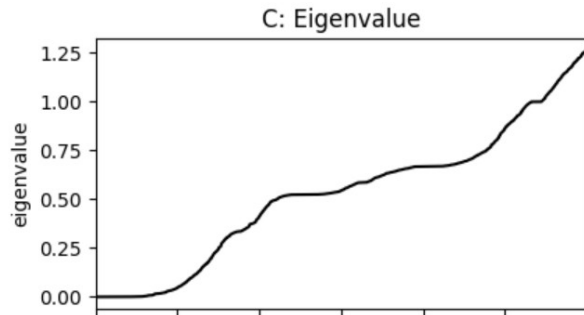
③ Edge "homotopy"



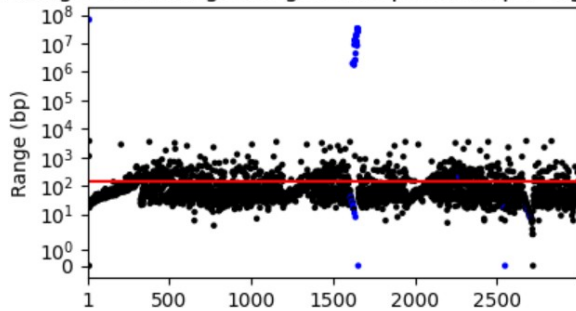
④ Reducing vertices  
(Kirch reduction / Schur complement)



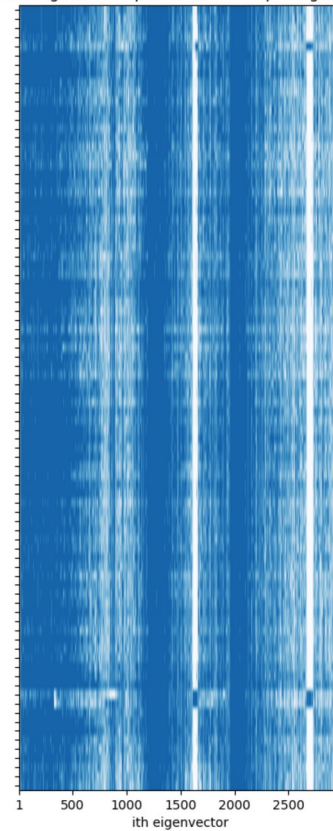




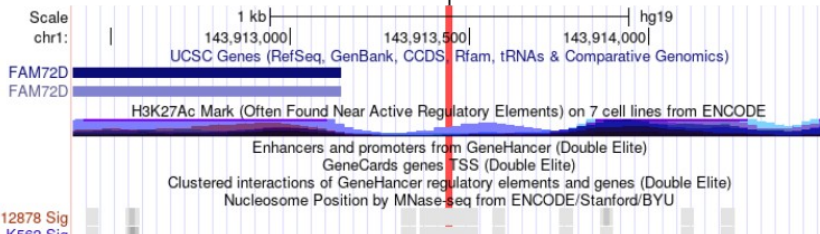
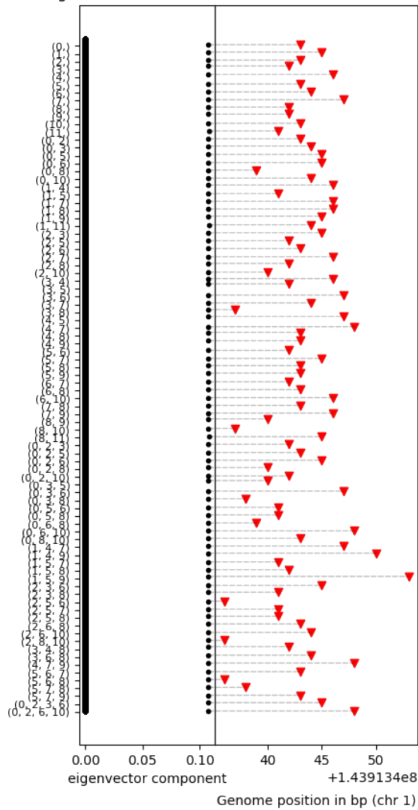
D: Range of non-negative genomic positions per eigenvector



:: Non-negative component in vertex per eigenvector

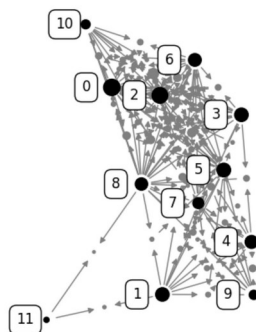
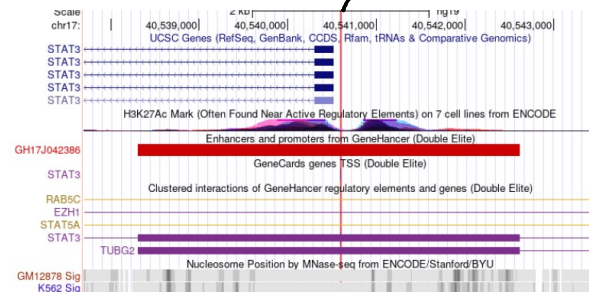
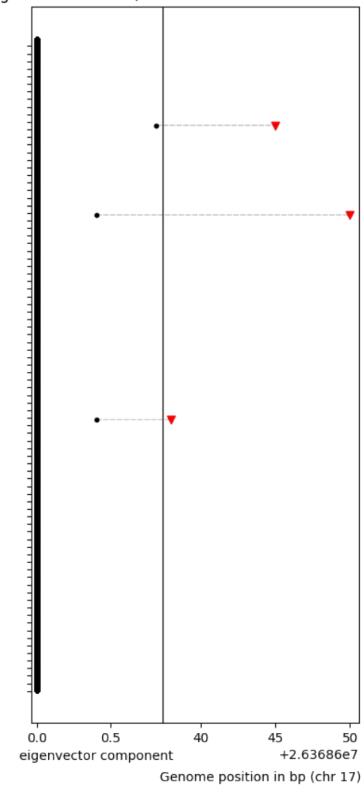


- Component is non-zero
- Component is zero

Eigenvector #11,  $\lambda \approx 0.00$ 

E

A: Nerve of cover

Eigenvector #2702,  $\lambda = 1.00$ GM12878 Sig  
K562 Sig