ChIP-seq and ATAC-seq

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Some slides adapted from: https://github.com/genome/bfx-workshop https://github.com/quinlan-lab/applied-computational-genomics



ChIP-seq/ATAC-seq

- Alterations of DNA state or accessibility
- Wrapped around histones
- Bound by transcription factors
- etc



105+ *-seq assays

Nucleo-Seq: Anton Valouev et al., "Determinants of Nucleosome Organization in Primary Human Cells," Nature 474, no. 7352 (June 23, 2011): 516–520, doi:10.1038/nature10002.

DNAse-Seq: Gregory E. Crawford et al., "Genome-wide Mapping of DNase Hypersensitive Sites Using Massively Parallel Signature Sequencing (MPSS)," *Genome Research* 16, no. 1 (January 1, 2006): 123–131, doi:10.1101/gr.4074106.

DNAseI-Seq: Jay R. Hesselberth et al., "Global Mapping of protein-DNA Interactions in Vivo by Digital Genomic Footprinting," Nature Methods 6, no. 4 (April 2009): 283–289, doi:10.1038/nmeth.1313.

Sono-Seq: Raymond K. Auerbach et al., "Mapping Accessible Chromatin Regions Using Sono-Seq," Proceedings of the National Academy of Sciences 106, no. 35 (September 1, 2009): 14926–14931, doi:10.1073/pnas.0905443106.

Hi-C-Seq: Erez Lieberman-Aiden et al., "Comprehensive Mapping of Long-Range Interactions Reveals Folding Principles of the Human Genome," Science 326, no. 5950 (October 9, 2009): 289–293, doi:10.1126/science.1181369.

Ch1A-PET-Seq: Melissa J. Fullwood et al., "An Oestrogen-receptor-a-bound Human Chromatin Interactome," Nature 462, no. 7269 (November 5, 2009): 58–64, doi:10.1038/nature08497.

FAIRE-Seq: Hironori Waki et al., "Global Mapping of Cell Type–Specific Open Chromatin by FAIRE-seq Reveals the Regulatory Role of the NFI Family in Adipocyte Differentiation," *PLoS Genet* 7, no. 10 (October 20, 2011): e1002311,

NOMe-Seq: Theresa K. Kelly et al., "Genome-wide Mapping of Nucleosome Positioning and DNA Methylation Within Individual DNA Molecules," Genome Research 22, no. 12 (December 1, 2012): 2497–2506, doi:10.1101/gr.143008.112.

ATAC-Seq: Jason D. Buenrostro et al., "Transposition of Native Chromatin for Fast and Sensitive Epigenomic Profiling of Open Chromatin, DNA-binding Proteins and Nucleosome Position," *Nature Methods* advance online publication (October 6, 2013), doi:10.1038/nmeth.2688.

from Lior Pachter's blog

Genome variation

RAD-Seq: Nathan A. Baird et al., "Rapid SNP Discovery and Genetic Mapping Using Sequenced RAD Markers," *PLoS ONE* 3, no. 10 (October 13, 2008): e3376, doi:10.1371/journal.pone.0003376.

Freq-Seq: Lon M. Chubiz et al., "FREQ-Seq: A Rapid, Cost-Effective, Sequencing-Based Method to Determine Allele Frequencies Directly from Mixed Populations," *PLoS ONE* 7, no. 10 (October 31, 2012): e47959, doi:10.1371/journal.pone.0047959.

CNV-Seq: Chao Xie and Martti T. Tammi, "CNV-seq, a New Method to Detect Copy Number Variation Using High-throughput Sequencing," *BMC Bioinformatics* 10, no. 1 (March 6, 2009): 80, doi:10.1186/1471-2105-10-80.

Novel-Seq: Iman Hajirasouliha et al., "Detection and Characterization of Novel Sequence Insertions Using Paired-end Next-generation Sequencing," Bioinformatics 26, no. 10 (May 15, 2010): 1277-1283, doi:10.1093/bioinformatics/btq152.

TAm-Seq: Tim Forshew et al., "Noninvasive Identification and Monitoring of Cancer Mutations by Targeted Deep Sequencing of Plasma DNA," Science Translational Medicine 4, no. 136 (May 30, 2012): 136ra68, doi:10.1126/scitransImed.3003726.

