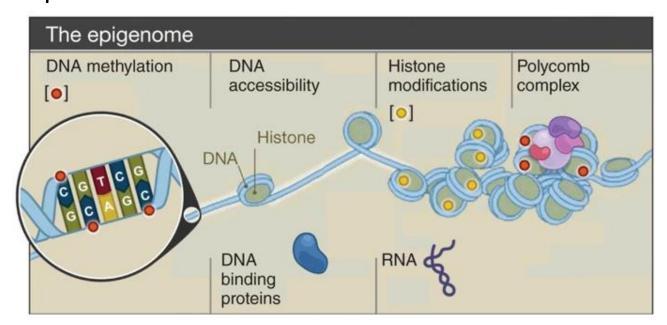


ChIP-Seq: Using High-Throughput Sequencing to Discover Protein-DNA Interactions

Dena Leshkowitz
Introduction to Deep Sequencing Analysis
for Biologists
Course 2019-2020

Epigenome

- ✓ How does the same genome sequence give rise to over 200 different cell types through remarkably consistent differentiation programs?
- ✓ Gene regulation and genome function are intimately related to the physical organization of genomic DNA
- Fpigenetic modifications are **reversible** modifications on a cell's DNA or histones that affect gene expression without altering the DNA sequence.





www.itsjustabadday.com

Definition

ChIP-seq is short for
 chromatin immuno-precipitation followed
 by sequencing

It provides quantitative, genome-wide view of DNA- protein binding events

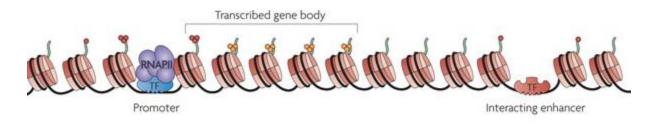
ChIP-Seq - Lecture Outline

- Experimental issues: how is a ChIP-Seq experiment done?
- Analysis of the sequence data: how to detect the binding regions?
- Downstream analysis: how to extract the biological relevance?

Aim: Transcription Regulation

Characterize genome wide DNA-protein interactions in vivo, such as:

- TF to promoter or enhancer
- RNA polymerase II
- Modified histones

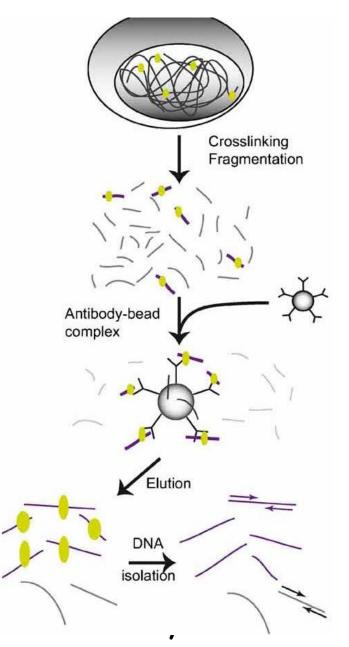


Nature Reviews | Genetics

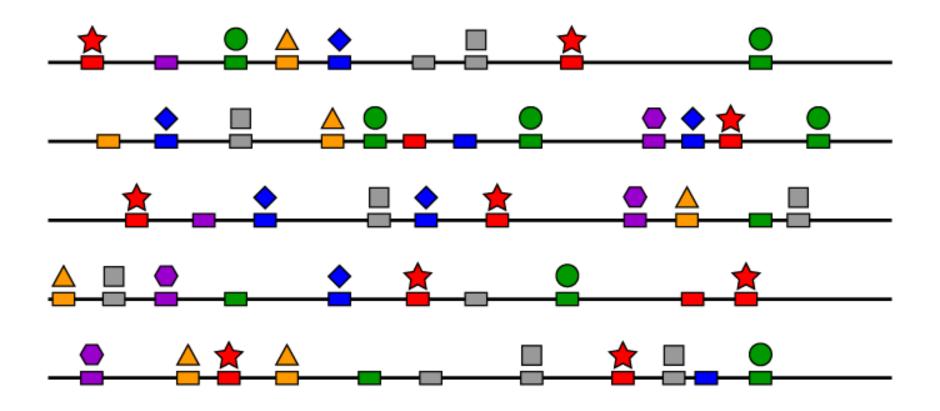
ChIP - How is it done?

ChIP is a technique that permits to

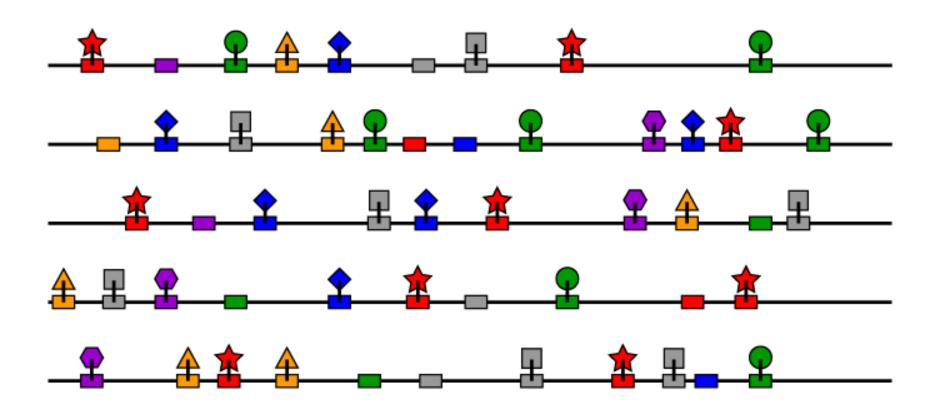
- "Freeze" the protein-DNA binding events inside the cell nucleus
- Use antibodies to extract the DNA bound by a specific protein



