

# Identify functional patterns in high throughput binding assays

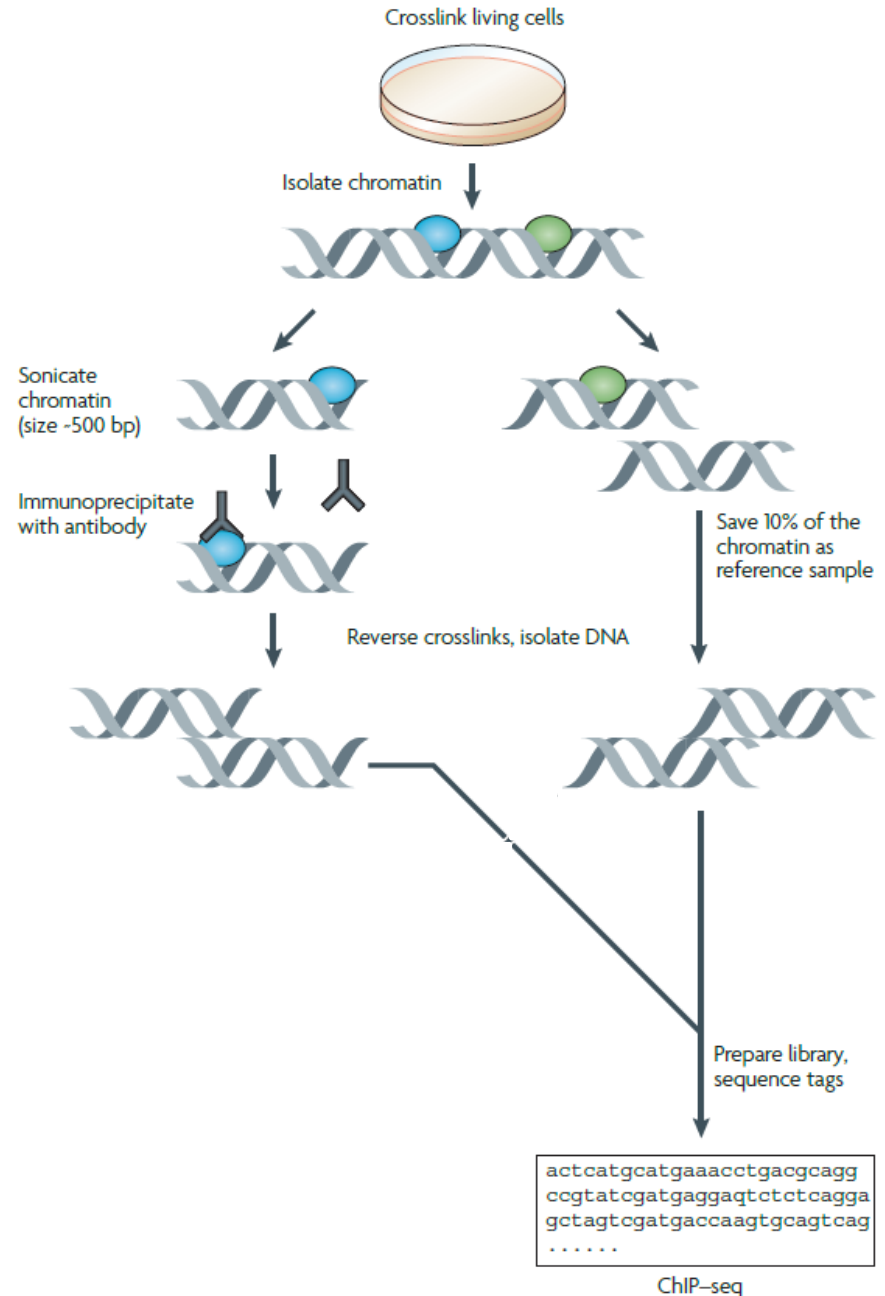
Alex Essebier

# Message

- By clustering ChIP-seq peaks we can identify different patterns in transcription factor binding

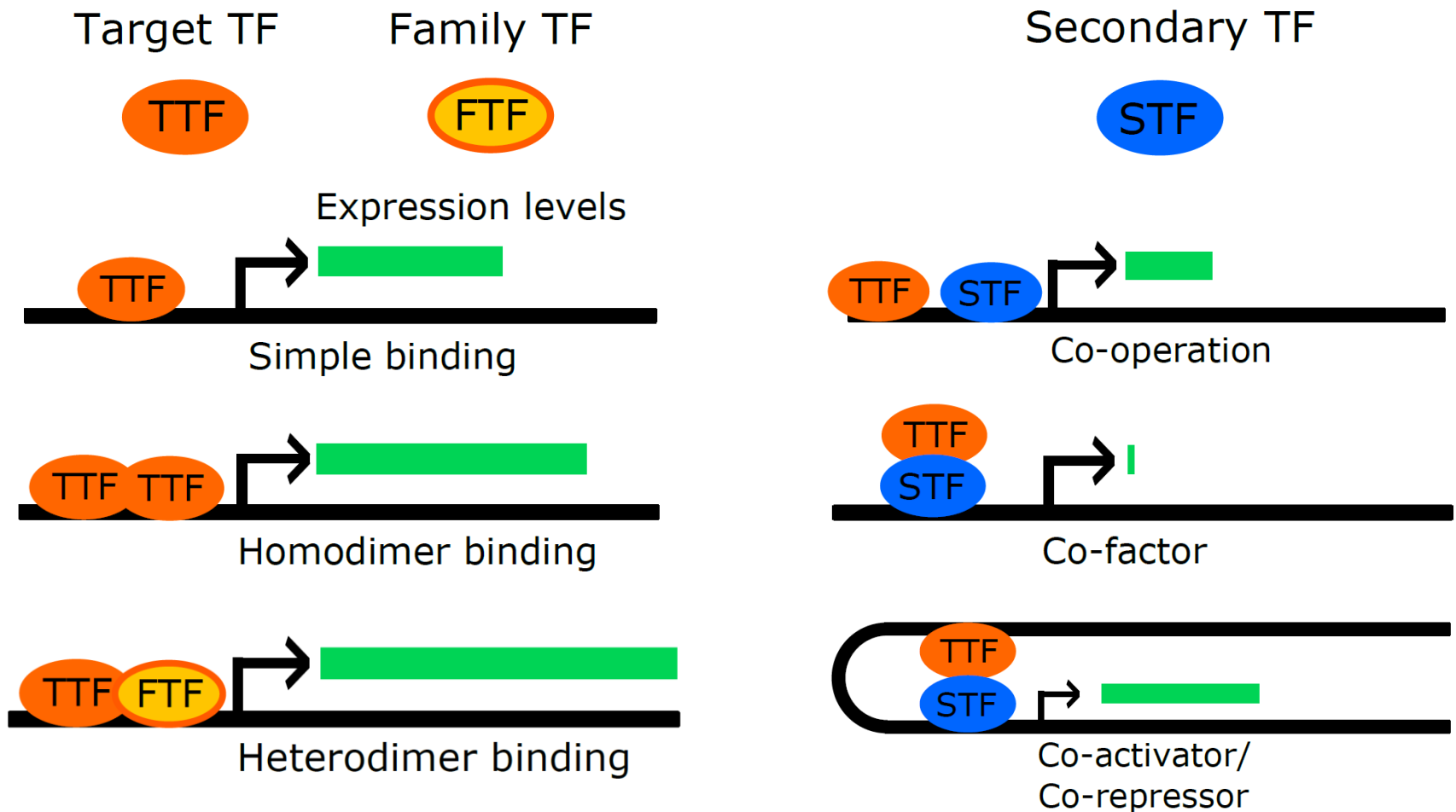
# ChIP-seq experiment

- Chromatin immunoprecipitation followed by sequencing
- To determine where a protein binds the genome
- e.g. for a **single TF** or histone modification