DNA replication

Repli-Seq: R. Scott Hansen et al., "Sequencing Newly Replicated DNA Reveals Widespread Plasticity in Human Replication Timing," Proceedings of the National Academy of Sciences 107, no. 1 (January 5, 2010): 139–144, doi:10.1073/pnas.0912402107

ARS-Seq: Ivan Llachko et al., "High-resolution Mapping, Characterization, and Optimization of Autonomously Replicating Sequences in Yeast," *Genome Research* 23, no. 4 (April 1, 2013): 698–704, doi:10.1101/gr.144659.112.

Sort-Seq: Carolin A. Müller et al., "The Dynamics of Genome Replication Using Deep Sequencing," Nucleic Acids Research (October 1, 2013): gkt878, doi:10.1093/nar/gkt878.

Transcription

RNA-Seq: Ali Mortazavi et al., "Mapping and Quantifying Mammalian Transcriptomes by RNA-Seq," *Nature Methods* 5, no. 7 (July 2008): 621– 628, doi:10.1038/nmeth.1226.

GRO-Seq: Leighton J. Core, Joshua J. Waterfall, and John T. Lis, "Nascent RNA Sequencing Reveals Widespread Pausing and Divergent Initiation at Human Promoters," Science 322, no. 5909 (December 19, 2008): 1845– 1848, doi:10.1126/science.1162228.

Quartz-Seq: Yohei Sasagawa et al., "Quartz-Seq: a Highly Reproducible and Sensitive Single-cell RNA-Seq Reveals Non-genetic Gene Expression Heterogeneity," Genome Biology 14, no. 4 (April 17, 2013): R31, doi:10.1186/gb-2013-14-4-r31.

CAGE-Seq: Hazuki Takahashi et al., "5' End-centered Expression Profiling Using Cap-analysis Gene Expression and Next-generation Sequencing," Nature Protocols 7, no. 3 (March 2012): 542–561, doi:10.1038/nprot.2012.005.

Nascent-Seq: Joseph Rodriguez, Jerome S. Menet, and Michael Rosbash, "Nascent-Seq Indicates Widespread Cotranscriptional RNA Editing in Drosophila," *Molecular Cell* 47, no. 1 (July 13, 2012): 27–37, doi:10.1016/j.molcel.2012.05.002.

Precapture RNA-Seq: Tim R. Mercer et al., "Targeted RNA Sequencing Reveals the Deep Complexity of the Human Transcriptome," Nature Biotechnology 30, no. 1 (January 2012): 99–104, doi:10.1038/nbt.2024.

Cel-Seq: Tamar Hashimshony et al., "CEL-Seq: Single-Cell RNA-Seq by Multiplexed Linear Amplification," *Cell Reports* 2, no. 3 (September 27, 2012): 666–673, doi:10.1016/j.celrep.2012.08.003.

3P-Seq: Calvin H. Jan et al., "Formation, Regulation and Evolution of Caenorhabditis Elegans 3'UTRs," Nature 469, no. 7328 (January 6, 2011): 97–101, doi:10.1038/nature09616.

NET-Seq: L. Stirling Churchman and Jonathan S. Weissman, "Nascent Transcript Sequencing Visualizes Transcription at Nucleotide Resolution," Nature 469, no. 7330 (January 20, 2011): 368–373, doi:10.1038/nature09652.

SS3-Seq: Oh Kyu Yoon and Rachel B. Brem, "Noncanonical Transcript Forms in Yeast and Their Regulation During Environmental Stress," RNA 16, no. 6 (June 1, 2010): 1256–1267, doi:10.1261/ma.2038810.

FRT-Seq: Lira Mamanova et al., "FRT-seq: Amplification-free, Strandspecific Transcriptome Sequencing," *Nature Methods* 7, no. 2 (February 2010): 130–132, doi:10.1038/nmeth.1417.

3-Seq: Andrew H. Beck et al., "3'-End Sequencing for Expression Quantification (3SEQ) from Archival Tumor Samples," *PLoS ONE* 5, no. 1 (January 19, 2010): e8768, doi:10.1371/journal.pone.0008768.