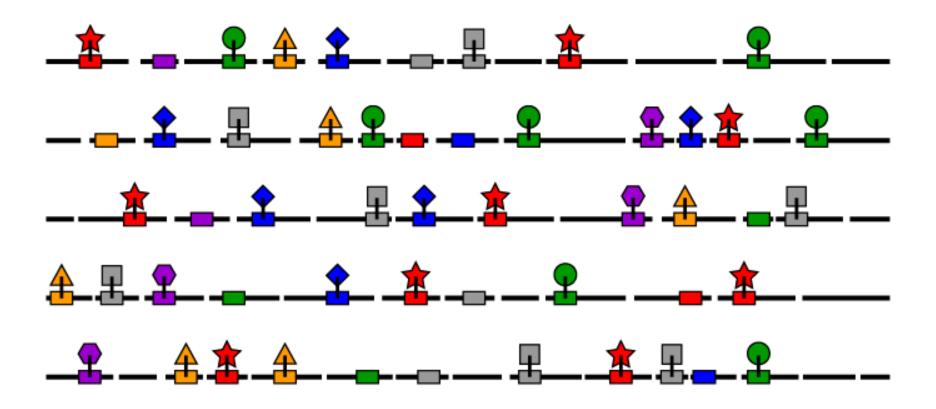
Chromatin ImmunoPrecipitation (ChIP)



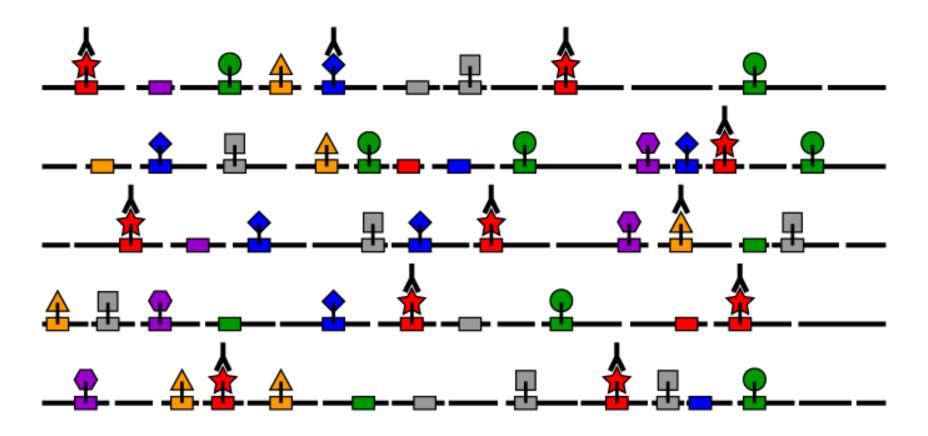
TF/DNA Crosslinking in vivo



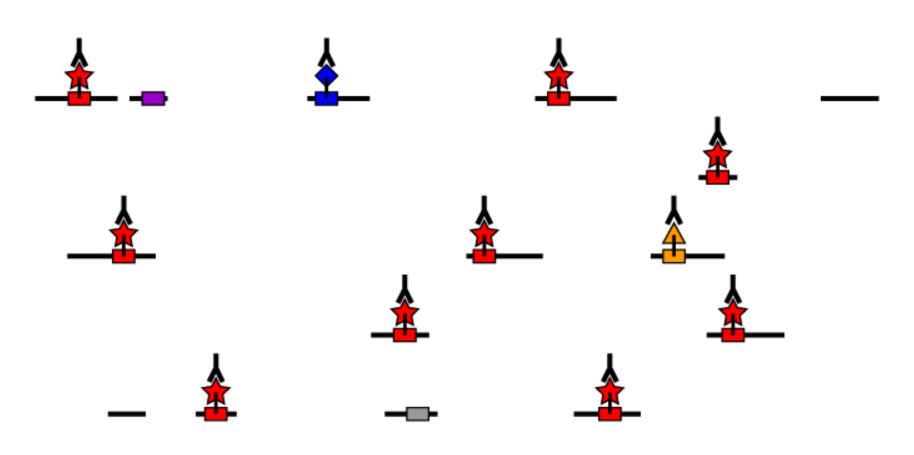
Sonication (~200bp)



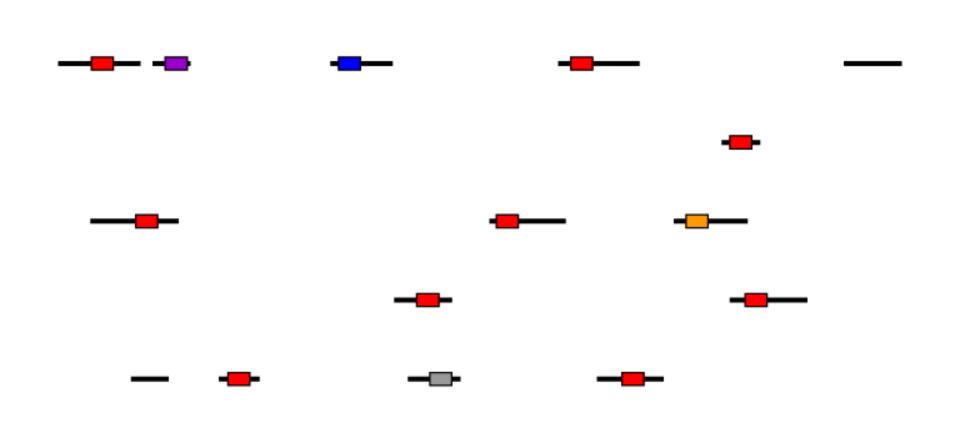
TF-specific Antibody



Immunoprecipitation



Reverse Crosslink and DNA Purification



ChIP High-throughput technology

Discover the DNA binding regions in the genomic scale

DNA Microarrays

Next Generation Sequencing

Hybridized Probe Cell
Single stranded, labeled RNA target
Oligonucleotide probe

Millions of copies of a specific oligonucleotide probe

AFFYMETE
Image of Hybridized Probe Array

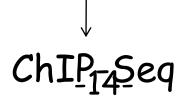
More attractive for where promoter chips are not sufficient to study regulation.

NGS in comparison has a wider dynamic range and GGAGATAGI

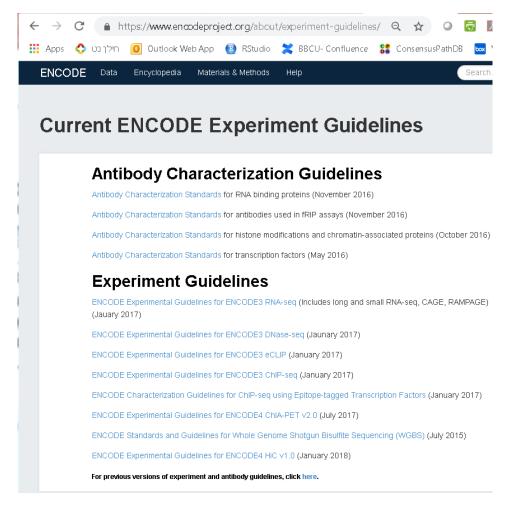
better base-resolution.



