UNIVERSITY OF WISCONSIN-MADISON
Probabilistic generative modeling of multimapping reads with $\mathrm{mHi}-\mathrm{C}$ advances analysis of Hi-C studies

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## Google atsnp search

## http://atsnp.biostat.wisc.edu/

CPCP

Search for effects of SNPs on transcription factor binding
Select a search type:

| SNPid List | SNPid Window | Genomic Location | Gene | Transcription Factor |
| :---: | :---: | :---: | :---: | :---: |
| Please type SNPids of interest in the box or upload a text file containing a list of SNPids. SNPids can be separated with commas, spaces, or newlines. <br> If more than 1,000 SNPids are specified, only the first 1,000 will be included in the search. <br> SNPids |  |  |  |  |
| File of SNPids Choose File No file chosen |  |  |  |  |
| Refine your search to identify GAIN and/or LOSS of function, and to narrow down PWMs based on their degeneracy. |  |  |  |  |
| P-value SNP impact ${ }^{\text {? }}$ | 0.05 |  |  |  |
| SNP impact type | CAIN of function | Specify sort order? |  | mpac $\downarrow$ rdinat $\downarrow$ E䧚 |
| P-value Reference ? | $\leq$ | Filter by motif degeneracy? |  | $\checkmark$ Low $\downarrow$ Moderate $\downarrow$ High $\downarrow$ Very High |
| P-value SNP? | $\leq$ |  |  |  |
| Search |  |  |  |  |
| Use an example search |  |  |  |  |

## High throughput chromatin conformation

 capture (Hi-C) for studying long-range interactions

ENCODE project generated catalogs of enhancers.

## Hi-C for studying long-range interactions



## Looping of DNA



ENCODE project generated catalogs of enhancers.

## Hi-C experimental protocol



Cut with restriction enzyme

Fill ends and mark with biotin

Ligate


Purify and shear DNA; Sequence using pull down biotin



Rao et al., Cell, 2014

## Hi-C experimental protocol

Data gets summarized as a contact count matrix.


## Just like any sequencing dataset, Hi-C analysis start with read alignment



# Signals from repetitive regions are under-represented 



## Signals from repetitive regions are under-represented




## Evaluation: 6 independent studies, with 8

 datasets, and multiple replicates per datasetTable 1. Hi-C Data Summary

| Cell line | Replicate | Read length (bp) | Restriction Enzyme | HiC Protocol | Source | Resolution (kb) |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| IMR90 | rep1-6 | 36 | HindIII | dilution | Jin et al. (2013) | 40 |
| GM12878 | rep2-9 | 101 | Mbol | in situ | Rao et al. (2014) | 5, 10*, 40* |
| GM12878 | rep32, rep33 | 101 | DpnII | in situ | Rao et al. (2014) | 5 |
| A549 | rep1-4 | 151 | Mbol | in situ | Dixon et al. (2018) | 10,40 |
| ESC(2012) | rep1, rep2 | 36 | HindIII | dilution | Dixon et al. (2012) | 40 |
| ESC(2017) | rep1-4 | 50 | DpnII | in situ | Bonev et al. (2017) | 10,40 |
| Cortex | rep1-4 | 50 | DpnII | in situ | Bonev et al. (2017) | 10,40 |
| P.falciparum | 3 stages | 40 | Mbol | dilution | Ay et al. (2014b) | 10,40 |
| * Replical |  |  |  |  |  |  |

* Replicates 2, 3, 4, and 6 of the GM12878 cell line datasets were process at 10kb and 40kb resolutions.