PRO-Seq: Hojoong Kwak et al., "Precise Maps of RNA Polymerase Reveal How Promoters Direct Initiation and Pausing," *Science* 339, no. 6122 (February 22, 2013): 950–953, dol:10.1126/science.1229386.

Bru-Seq: Artur Veloso et al., "Genome-Wide Transcriptional Effects of the Anti-Cancer Agent Camptothecin," PLoS ONE 8, no. 10 (October 23, 2013): e78190, doi:10.1371/journal.pone.0078190.

ChIP-seq



Mapping transcription-factor binding locations



NFR = nucleosome free region CRE = Cis regulatory element

http://journal.frontiersin.org/article/10.3389/fgene.2015.00188/full

Mapping histone modifications



NFR = nucleosome free region

http://journal.frontiersin.org/article/10.3389/fgene.2015.00188/full



Examining 3-D DNA interactions in the nucleus





Nature Reviews Genetics 2012 13:840

Peak-calling



Fundamentally a signal vs noise problem

Nature Reviews Genetics 10, 669-680 (October 2009)

Proteins bind in different ways



https://www.ebi.ac.uk/sites/ebi.ac.uk/files/content.ebi.ac.uk/materials/2013/131021_HTS/introduction_to_chip_seq_data_and_analysis-b.gerle_.pdf

How much sequence coverage do we need?

Transcription factor – tight, highly-peaked binding region



For mammalian TFs, chromatin mods like enhancerassociated histone marks:

- have on the order of thousands of binding sites,
- 20 million reads may be adequate
- (4 million reads for worm and fly TFs).

How much sequence coverage do we need?

More binding sites (e.g., RNA Pol II) or broader factors, including most histone marks,

- require more reads, up to 60 million for mammalian ChIP-seq.



https://www.ebi.ac.uk/sites/ebi.ac.uk/files/content.ebi.ac.uk/materials/2013/131021_HTS/introduction_to_chip_seq_data_and_analysis-b.gerle_.pdf

How much sequence coverage do we need?

• Importantly, control samples should be sequenced significantly deeper than the ChIP ones in a TF experiment and in experiments involving diffused broad-domain chromatin data. This is to ensure sufficient coverage of a substantial portion of the genome and non-repetitive autosomal DNA regions.

ChIP-seq statistics

Continuous variables:

- Your exact height
- Your dog's exact weight
- The winning time in a race
- Exact distance between stars
- Your exact age
- Time it takes a computer to complete a task.

Discrete variables:

- The number of lightbulbs that burnout in a warehouse in a given week.
- The number of heads when flipping a coin 50 times.
- The number of students in a class
- The number of times you forget the attachment to an email on Fridays.
- The number of green M&Ms in a bag
- The number of times a given base is sequenced.

The Poisson distribution:

discrete distribution to model coverage

P(k discrete events) = $\lambda^k e^k / k!$

Where e is Euler's constant (2.718), and λ is the average number of occurrences of an event

Example: the "hundred year flood". Thus $\lambda=1$ (1 catastrophic flood every 100 years

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$$egin{aligned} P(k ext{ overflow floods in 100 years}) &= rac{\lambda^k e^{-\lambda}}{k!} = rac{1^k e^{-1}}{k!} \ P(k = 0 ext{ overflow floods in 100 years}) &= rac{1^0 e^{-1}}{0!} = rac{e^{-1}}{1} = 0.368 \ P(k = 1 ext{ overflow flood in 100 years}) &= rac{1^1 e^{-1}}{1!} = rac{e^{-1}}{1} = 0.368 \ P(k = 2 ext{ overflow floods in 100 years}) &= rac{1^2 e^{-1}}{2!} = rac{e^{-1}}{2} = 0.184 \end{aligned}$$

k	P(<i>k</i> overflow floods in 100 years)
0	0.368
1	0.368
2	0.184
3	0.061
4	0.015
5	0.003
6	0.0005

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

Example: expected number of goals in a World Cup game. Average number of goals is 2.5 $k = \frac{k}{k} = \frac{P(k \text{ goals in a World})}{k}$

$$egin{aligned} P(k ext{ goals in a match}) &= rac{2.5^k e^{-2.5}}{k!} \ P(k=0 ext{ goals in a match}) &= rac{2.5^0 e^{-2.5}}{0!} = rac{e^{-2.5}}{1} = 0.082 \ P(k=1 ext{ goal in a match}) &= rac{2.5^1 e^{-2.5}}{1!} = rac{2.5 e^{-2.5}}{1} = 0.205 \ P(k=2 ext{ goals in a match}) &= rac{2.5^2 e^{-2.5}}{2!} = rac{6.25 e^{-2.5}}{2} = 0.257 \end{aligned}$$

Note that λ does not have to be a countable integer.