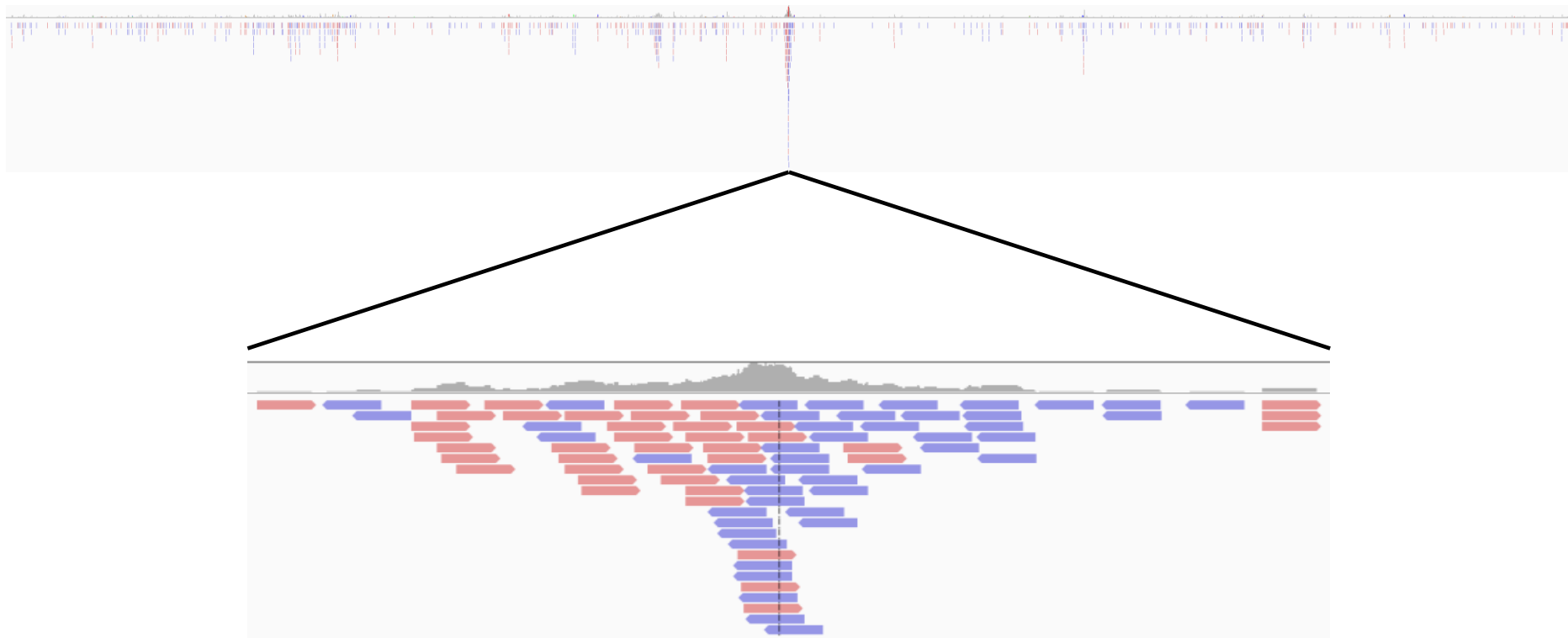
# Why TFs?

- Important role in gene expression, cell differentiation and homeostasis



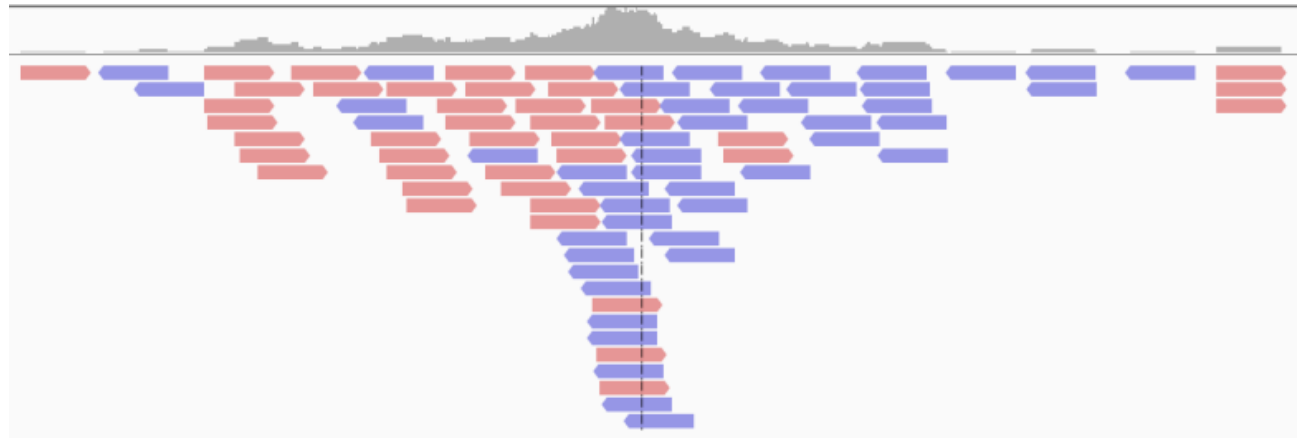
# Peak calling

- Raw sequencing data
  - Single end reads
  - Red mapped 'forward', blue mapped 'reverse'
  - Distribution across genome



# Peak calling

**Sample** –  
exposed to  
antibody

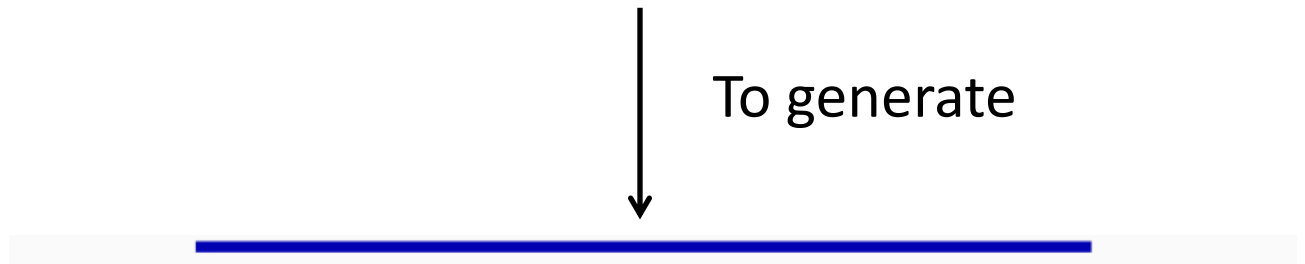


**Input** –  
no antibody  
exposure



Compared to

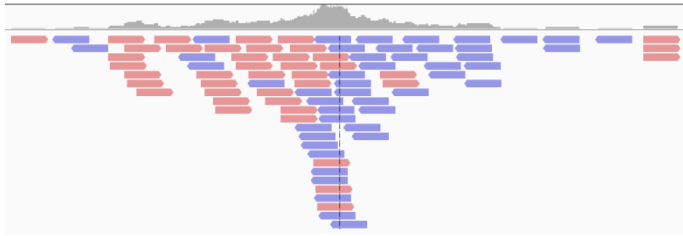
**Peak** –  
with statistical  
significance



To generate

# Peak calling

A



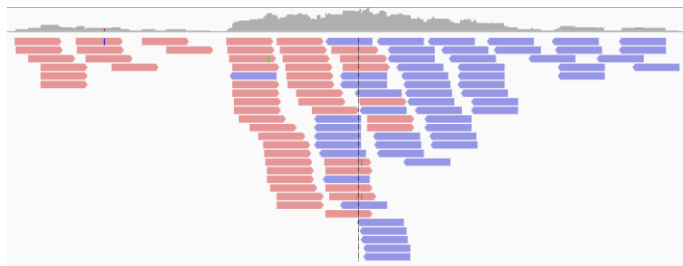
B

ATTGCC



C

ATTTCC

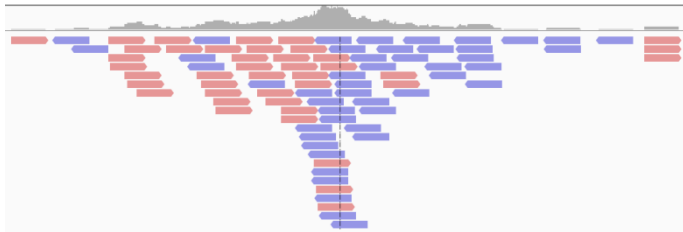


ATACCC

- Peaks have different features within a ChIP-seq experiment

Peak	Width	Enrichment	Location	Epigenetic Environment
A	205	298	Distal Intergenic	Insulator
B	162	218	Promoter	Active Promoter
C	194	361	Promoter	Weak Promoter