ChIP-Chip



ENCODE Guidelines



Experimental Design

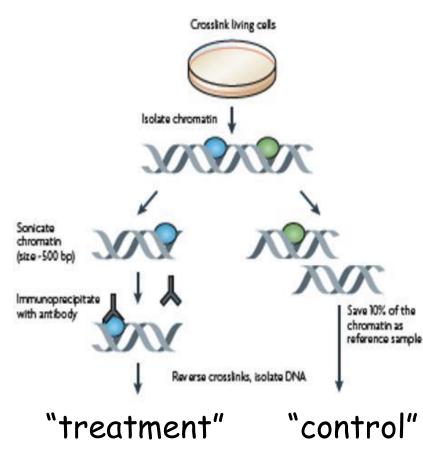
ENCODE consortium's Standards,
 Guidelines and Best Practices

Genome Res. 2012 Sep;22(9):1813-31. doi: 10.1101/gr.136184.111.

- Consult with the person who will analyse the data before performing the experiment
- Kick-off meeting

Types of ChIP Controls

- ✓ "Input" DNA before IP
- ✓ "Mock" IP with no antibody
- ✓ IP with Pre-Immune Serum
- ✓ IP with a non-relevant antibody
- ✓ IP with knock out (cells without the relevant protein)
- ✓ Control should be same cell and condition as the IP in order to account for genetic and epigenetic features



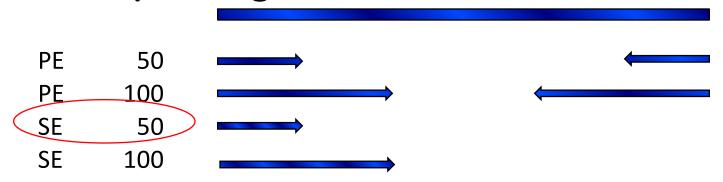
-17-Nat Rev Genet. 2009 10(9): 605-616.

Why Do I Need a Control Sample?

- Majority of DNA sequenced in a ChIP reaction is background, the IP is an enrichment method
- We will have a lot of biased DNA fragments that did not bind our protein of interest
 - DNA that is more prone to breakage (openchromatin regions)
 - Specific amplified DNA in the genome we sequence (but not in the reference genome)
 - Artificially high signal in some types of repeat regions such as satellite, telomeric and centromeric repeats
 - Other technical or sequence bias
- Need to have a control!

Other Experimental Design Issues

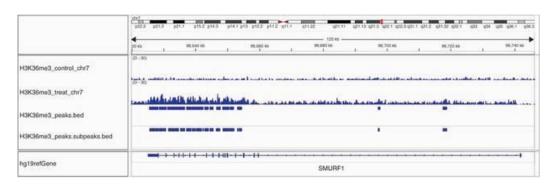
- Use validated antibody maybe even two different antibodies
- Need to have biological replicates
- If we have a good reference genome (mouse, human...) no need to sequence long reads (>50 bases) and no need in pairedend sequencing



How much reads (sequences) per sample?

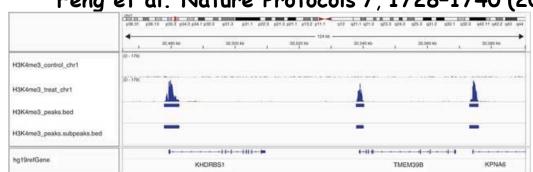
Coverage Required - Types of Peaks

Broad peaks-H3K36me3 (exon regions)



Feng et al. Nature Protocols 7, 1728-1740 (2012)

Sharp peaks-H3K4me3 (promoter regions)



ENCODE recommendations:

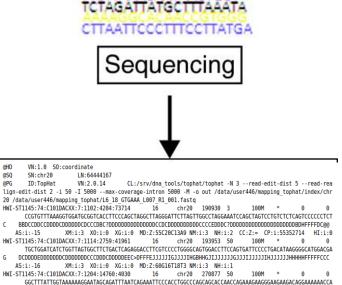
uniquely aligned read	Sharp Peaks	Broad peaks
mammalian cells	10M	15-20M
flies and worms	2M	5-10M

ChIP-Seq - Lecture Outline

- Experimental issues: how is a ChIP-seq experiment done?
- Analysis of the sequence data: how to detect the binding regions?
- Downstream analysis: how to extract the biological relevance?

From Sequences to Mapped Reads

- Mapping million of sequencesreads:
 - find their best alignment to the genome
- Instead of sequence we have coordinates and orientation
- Usually exclude sequences that map to more than one location on the genome



SN:chr20

HWI-ST1145:74:C101DACXX:7:1210:11167:8699

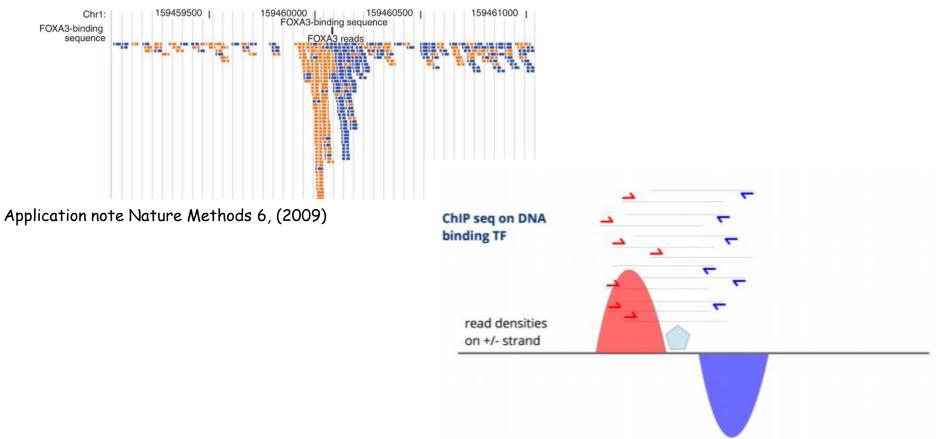
Mapped Reads - bam

DDDDDDDDDCCDDDDDDDDDEEEEEEEFFFEFFGHHHHFGDJJHJJIJJJJJIIIIGGFJJIHIIIIJJJJJJJJIGHHFAHGFHJHFGGHFFFDD@BE XM:i:2 X0:i:0 XG:i:0 MD:Z:0A85G13 NM:i:2 NH:i:1