## Criteria for selection

- Genome size (large, small)
- Sequencing depth, coverage
- Cis-to-Trans ratio
- Proportion of mappable and valid reads


## Multi-reads are abundant




## Multi-reads are abundant



## Results across eight studies

Uni-reads $\square$ Multi-reads (High Quality) $\square$ Multi-reads (Low Quality) $\square$ Singleton

| IMR90 | GM12878 | A549 |
| :---: | :---: | :---: | :---: |
| $(36 \mathrm{bp})$ | $(101 \mathrm{bp})$ | E |


| ESC-2012 | ESC-2107 |
| :---: | :---: |
| $(36 \mathrm{bp})$ | $(50 \mathrm{bp})$ |



| IMR90 |
| :---: |
| $(36 b p)$ |


| A549 | ESC-2012 |
| :--- | :--- |
| (151bp) | $(36 \mathrm{bp})$ |


3


## Sometimes, there is free lunch

## mHi-C Pre-processing Rescues Multi-reads

Validation Checking Genome Binning


Valid read pair

## Sometimes, there is free lunch



[^0]
## Sometimes, there is free lunch

No-cost multi-reads: add $\sim 5 \%$


## Sometimes, there is free lunch

No-cost multi-reads: add $\sim 5 \%$
Multi-reads need rescuing: add ~ 23\%



# mHi-C: multi-read allocation for $\mathrm{Hi}-\mathrm{C}$ 




Local Bin-pair Contact Counts

## $\mathrm{mHi}-\mathrm{C}$ model

## Observed: $\quad Y_{i,(j, k)}=1$.

Valid read pair $i$ aligned to contact unit $(j, k)$.

## $\mathrm{mHi}-\mathrm{C}$ model

Observed: $\quad Y_{i,(j, k)}=1$.
Valid read pair $i$ aligned to contact unit $(j, k)$.

Uni


## $\mathrm{mHi}-\mathrm{C}$ model

## Observed: $\quad Y_{i,(j, k)}=1$. <br> Valid read pair $i$ aligned to contact unit $(j, k)$. <br> Uni <br> 

$$
\sum_{j, k}^{\mathrm{e} . \mathrm{g} .} Y_{i,(j, k)}=4
$$

## $\mathrm{mHi}-\mathrm{C}$ model

Observed: $\quad Y_{i,(j, k)}=1$.
Uni
Valid read pair $i$ aligned to contact unit $(j, k)$.

Hidden: $\quad Z_{i,(j, k)}=1$,


Valid read pair $i$ originated from contact unit $(j, k)$.

## $\mathrm{mHi}-\mathrm{C}$ model

Observed: $\quad Y_{i,(j, k)}=1$.

## Uni

Valid read pair $i$ aligned to contact unit $(j, k)$.


Hidden: $\quad Z_{i,(j, k)}=1$,

## Multi

Valid read pair $i$ originated from contact unit $(j, k)$.

## mHi-C model

$Z_{i} \sim \operatorname{Multinomial}\left(\pi_{(1,2)}, \pi_{(j, k)}, \cdots, \pi_{(M, M-1)}\right)$ $\pi \sim \operatorname{Dirichlet}\left(\gamma_{(1,2)}, \cdots, \gamma_{(j, k)}, \cdots, \gamma_{(M, M-1)}\right)$ $\gamma_{(j, k)}$ is modeled as a function of the distance between contact units $j$ and $k$
$\gamma_{(j, k)}$ play the role of pseudo-counts in the DirichletMultinomial framework.
 Genome research (2014)


## $\mathrm{mHi}-\mathrm{C}$

$$
P\left(Z_{i,(j, k)}=1 \mid Y_{i,\left(j^{\prime}, k^{\prime}\right)}, \forall j^{\prime}, k^{\prime}\right)
$$

Threshold posterior probabilities to use resulting alignments with existing significant contact identification methods (e.g., fit-HiC).