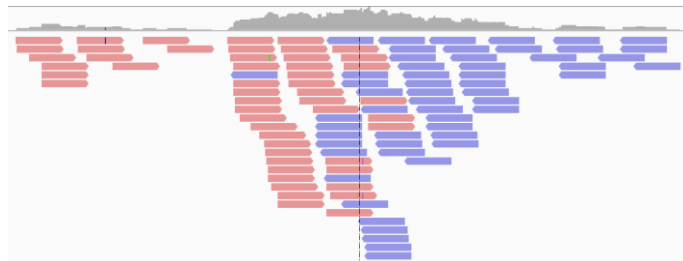
# Peak calling



ATTGCC



ATTTCC

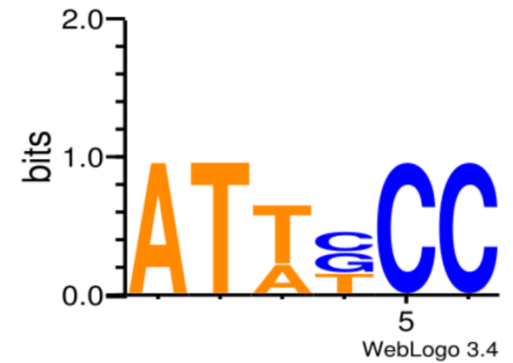


ATACCC

Analyse

Confirm *in vitro* results

Identify consensus motif



Identify target genes of TF



# Hypothesis

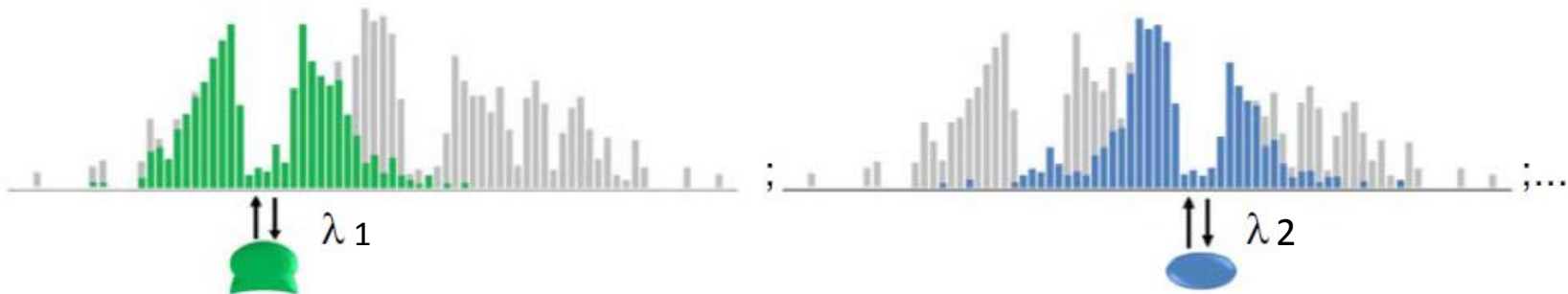
- We propose that ChIP-seq peaks from a TF experiment can be clustered based on their read density or 'shape' leading to identification of different binding modes and functional patterns of a TF

# Previous use of peak shape

- Differential binding
  - Compare two conditions
  - Compare two TFs
  - Based on read depth
- TF binding from DNase I hypersensitivity

TF binding estimation from modelled DNase I hypersensitivity profiles

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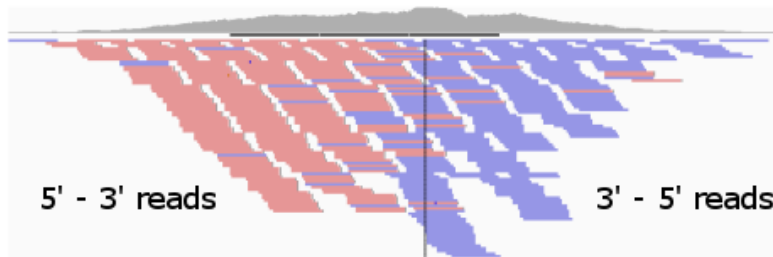


# Aims

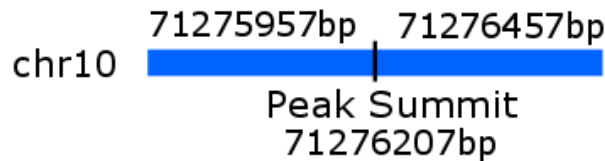
- Develop a modelling technique to identify functionally relevant clusters, based on ChIP-seq read density, defining TF binding events
- Identify functional patterns associated with clusters and provide more information about TF binding from ChIP-seq data

# Processing peak data

## Binding Site aka Peak



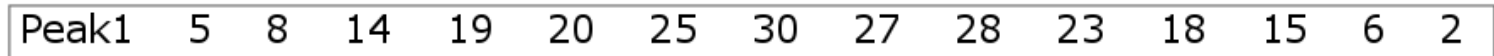
Read pile up showing distribution of reads in peak



500bp window around summit



Split window into even segments  
Count read depth in each segment



This creates a count vector for each peak with equal numbers of columns

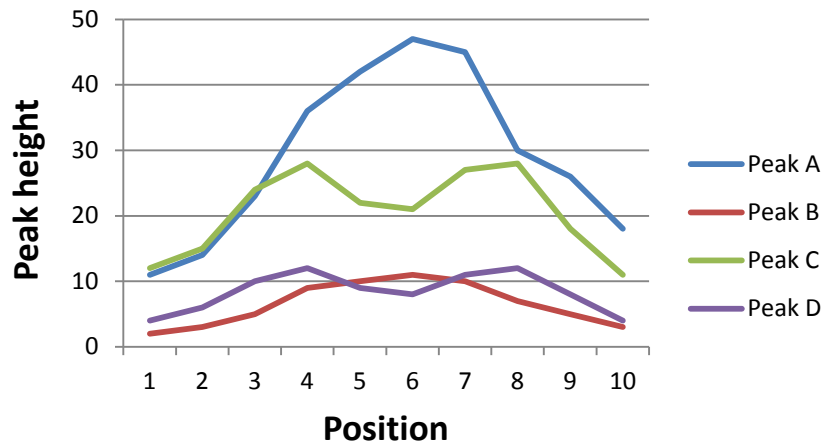
Combining all count vectors creates a **Dirichlet distribution** that can be clustered

# Dirichlet clustering

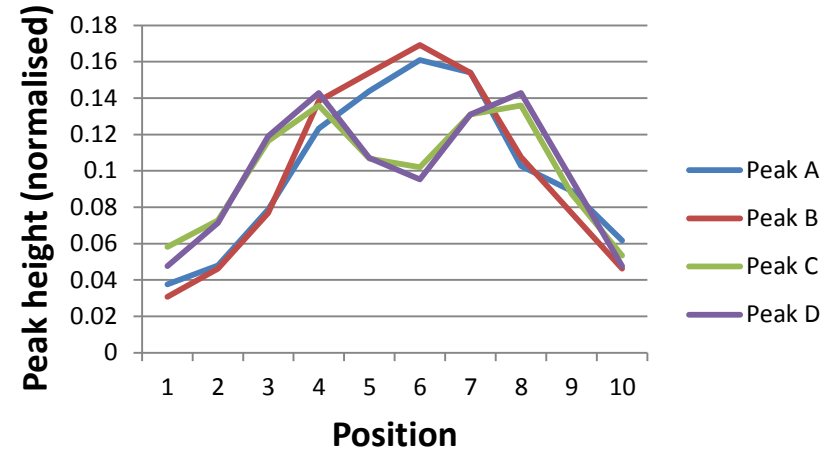
- Dirichlet distribution – distribution of distributions
- The model is a Dirichlet mixture
- Unsupervised clustering of peaks
- Evidence based clustering using raw counts
- **No normalisation** of data