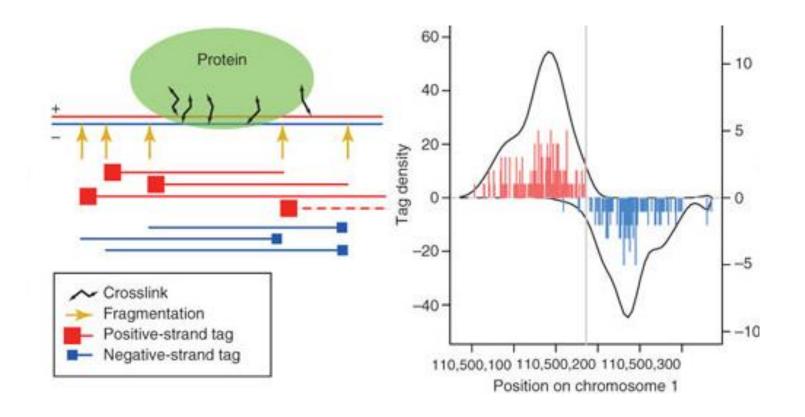
Alignment

Bioinformatics Challenge-Detecting the Binding Regions

View mapped reads in a genome browser



ChIP-Seq Bimodal distribution



Kharchenko at al. Nature Biotechnology 26, 1351 - 1359 (2008)

Bioinformatics Challenge-Detecting the Binding Regions

Method

Open Access

Model-based Analysis of ChIP-Seq (MACS)

Yong Zhang^{**}, Tao Liu^{**}, Clifford A Meyer^{*}, Jérôme Eeckhoute[†], David S Johnson[‡], Bradley E Bernstein^{§¶}, Chad Nussbaum[¶], Richard M Myers[¥], Myles Brown[†], Wei Li[#] and X Shirley Liu^{*}

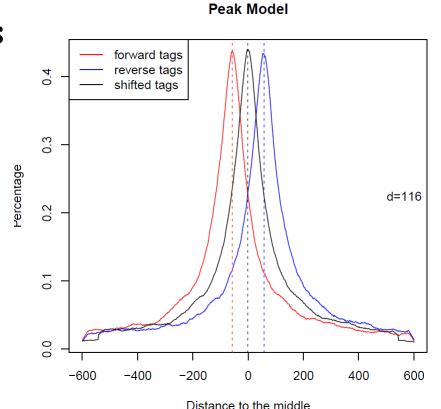
Addresses: "Department of Biostatistics and Computational Biology, Dana-Farber Cancer Institute and Harvard School of Public Health, 44
Binney Street, Boston, MA 02115, USA. †Division of Molecular and Cellular Oncology, Department of Medical Oncology, Dana-Farber Cancer
Institute and Department of Medicine, Brigham and Women's Hospital and Harvard Medical School, 44 Binney Street, Boston, MA 02115, USA.

*Gene Security Network, Inc., 2686 Middlefield Road, Redwood City, CA 94063, USA. *Molecular Pathology Unit and Center for Cancer
Research, Massachusetts General Hospital and Department of Pathology, Harvard Medical School, 13th Street, Charlestown, MA 02129, USA.

*Broad Institute of Harvard and MIT, 7 Cambridge Center, Cambridge, MA, 02142, USA. *Department of Genetics, Stanford University Medical
Center, Stanford, CA 94305, USA. *Division of Biostatistics, Dan L Duncan Cancer Center, Department of Molecular and Cellular Biology,
Baylor College of Medicine, One Baylor Plaza, Houston, TX 77030, USA.

MACS

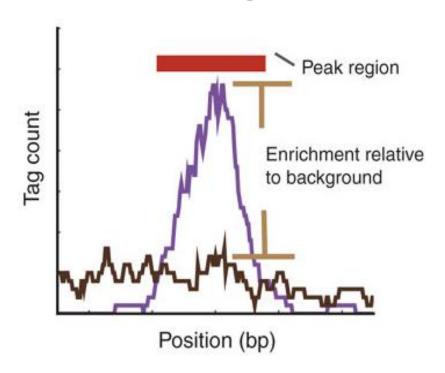
- Building peak model
 - Uses `high-quality' peaks to estimate fragment width d
 - Searches for highly significant enriched regions (above a certain fold)
 - Separates +/- reads and detects the distance between the +/- read distribution
 - Shifts all reads d/2 towards the 3' end



MACS2- Paired end reads

If the sequencing was paired end, MACS2 will use the actual insert sizes of pairs of reads (properly paired) to build fragment

How to Assess If a Peak is Significant?



Poisson distribution

- MACS models the reads distribution along the genome by a Poisson distribution
- The Poisson distribution is a discrete probability distribution that expresses the probability of a number of events occurring in a fixed area, if these events occur with a known average rate and independently. (wikipedia)

Poisson Distribution

The Poisson distribution is sometimes called the law of small numbers because it is the probability distribution of the number of occurrences of an event that happens rarely but has very many opportunities to happen.