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

k	P(<i>k</i> goals in a World Cup soccer match)
0	0.082
1	0.205
2	0.257
3	0.213
4	0.133
5	0.067
6	0.028

Poisson distribution with different values of $\boldsymbol{\lambda}$



https://www.umass.edu/wsp/resources/poisson/

Ideally, sequencing coverage will follow a Poisson distribution. But...



Poisson

Not Poisson. Overly "dispersed"

https://www.umass.edu/wsp/resources/poisson/

Negative binomial fits sequencing coverage data much better. Ask Rafael Irizarry



https://www.umass.edu/wsp/resources/poisson/

Comparative ChIP-seq: scaling and normalizing



Sequencing depths from TF ChIP should be compared to control (input DNA) to get a sense of the noise.

When comparing to ChIPseq experiments, you need to normalize the counts / peaks before doing so. E.g., comparing experiments where one had 10 million reads and the other had 100 million reads.

Peak-calling

MACS2, HOMER, SEACR, etc



ChIP-seq peak callers

Table S1. Examples of peak callers employed in ChIP-seq.

Software tool	Version	Availability	Point- source (peaks)	Broad regions (domains)
BayesPeak [88]	1.10.0	http://bioconductor.org/packages/release/bioc/html/BayesPeak.html	Yes	
BEADS § [84]	1.1	http://beads.sourceforge.net/	Yes	Yes
CCAT [91]	3.0	http://cmb.gis.a-star.edu.sg/ChIPSeq/paperCCAT.htm		Yes
CisGenome [56]	2.0	http://www.biostat.jhsph.edu/~hji/cisgenome/	Yes	
CSAR [85]	1.10.0	http://bioconductor.org/packages/release/bioc/html/CSAR.html	Yes	
dPeak	0.9.9	http://www.stat.wisc.edu/~chungdon/dpeak/	Yes	
GPS/GEM [67,18]	1.3	http://cgs.csail.mit.edu/gps/	Yes	
HPeak [87]	2.1	http://www.sph.umich.edu/csg/qin/HPeak/	Yes	
MACS [17]	2.0.10	https://github.com/taoliu/MACS/	Yes	Yes
NarrowPeaks§	1.4.0	http://bioconductor.org/packages/release/bioc/html/NarrowPeaks.htm	nl Yes	
PeakAnalyzer/ PeakSplitter [§] [89]	1.4	http://www.bioinformatics.org/peakanalyzer	Yes	
PeakRanger [93]	1.16	http://ranger.sourceforge.net/	Yes	Yes
PeakSeq [24]	1.1	http://info.gersteinlab.org/PeakSeq	Yes	
polyaPeak§	0.1	http://web1.sph.emory.edu/users/hwu30/polyaPeak.html	Yes	
RSEG [92]	0.6	http://smithlab.usc.edu/histone/rseg/		Yes
SICER [90]	1.1	http://home.gwu.edu/~wpeng/Software.htm		Yes
SIPeS [21]	2.0	http://gmdd.shgmo.org/Computational-Biology/ChIP- Seq/download/SIPeS	Yes	
SISSRs [19]	1.4	http://sissrs.rajajothi.com/	Yes	
SPP [9]	1.1	http://compbio.med.harvard.edu/Supplements/ChIP-seq/	Yes	Yes
USeq [97]	8.5.1	http://sourceforge.net/projects/useq/	Yes	
ZINBA [86]	2.02.03	http://code.google.com/p/zinba/	Yes	Yes

MACS is probably the most widely used

§ Only for post-processing.

http://journals.plos.org/ploscompbiol/article?id=10.1371/journal.pcbi.100332

Replicates, replicates, replicates



Pearson Correlation is one metric indicative of overall reproducibility

(b) Scatterplots of pairwise Zic ChIP-seq replicates with Pearson correlation (*r*) displayed. Note the correlations are much higher between biological replicates of the same developmental stage than between P7 and P60 cerebellum.

http://www.nature.com/neuro/journal/v18/n5/full/nn.3995.html

Irreproducibility Discovery Rate (IDR)



Peaks that show up consistently among replicates are more likely to be real!