# Evidence based clustering

## Shape of read counts



## Shape of normalised read counts



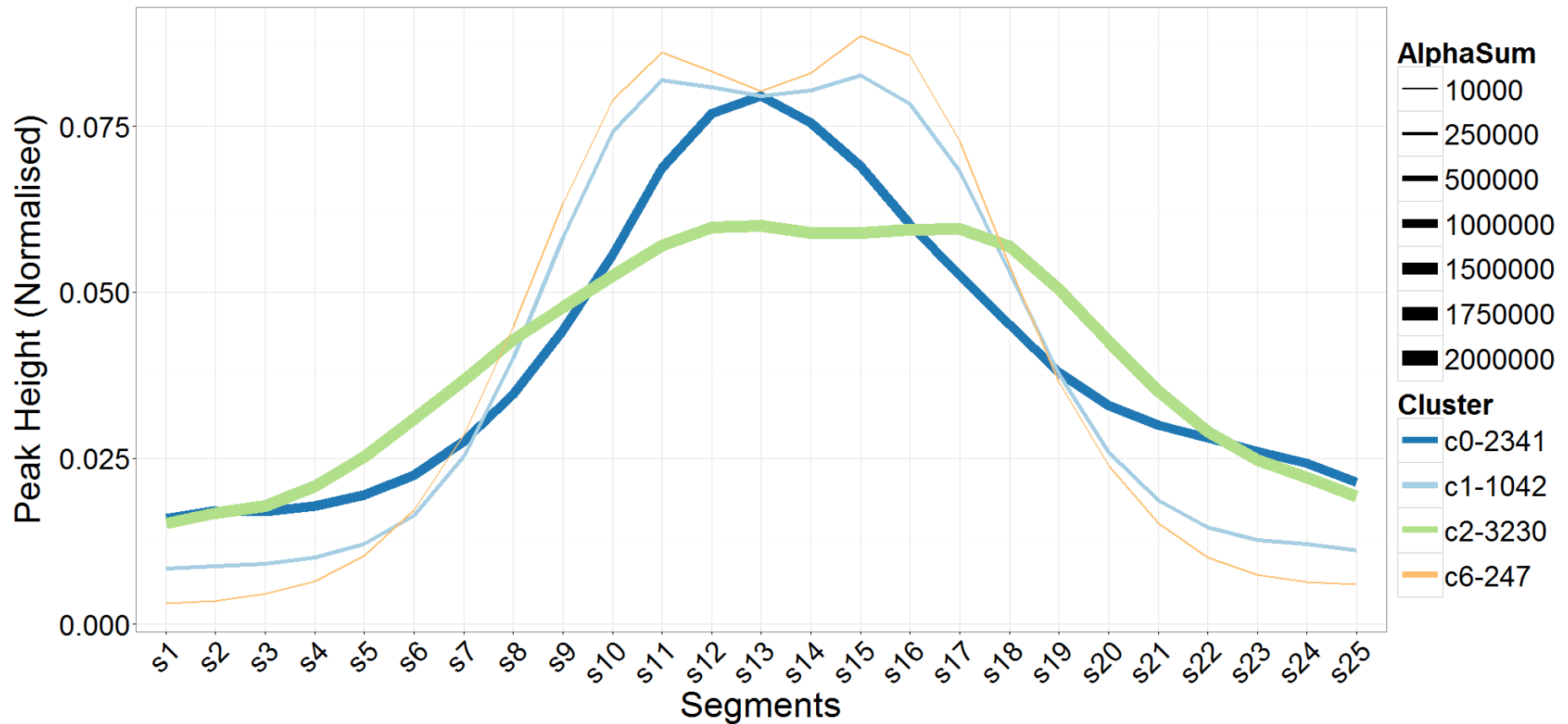
K-means	
Peak	Cluster
A	1
B	1
C	2
D	2

Dirichlet	
Peak	Cluster
A	1
B	2
C	3
D	4

- Read depth is key and can be masked by normalisation
- Dirichlet approach does not require normalisation

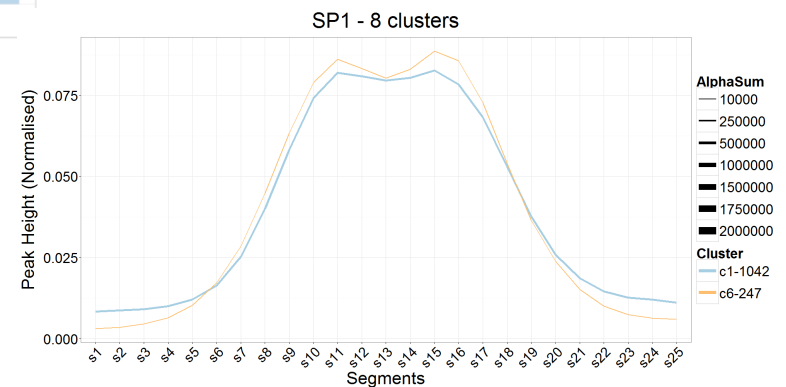
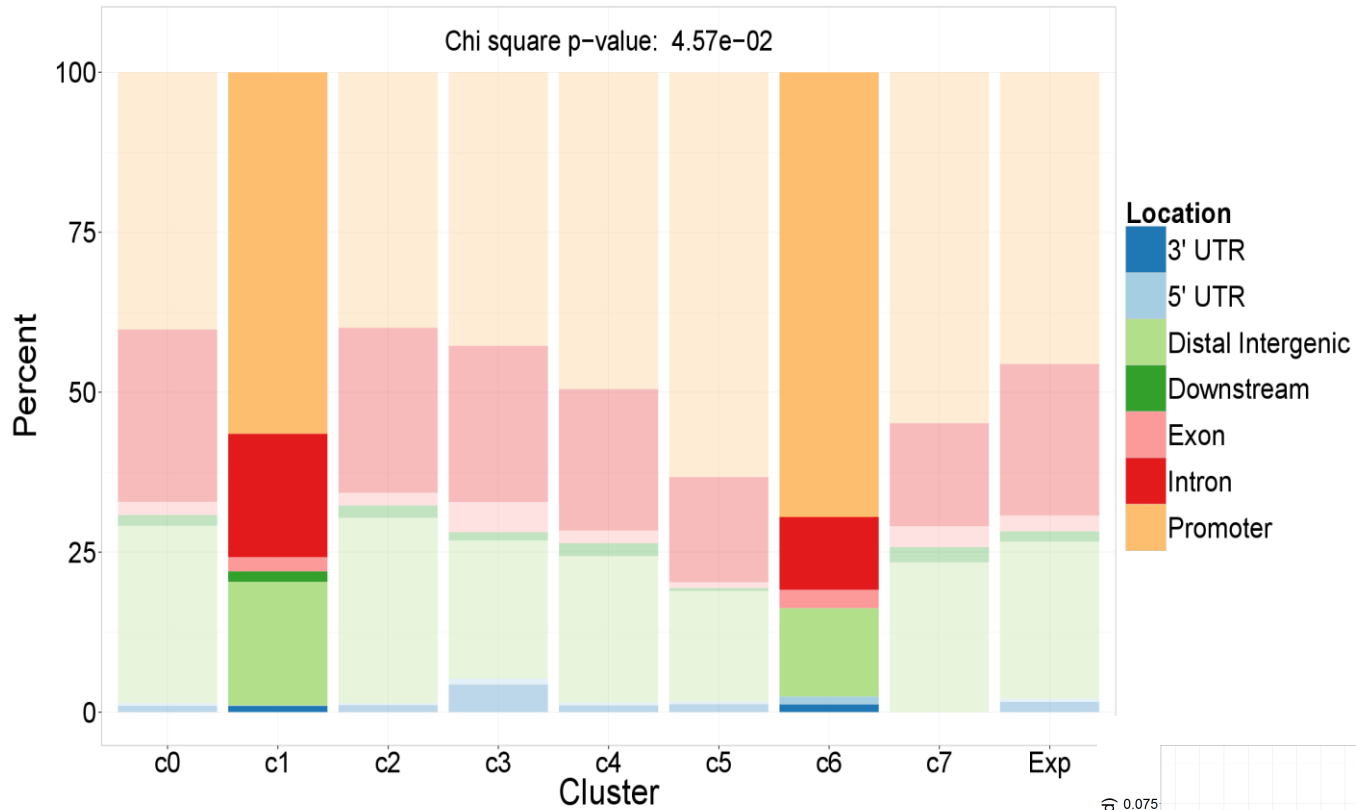
# Clustering example – SP1