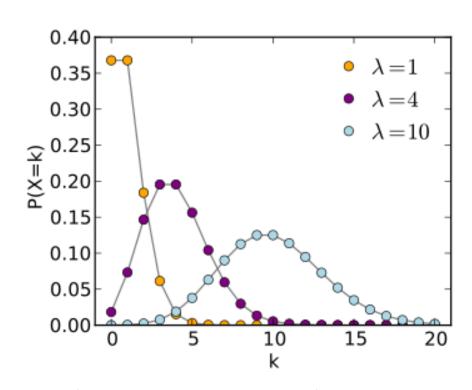
Peak Detection

- MACS models the reads distribution along the genome by a Poisson distribution
 - We are counting reads in a fixed region
 - We can compute the expected (mean) number of events, i.e. number of reads in a specified region:
 - λ_{BG} = total read counts / effective genome size
 - The expectation is a small number
 - We have many reads
- In this model Λ_{BG} is also the variance of the distribution

Poisson Distribution Probability

$$P(k; \lambda) = \frac{\lambda^k}{k!} \cdot e^{-\lambda}$$

Is the probability of observing k, for which λ is the expectation

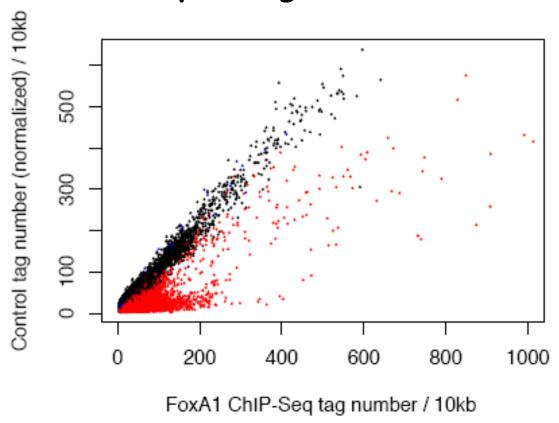


http://en.wikipedia.org/wiki/Poisson_distribution



Peak Detection

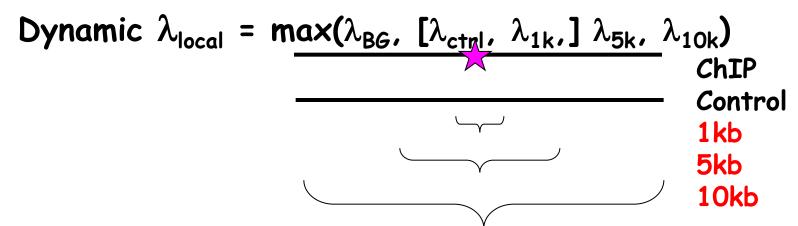
ChIP-Seq show local biases in the genome Chromatin and sequencing bias





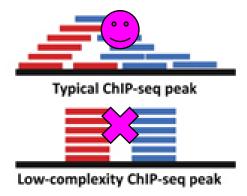
Peak Calls

- The expected number of reads is
 - λ_{BG} = total read counts / effective genome size
- Since ChIP-Seq data show local biases in the genome, a local expected value is calculated for each peak!

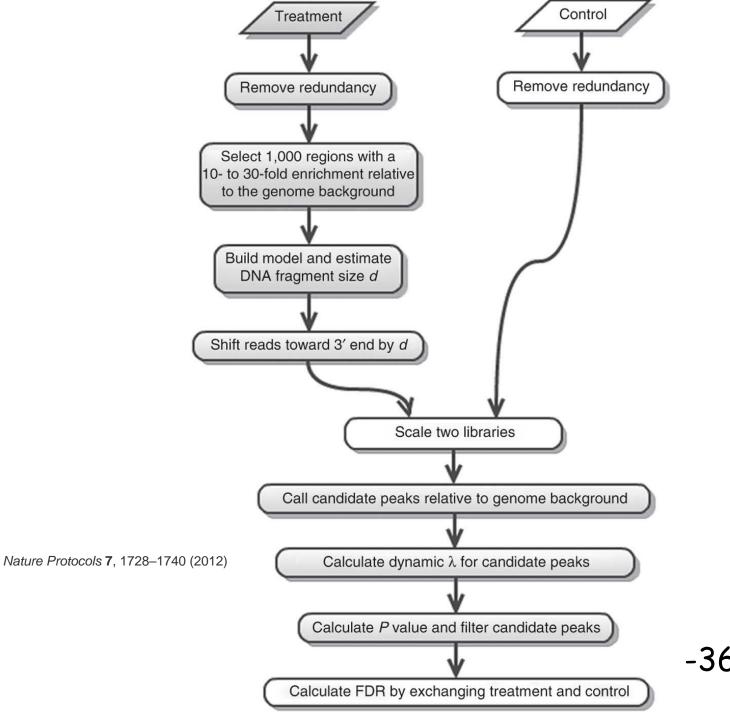


MACS: Zhang et al, Genome Biol 2008 _34_

Redundant Reads - Tags



- Over amplification of ChIP-DNA by PCR may cause the same original DNA fragment to be sequenced repeatedly
- MACS removes the redundant reads i.e. reads at the exact same genome location and the same strand if their number exceeds the expected redundancy.
- Expected is based on the genome size and the number of reads.
- ENCODE guidelines 10M uniquely mapped_reads should have non-redundant frequency >=0.8



-36-

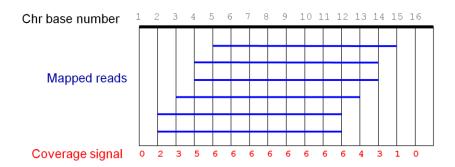
MACS Peak Information (.xls)

- Summit
 peak summit position related to the start position of peak region,
- Tags number of tags-reads in peak region
- -10*log₁₀(pvalue)
 - a PHRED like quality score for the peak region e.g. this value would be 100 for a p-value of 1e-10
- Fold enrichment
 - for this region against random Poisson distribution with local λ

chr	start	end	length	summit	tags	-10LOG ₁₀ *(pvalue)	Fold enrich ment	FDR (%)
chr1	4838075	4838758	684	278	68	459.98	42.53	0.84

MACS: Shifted Wiggle Files

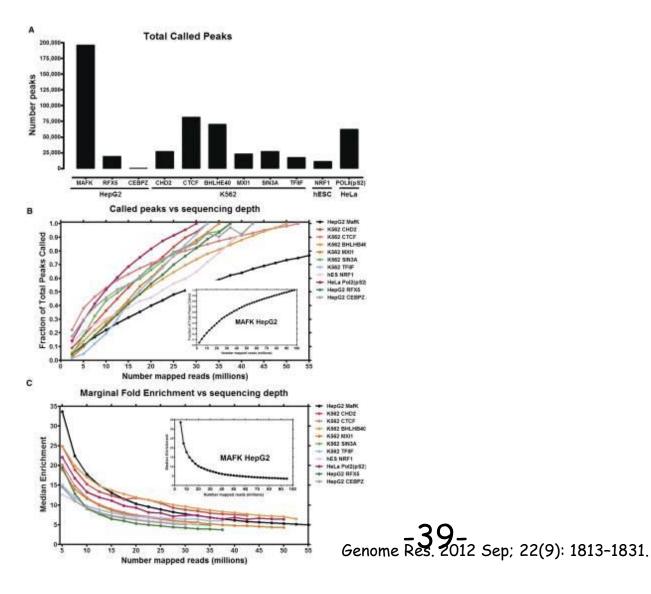
Shifted reads displayed as a coverage signal