# $\mathrm{mHi}-\mathrm{C}$ : from read-pairs to significant contacts 

Process reads to get valid read pairs
Partition genome into non-overlapping intervals (5-300Kb or 10 RE sized units)

Generate raw contact map
mHiC makes these steps multi-read aware

Normalize contact map
Identify significant contacts

## Evaluation

| A. Sequencing depth | $\boldsymbol{v}$ |
| :--- | :--- |
| B. Accuracy of multi-read assignment by trimming <br> experiments |  |
| C. Impact on coverage |  |
| D. Reproducibility across replicates: both raw <br> contact count matrix and also identified contacts |  |
| E. Biological impact: Novel promoter-enhancer <br> interactions |  |
| F. Biological impact: TAD inference |  |

## B. Alternative read rescue




## Trimming experiments:

Start with long read datasets (e.g., $\geq 100 \mathrm{bp}$ ).

Align and get uni-reads (long uni-reads).

Trim the long uni-reads to generate short reads.

Align trimmed reads, some of which are now multi-reads.

Evaluate them against their true alignment positions from the longer uni-read set.

## B. Accuracy



## B. Accuracy

■Correctly Assigned

- Falsely Assigned

Not Assigned



## B. Accuracy





## B. Recovering the full length contact matrix



$-36-50+75-100-125$-TrimUni - - TrimUni\&Multi



## C. Major improvement in coverage



## D. Reproducibility of the contact matrix



# D. Reproducibility of the significant interactions 



Uni-\&Multi-reads



# D. ROC- and PR-based on replicate gold standard 




High depth replicates are used to define "true" positives and negatives.

## E. Impact on TAD inference

\# of TADs detected do not change significantly.


TAD: Topologically associated domain

97.55 MB


```
30
```

Chromosome 10

## E. Impact on TAD inference

\# of TADs detected do not change significantly.

■Uni-setting Uni\&Multi-setting

\# of reproducible TADs increases by $2.01 \%$.
\# of irreproducible TADs decreases by $2.36 \%$.

## E. Impact on TAD inference

Uni-setting
Uni\&Multi-setting


## E. Impact on TAD inference

Uni-setting
Uni\&Multi-setting


## F. Repetitive elements at the boundaries of reproducible TADs



## F. Disease-Associated short tandem repeats co-localize with domain boundaries

## Cell

Disease-Associated Short Tandem Repeats Colocalize with Chromatin Domain Boundaries Authors James H. Sun, Linda Zhou, Daniel J. Emerson, ..., Beverly L. Davidson, Flora Tassone, Jennifer E. Phillips-Cremins


C


## F. Novel promoter-enhancer interactions

15.8\% more promoter-enhancer interactions that are reproducible in at least 2 replicates.


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## Summary

- Software https://github.com/keleslab/mhic
- Paper
https://www.biorxiv.org/content/early/2018/10/03/301705
- More results on chimeric reads, impact on differential $\mathrm{Hi}-\mathrm{C}$ analysis are available in the manuscript.


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U01 HG007019

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## http://atsnp.biostat.wisc.edu/

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$\square \mathrm{He}$
(2) FAQ
(i) About

СРСР

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| P-value SNP impact? | 0.05 |  |  |  |
| SNP impact type | GAIN of function LOSS of function | Specify sort order? |  | mpac $\ddagger$ rdinat $\downarrow$ ! |
| P-value Reference? | $\leq$ | Filter by motif degeneracy? |  | $\checkmark$ Low $\checkmark$ Moderate $\checkmark$ High $\downarrow$ Very High |
| P-value SNP? | $\leq$ |  |  |  |
| Search |  |  |  |  |
| Use an example search |  |  |  |  |

## Available positions



1-2 postdoctoral researcher positions in statistical genomics.
If interested. send CV to keles@stat.wisc.edu

## F. Genomic characteristics



## C. Count matrices

Uni-setting (Raw Counts)


Uni-setting (Normalized Counts)


Uni\&Multi-setting (Raw Counts)


Uni\&Multi-setting (Normalized Counts)


## POSTER <br> SNPs in high LD: a formidable challenge

Full loci



Labeling by Massively parallel reporter assays (MPRA)

Zoomed




peak \%
$\begin{array}{llll}0.04 & 0.08 & 0.12 & 0.16\end{array}$


[^0]:    rep1 rep2 rep3 rep4 rep5 rep6