SP1 - 8 clusters



# Genomic location

## Genomic Locations of Binding Sites

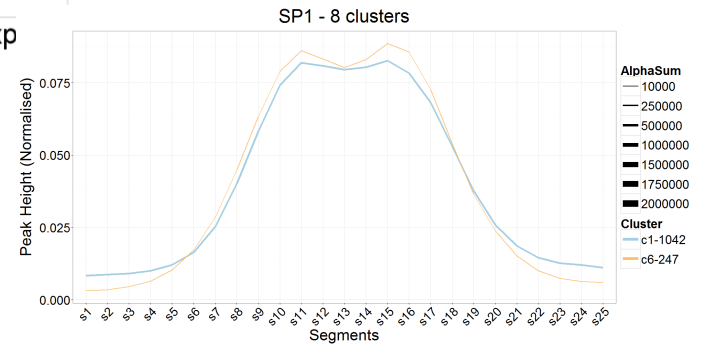
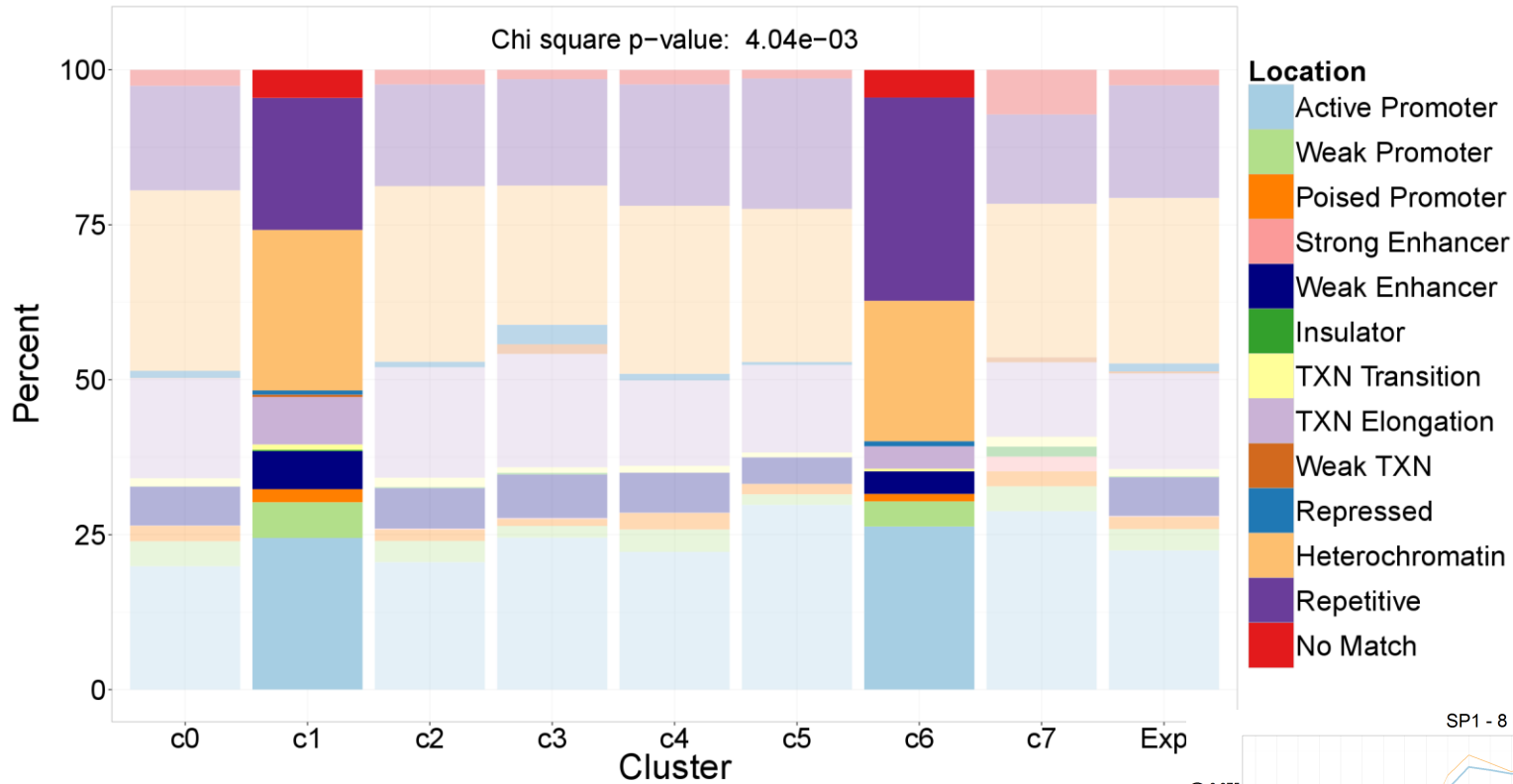




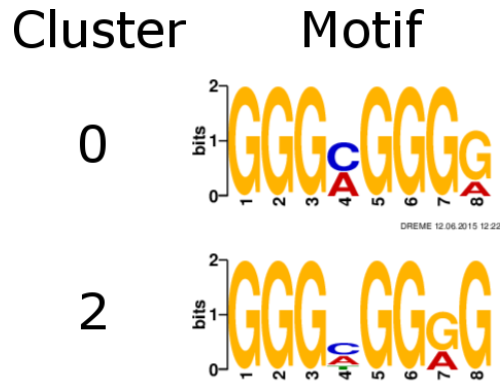
# Epigenetic environment

## Chromatin State Across Binding Sites

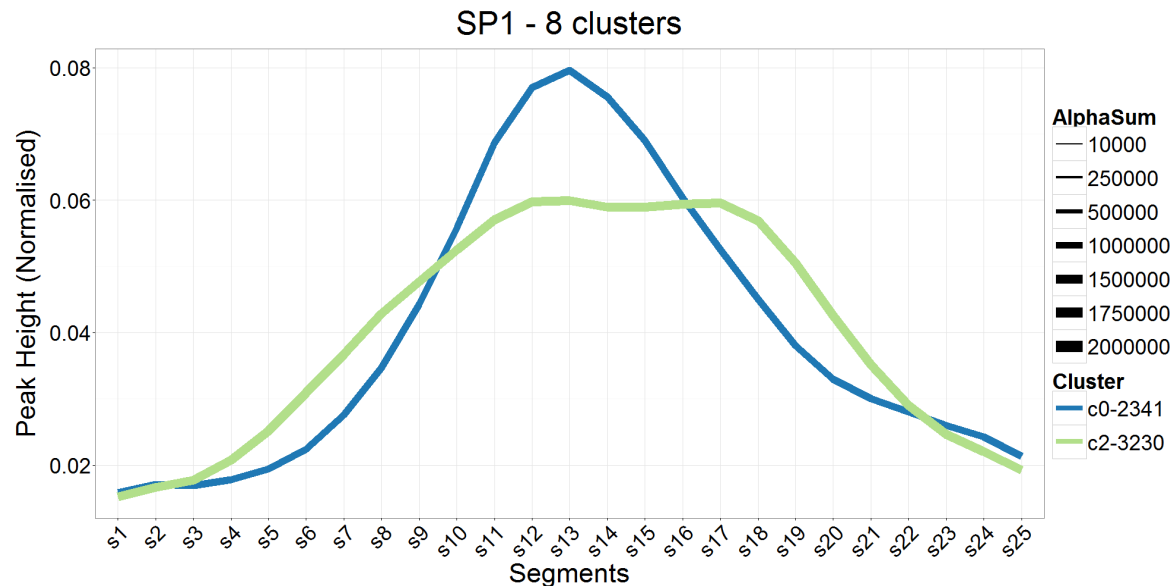
Chi square p-value:  $4.04e-03$



# Consensus motifs



- SP1 motif
- Differentiating feature in c0 and c2 is binding affinity or read depth