Wiggle format example

variableStep chrom=chr1						
1	0					
2	2					
2 3	3					
4 5	5					
5	6					
6	6					
7	6					
8	6					
	6					
10	6					
11	6					
12	6					
13	4					
14	3					
15	1					

Peak Counts Depend on Sequencing Depth



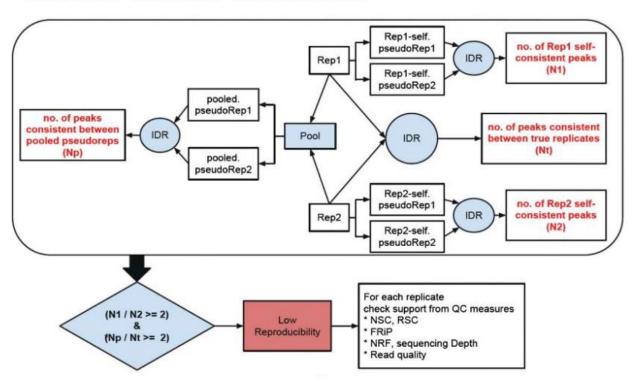
Biological Replicates ENCODE

- Biological replicates are required for each dataset
- Criteria to decide that the biological replicates are in agreement- Irreproducible discovery rate (IDR)
- Reads from replicates which meet these criteria are usually combined and the data rescored.
- If requirement is not meet a third replicate is required.

Biological Replicates Evaluation

https://hbctraining.github.io/Intro-to-ChIPseq/lessons/09_handling-replicates-idr.html

- 1. Evaluate peak consistency between true replicates
- 2. Evaluate peak consistency between pooled pseudo-replicates
- 3. Evaluate self-consistency for each individual replicate



How to Run MACS

- As a command line program (on a Linux server - exercise)
- Web portals such as:
 - GALAXY (public)
 - CISTROME (public)

Disadvantage - They require you to load the mapped reads takes a LONG TIME; Usually do not run the latest version of MACS.

UTAP



Tools

1

FASTA manipulation

Filter and Sort

Join, Subtract and Group

Extract Features

Fetch Sequences

Fetch Alignments

Get Genomic Scores

Operate on Genomic Intervals

Statistics

Graph/Display Data

Regional Variation

Multiple regression

Multivariate Analysis

Evolution

Motif Tools

Multiple Alignments

Metagenomic analyses

Genome Diversity

NGS TOOLBOX BETA

Phenotype Association

NGS: OC and manipulation

NGS: Mapping

NGS: SAM Tools

NGS: GATK Tools (beta)

NGS: Peak Calling

SICER Statistical approach for the Identification of ChIP-

Enriched Regions

MACS Model-based Analysis

of ChIP-Seq

NGS: RNA-sea

NGS: Picard (beta)

NGS: Variant Analysis

<u>snpEff</u>

BEDTools

EMBOSS

Public Tools for ChIP-Seq **Analysis**

REVIEW

Table 1 | Publicly available ChIP-seq software packages discussed in this review

							User input	Artifact filtering: strand-based/	
	Profile	Peak criteria*	Tag shift	Control data ^b	Rank by	FDR ^c	parameters ^d	duplicate*	Refs.
CisGenome v1.1	Strand-specific window scan	1: Number of reads in window 2: Number of ChIP reads minus control reads in window	Average for highest ranking peak pairs	Conditional binomial used to estimate FDR	Number of reads under peak	1: Negative binomial 2: conditional binomial	Target FDR, optional window width, window interval	Yes / Yes	10
v3.1	Tag aggregation	1: Height cutoff High quality peak estimate, per- region estimate, or input	High quality peak estimate, per-region estimate, or input	Used to calculate fold enrichment and optionally P values	P value	1: None 2: # control # ChIP	Optional peak height, ratio to background	Yes / No	4,18
FindPeaks v3.1.9.2	Aggregation of overlapped tags	Height threshold	Input or estimated	NA	Number of reads under peak	1: Monte Carlo simulation 2: NA	Minimum peak height, subpeak valley depth	Yes / Yes	19
F-Seq v1.82	Kernel density estimation (KDE)	s s.d. above KDE for 1: random background, 2: control	Input or estimated	KDE for local background	Peak height	1: None 2: None	Threshold s.d. value, KDE bandwidth	No / No	14
GLITR	Aggregation of overlapped tags	Classification by height and relative enrichment	User input tag extension	Multiply sampled to estimate background class values	Peak height and fold enrichment	2: # control # ChIP	Target FDR, number nearest neighbors for clustering	No / No	17
MACS v1.3.5	Tags shifted then window scan	Local region Poisson P value	Estimate from high quality peak pairs	Used for Poisson fit when available	P value	1: None 2: # control # ChIP	P-value threshold, tag length, mfold for shift estimate	No / Yes	13
PeakSeq	Extended tag aggregation	Local region binomial <i>P</i> value	Input tag extension length	Used for significance of sample enrichment with binomial distribution	q value	1: Poisson background assumption 2: From binomial for sample plus control	Target FDR	No / No	5
QuEST v2.3	Kernel density estimation	2: Height threshold, background ratio	Mode of local shifts that maximize strand cross- correlation	KDE for enrichment and empirical FDR estimation	q value	1: NA 2: # control # ChIP as a function of profile threshold	KDE bandwidth, peak height, subpeak valley depth, ratio to background	Yes / Yes	9
SICER v1.02	Window scan with gaps allowed	P value from random background model, enrichment relative to control	Input	Linearly rescaled for candidate peak rejection and P values	q value	1: None 2: From Poisson P values	Window length, gap size, FDR (with control) or E-value (no control)	No / Yes	15
SiSSRs v1.4	Window scan	N ₊ – N ₋ sign change, N ₊ + N ₋ threshold in region ^f	Average nearest paired tag distance	Used to compute fold-enrichment distribution	P value	1: Poisson 2: control distribution	1: FDR 1,2: N ₊ + N ₋ threshold	Yes / Yes	11
spp v1.0	Strand specific window scan	Poisson P value (paired peaks only)	Maximal strand cross- correlation	Subtracted before peak calling	P value	1: Monte Carlo simulation 2: # control # ChIP	Ratio to background	Yes / No	12
USeq v4.2	Window scan	Binomial P value	Estimated or user specified	Subtracted before peak calling	q value	1, 2: binomial 2: # control # ChIP	Target FDR	No / Yes	20