SPT20 Replicates (low reproducibility)



Fantastic resource for learning ChIP-seq analysis

https://github.com/hbctraining/Intro-to-ChIPseq

Interpretation





https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5888983/



Genome Segmentation with ChromHMM

Be aware that segmentation may be tissue or cell-type specific!

https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5888983/

The Encyclopedia of DNA Elements Project



https://www.encodeproject.org/

Roadmap Epigenomics Project



http://commonfund.nih.gov/epigenomics/index

Chris Miller, Ph.D. Washington University in St. Louis

Some slides adapted from: https://github.com/genome/bfx-workshop https://github.com/quinlan-lab/applied-computational-genomics



Epigenetics



http://www.nature.com/nature/journal/v441/n7090/full/441143a.html

DNA Methylation



- Mostly happens at CpGs
- About 25 million CpGs in human genome



https://en.wikipedia.org/wiki/CpG_site#/media/File:CpG_vs_C-G_bp.svg

DNA Methylation

- CpG Islands
- Length >= 200 bp
 GC% > 50%
 o/e CpG ratio > 60%
- Selective pressure/ Evolutionary constraint



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was a fundamentary in hyperan and marries (A Dynamic of Carc acar managementary. Dad haves and amore

Islands, shores, and shelves



https://bioconductor.org/packages/release/bioc/vignettes/annotatr/inst/doc/annotatr-vignette.html

What does DNA methylation do?

- The short answer: It depends!
- X-chromosome inactivation
- Silencing of transposable elements
- Cellular differentiation
- Cancer hypo/hypermethylation



MGMT and Temozolomide

- TMZ is an alkylating agent damages DNA, causes cell death
- MGMT "cleans up" the damage

 Methylation of the MGMT promoter is linked to better outcomes!



Methylation Patterns

- Methyltransferases that act locally



Methylation Patterns

- Methyltransferases that act locally

- Other alterations (or treatments) that act globally







5-methylcytosine

https://en.wikipedia.org/wiki/File:Bisulfite_conversion.svg



https://en.wikipedia.org/wiki/File:Wiki_Bisulfite_sequencing_Figure_1_small.png



BSMAP: whole genome bisulfite sequence MAPping program. BMC Bioinformatics 10:232

Whole-genome Bisulfite Sequencing (WGBS)

- Need a special aligner has to expect many C > T mismatches!
- BSMAP
- bismark
- BWA-meth
- biscuit

Methylation calling

- Determine methylation fraction at each site in the genome
 - Count the Cs and Ts, taking strandedness into account
 - Some tools account for SNPs while doing this

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- Why isn't every position 0%, 50% or 100%?



Methylation calling

- Determine methylation fraction at each site in the genome
 - Count the Cs and Ts, taking strandedness into account
 - Some tools account for SNPs while doing this

- Why isn't every position 0%, 50% or 100%?
 - we're sequencing a population of cells!



Workflow/File formats

- Aligning: FASTQ > BAM/CRAM
- Pileup: BAM/CRAM > VCF
 - (entries for every site, allele frequencies)
- VCF > bedgraph
 - chr, start, stop, beta_value (methylation fraction)
- bedgraph > bigwig (for visualization in IGV)
- There are workflows for this!

IGV visualization



Differentially methylated regions

- Comparing two groups to find changes

 Finding DMRs is a segmentation problem

- We use a tool called metilene



https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4728377/

Differentially methylated regions



Number of samples matters!



Heatmaps



Canyon Plots



DNMT3A deficiency



DNMT3A deficiency

- Mouse models (and human data)
- Looking at context, effects, and reversibility



https://www.pnas.org/content/117/6/3123.full

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