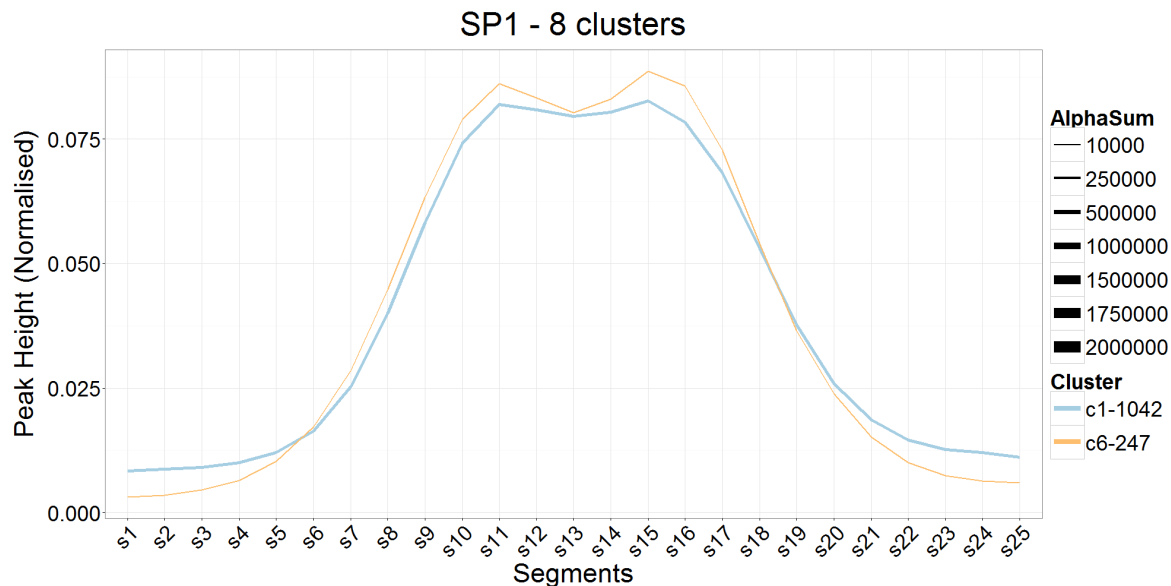
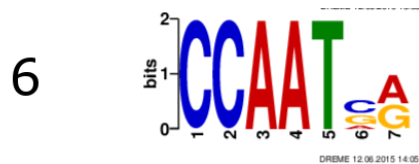
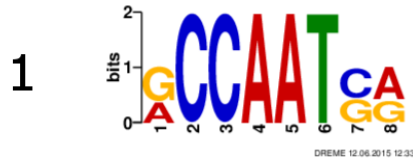


# Consensus motifs

Cluster

Motif

- NFY motif
- Known interaction between two TFs
- A bimodal peak shape indicates increased NFY binding



# Applications

- Explore TF families by comparing clustering outcomes
- Explore TF dimers using clustering in combination with *in vitro* sequence data
- Explore cooperative interactions

# Summary

- We successfully clustered ChIP-seq peaks based on their shape, density and magnitude then demonstrated how each cluster contains unique, biologically relevant, features

# Thanks

## **Supervisor**

Mikael Bodén

## **Bodén Group**

Ralph Patrick

Tim O'Connor

Julian Zaugg

Gabe Foley

## **Piper Group**

Michael Piper

## **Rostlab (TUM)**

Burkhard Rost

Tatyana Goldberg

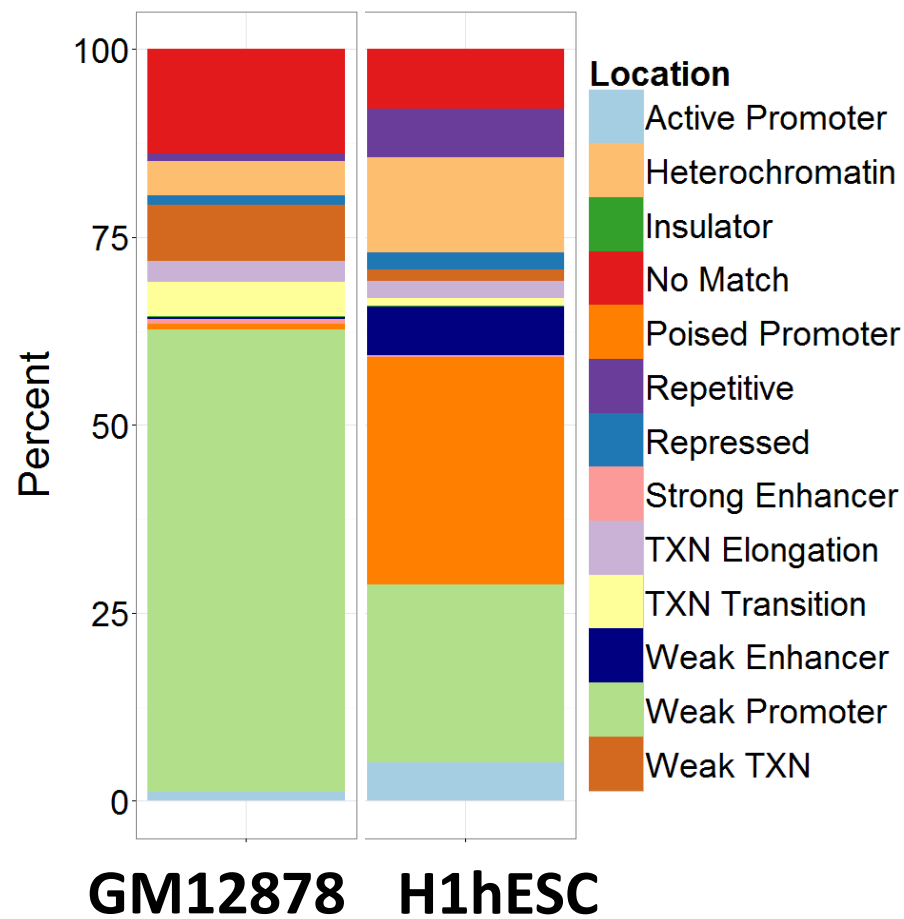
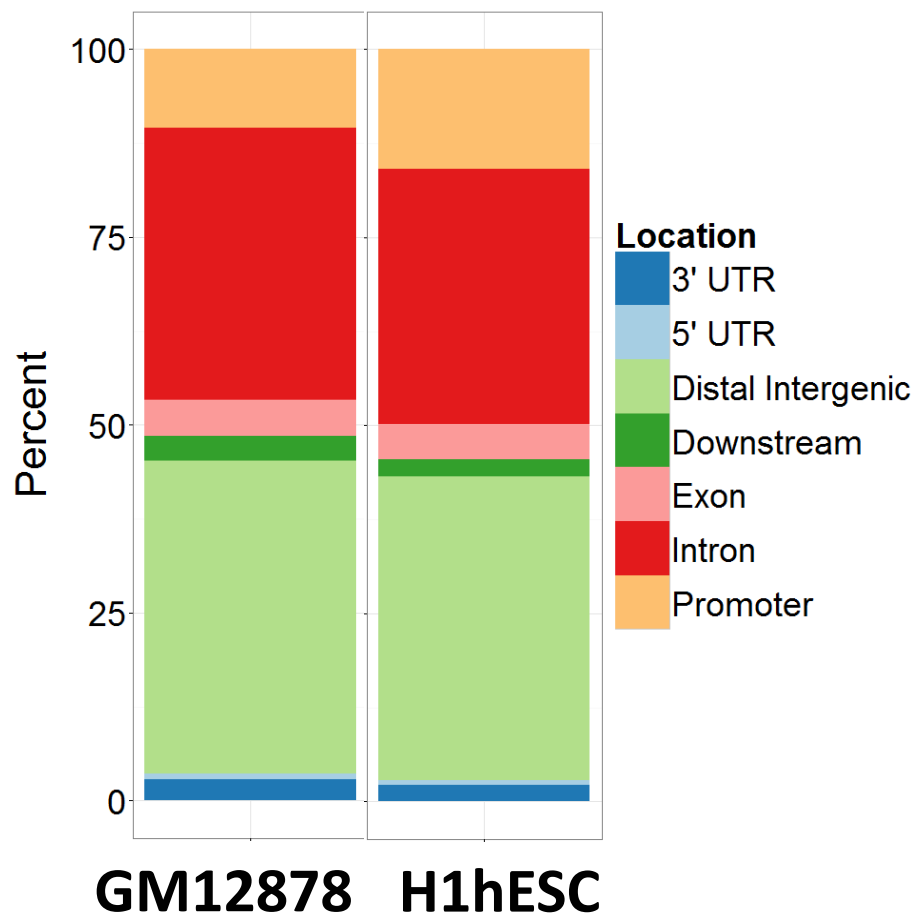