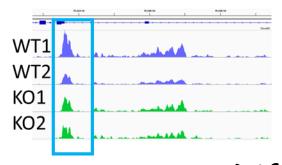
The labels 1: and 2: refer to one-sample and two-sample experiments, respectively. These descriptions are intended to give a mough idea of how control data is used by the software. We means that central data are not handled. "Description of how FIR is or optionally may be computed. Those indicates an FIR is not computed, but the experimental data may still be analyzed; We indicates the experimental stup (1 sample or 2) is not yet handled by the software. E central f & Dill. Pleas colled with control (or some portion theseoff) and unaple reversed. "The list of 'use inpair." parameters' for each program are not exhaustive but rather comprise a subset of quatest interest to new users. "Strand-based artifact filtering rejects peaks if the strand-specific distributions of reads do not conform to expectation, for example by exhibiting extreme bias of tag populations for one strand or the other in a region. Deplicate filtering refers to either removal of reads that occur in excess of expectation at a location or filtering of called peaks to eliminate those due to low complexity read pileups that may be associated with, for example, microsatellite DNA. 'N, and N, are the numbers of positive and negative strand reads, respectively.



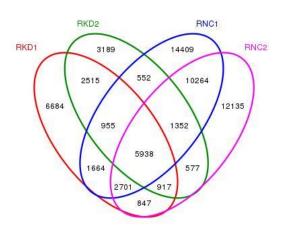


Comparing Peaks

Is the binding to WT higher than to KO?



Venn Diagram using peaks regions

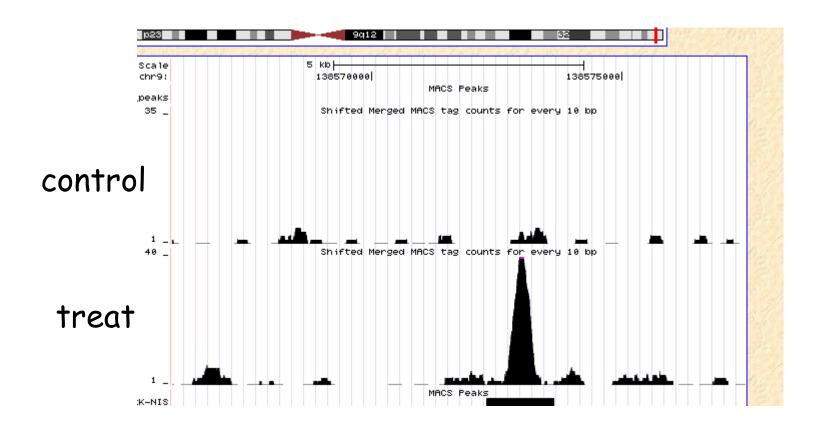


DiffBind: Differential binding analysis of ChIPSeq peak data Extract fragment counts for all peaks in all samples and perform a statistical test, such as DESeq2

ChIP-Seq - Lecture Outline

- Experimental issues: how is a ChIP-seq experiment done?
- Analysis of the sequence data: how to detect the binding regions?
- Downstream analysis: how to extract the biological relevance?

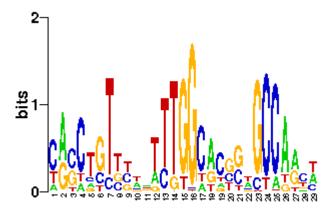
Loading to a Genome Browser



TF Motifs Tools

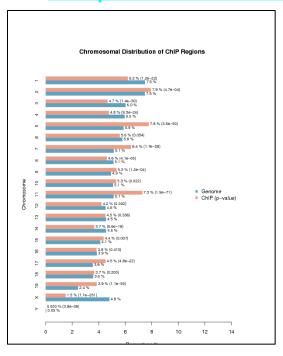
Suppose I have the list of enriched genomic regions, what next?

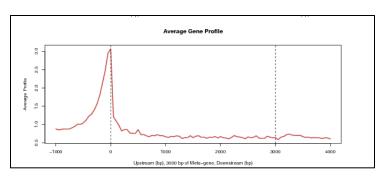
- Find the TF binding motifs enriched in comparison to genomic background
- Predict the TF motif
 Recommended portals:
- MEME-ChIP (public)
- Homer command line