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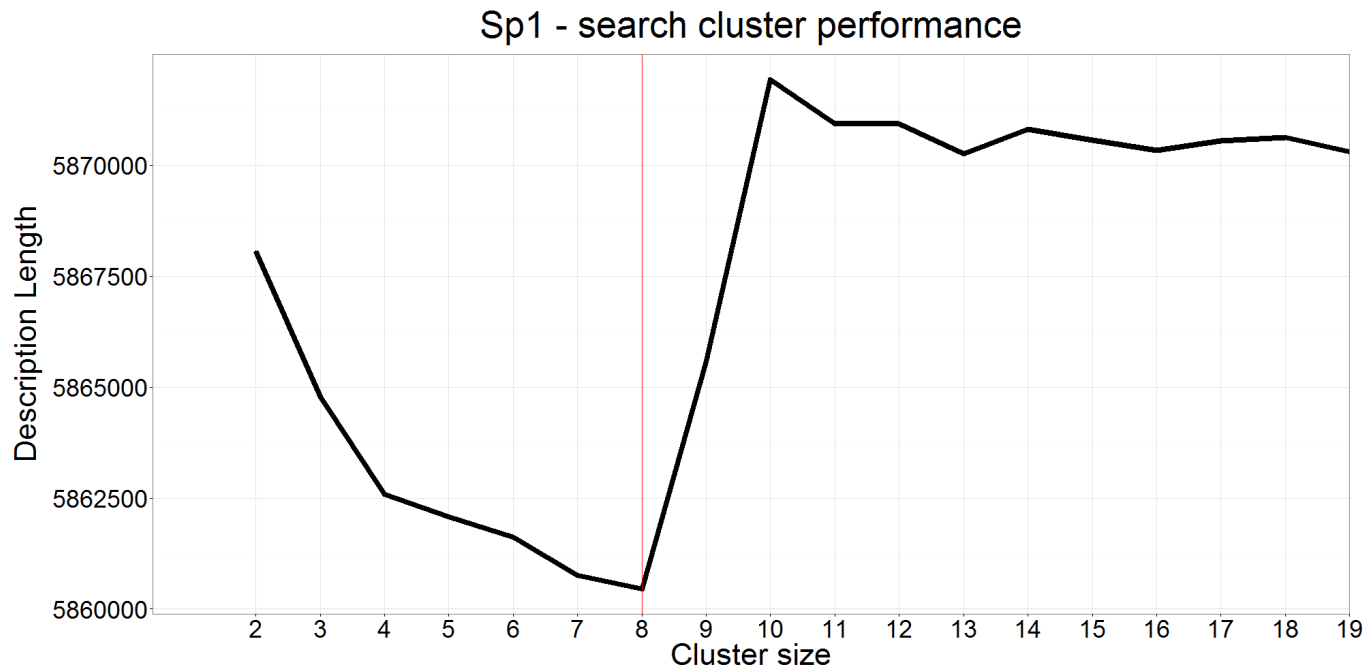


# Cell type

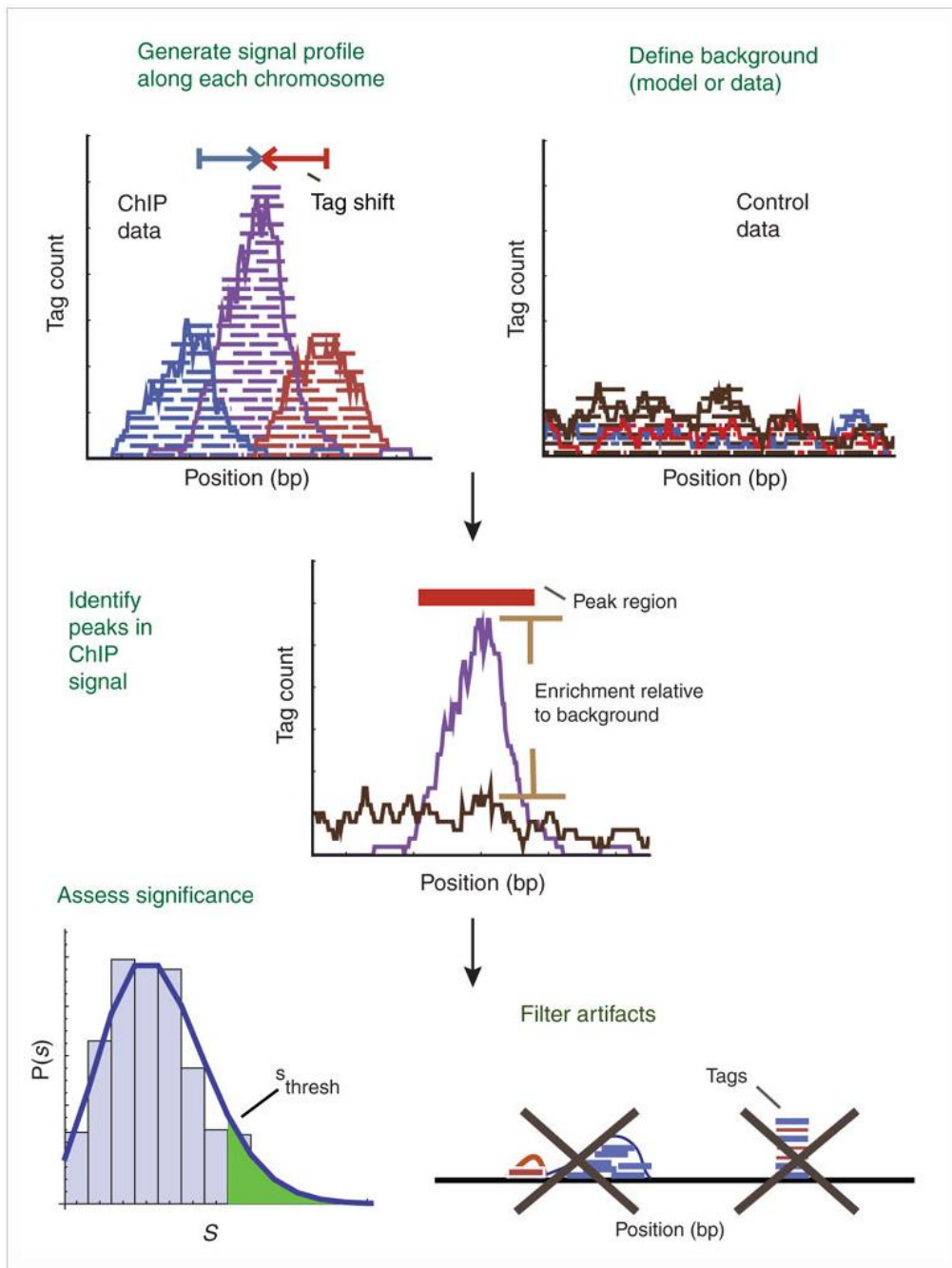


# Cluster size optimisation

- Minimum description length (MDL)
- Description length (DL)
  - A measure of information content and model complexity
- Larger models will always be more complex



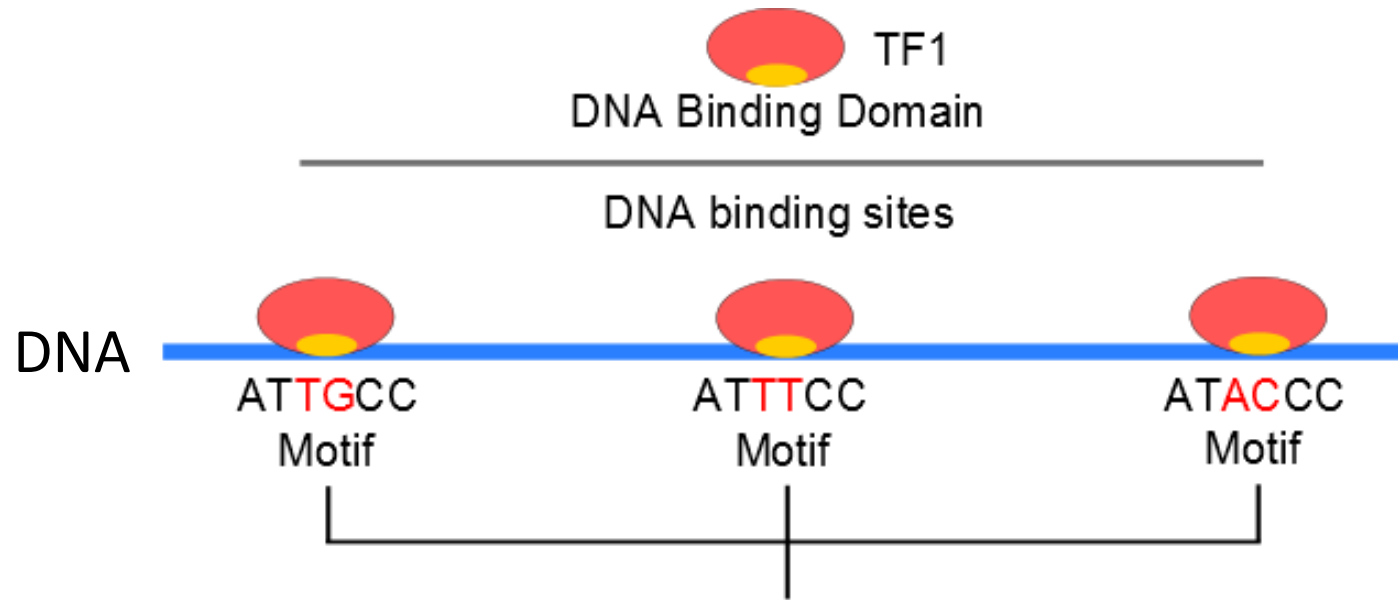




# ChIP-seq peak calling

- Shift reads on both strands to find peak
- Compare to control reads
- Identify significant hits according to a threshold
- Remove potential artefacts

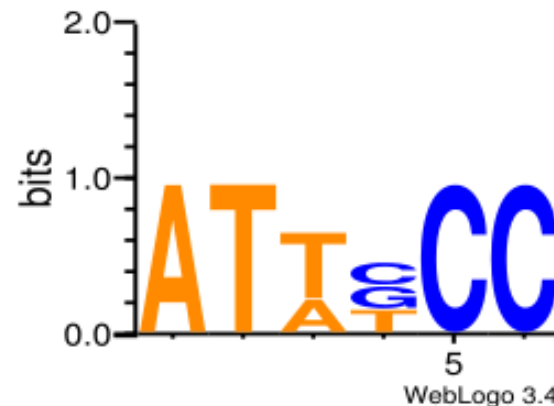
# DNA binding sites



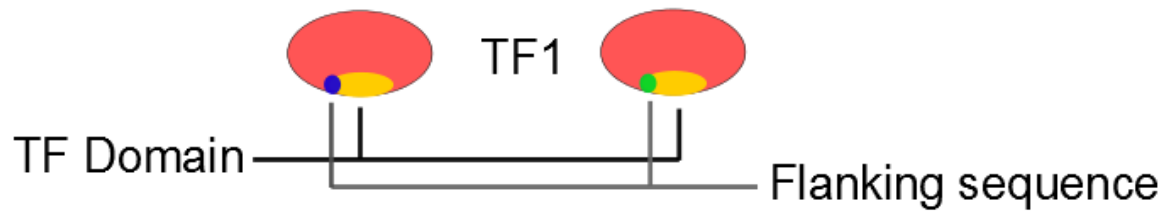
Position Weight Matrix (PWM)

Position	A	T	C	G
1	1	0	0	0
2	0	1	0	0
3	0.33	0.66	0	0
4	0	0.33	0.33	0.33
5	0	0	1	0
6	0	0	1	0

Consensus Motif



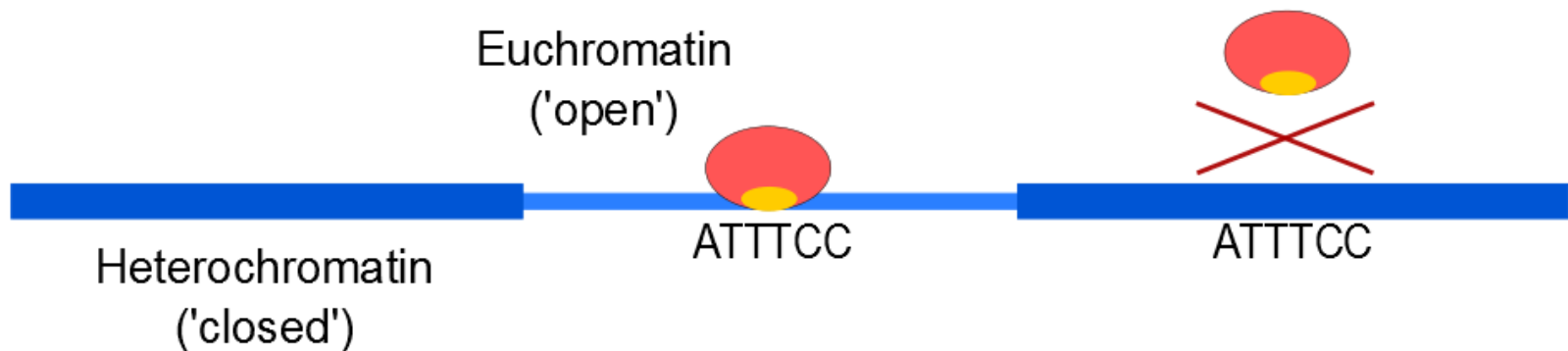
## Variation in flanking sequence of TF domains



## Sequence polymorphism in target DNA



## Site accessibility within chromatin landscape



# Minimum description length (MDL) Principle

- Calculate model complexity
- Calculate smallest data description length (DDL)
- Total DL = sum of complexity and DDL
- Plot total DL as number of clusters increases and search for global minima
- Global minima = optimal number of clusters