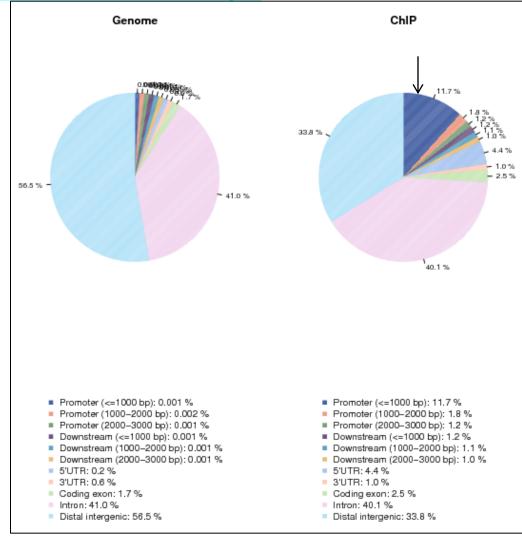


CEAS: Enrichment of Genome Features

http://cistrome.dfci.harvard.edu/ap/

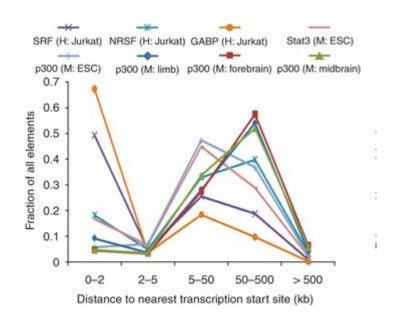






Functional Interpretation

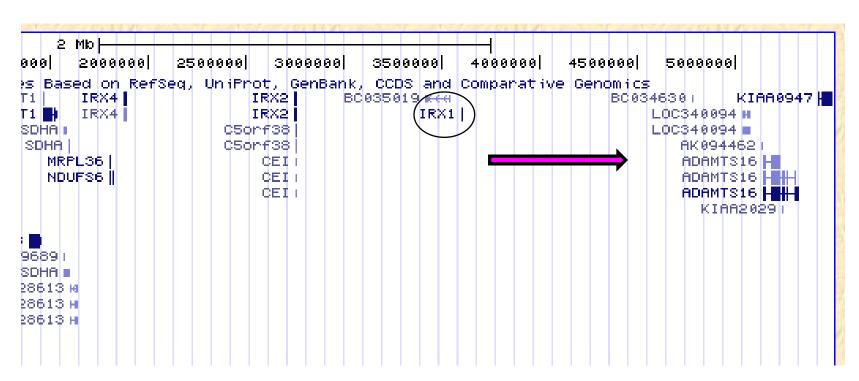
- Which processes and functions does our TF regulate?
 - Associate peaks with genes
 - Associating only proximal genomic regions to genes (<5 kb) - for most TF ignores a large fraction of binding data



Nature Biotechnology 28, 495–501 (2010)

Functional Interpretation

Some genes are found in "gene deserts" and therefore the regulatory genomic region we can assign to them is large (<1Mb)</p>



In Which Processes and Functions is Our TF Involved?

Associating Peaks-Genes-Ontology

- Ontology term 1: gene1,gene2,gene3 ...
- Ontology term 2: gene2,gene5,gene8 ...
- •••
- Are my peaks located near genes enriched for certain ontology terms?
- Which statistical test should we apply?

GREAT improves functional interpretation of *cis*-regulatory regions

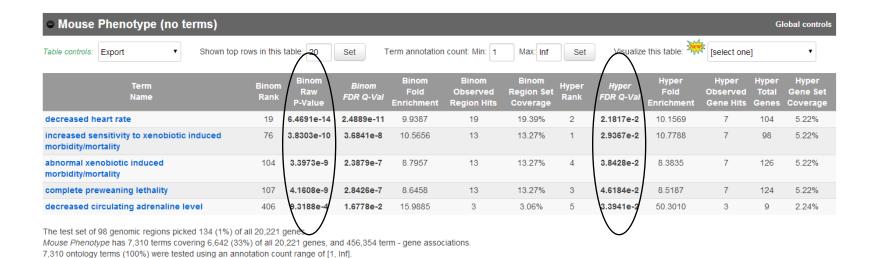
Cory Y McLean, Dave Bristor, Michael Hiller, Shoa L Clarke, Bruce T Schaar, Craig B Lowe, Aaron M Wenger & Gill Bejerano

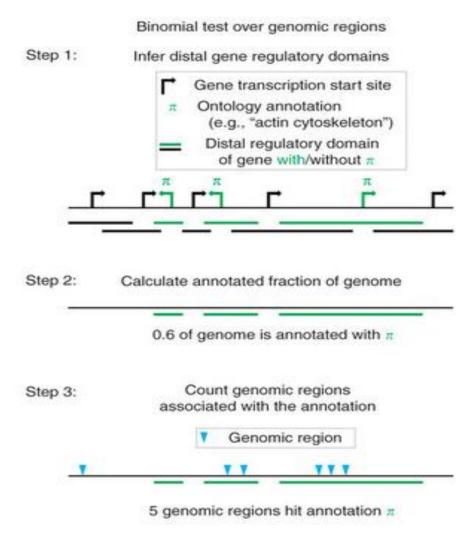
Affiliations | Contributions | Corresponding author

Nature Biotechnology 28, 495-501 (2010) | doi:10.1038/nbt.1630 | Published online 02 May 2010

- GREAT's genomic region-based statistical test
- The probability of hitting a term is calculated as the fraction of the genome that is associated with that term

GREAT ANALYSIS





Nature Biotechnology 28, 495–501 (2010)

Step 4: Perform binomial test over genomic regions
$$n=6$$
 total genomic regions $p_{\pi}=0.6$ fraction of genome annotated with π $k_{\pi}=5$ genomic regions hit annotation π

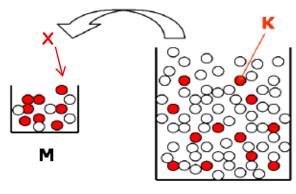
$$P = Pr_{binom} (k \ge 5 \mid n = 6, p = 0.6)$$

Gene List Enrichment Test

The hypergeometric test is the standard gene enrichment test for gene lists (such as differential gene lists from microarray expression studies).

The hypergeometric p-value equals the probability of choosing x from K (red balls- genes with a certain ontology) when randomly drawing M genes from the genome with N genes.

$$P(X = x | N, M, K) = \frac{\binom{M}{x} \binom{N - M}{K - x}}{\binom{N}{K}}$$



Binomial vs Hypergeometric

statistical test calculated for a set of genomic regions

GREAT expects 33% of all input peaks to be associated with 'multicellular organismal development'

statistical test calculated for a set of genes

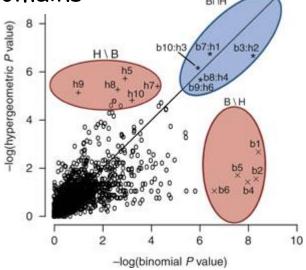
A gene based approach would expect 14% of the genes near peaks to be associated with 'multicellular organismal development'

Why do we have this discrepancy? -56-

GREAT Uses Both the Hypergeometric and the Binomial Test

Significant by hypergeometric: general terms arising from genes with large regulatory domains

Significant in both tests: specific and accurate -supported by multiple genes and binding events



Significant by binomial test: many peaks near few genes

Nature Biotechnology 28 , 495–501 (2010)

Ontologies Included in GREAT

Currently, GREAT includes

- Gene Ontology (GO)
- Ontologies covering phenotypes and human disease
- Pathways
- Gene expression
- Regulatory motifs
- Gene families

ChIP-Seq - Lecture Outline

- Experimental issues: how is a ChIP-seq experiment done?
- Analysis of the sequence data: how to detect the binding regions?
- Downstream analysis: how to extract the biological relevance?

My Peak

