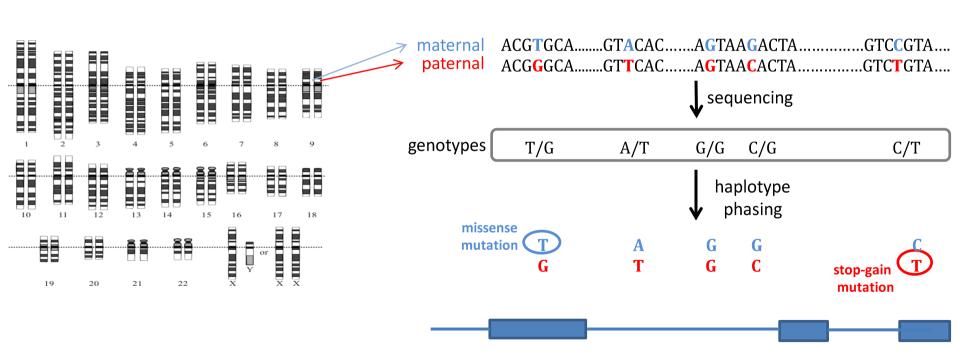
# Integrating read-based and population-based phasing for dense and accurate haplotyping of individual genomes

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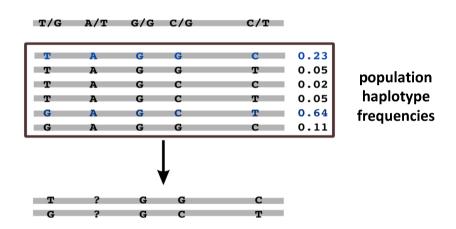
**ISMB 2019** 

### Humans are diploid



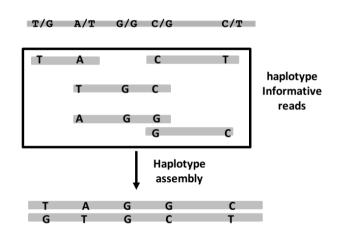
### Two approaches for haplotype phasing

#### 1. Population-based (statistical phasing)



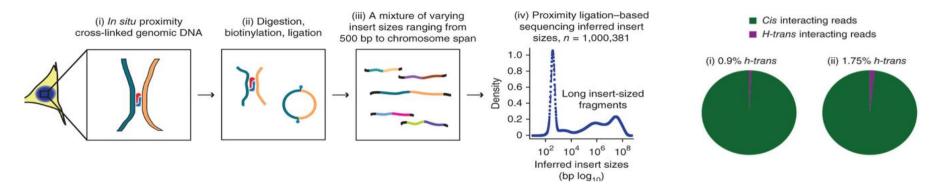
- Uses linkage disequilibrium patterns to infer most likely haplotypes
- Many statistical methods (SHAPEIT, Beagle)
- Limited ability to phase rare variants

#### 2. Read-based (haplotype assembly)



- Requires sequencing with long reads or long-range information
- Equally accurate for common and rare variants

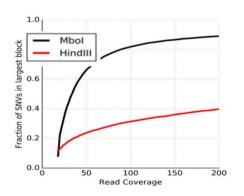
# Illumina sequencing using Hi-C enables whole-genome haplotype phasing



- 98-99% of intra-chromosomal read-pairs are 'cis'
- haplotypes for human genome (NA12878) assembled from 18x whole-genome Hi-C using HapCUT
  - 1. Contiguity: chromosome-spanning haplotype block
  - 2. Completeness: 18-22% variants phased per chromosome
  - **3. Accuracy**: switch error rate of 2-3%

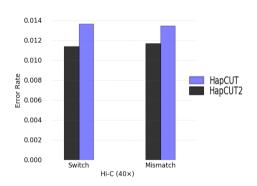
### Improving Hi-C based haplotype phasing

 Using the Mbol (4 bp cut-site) restriction enzyme for Hi-C library preparation

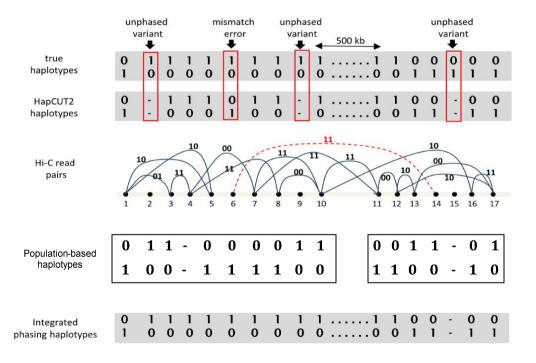


high-depth Hi-C data (Rao et al. 2014)

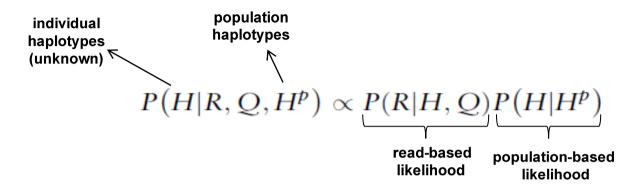
 Modeling trans-errors in Hi-C using a likelihood-based model for haplotyping (HapCUT2)



# Population-based phase information can improve Hi-C phasing

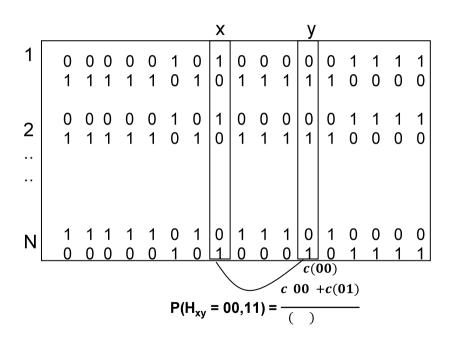


### Joint likelihood model for phasing



- SHAPEIT2 HMM cannot model long-range Hi-C information (Delaneau et al. 2013)
- HapCUT2 can optimize read-based likelihood for Hi-C reads
- Approach: approximate population-based likelihood using second-order probability distributions (estimated using SHAPEIT2) and optimize using HapCUT2

## Approximating population-based likelihood using second-order probability distributions

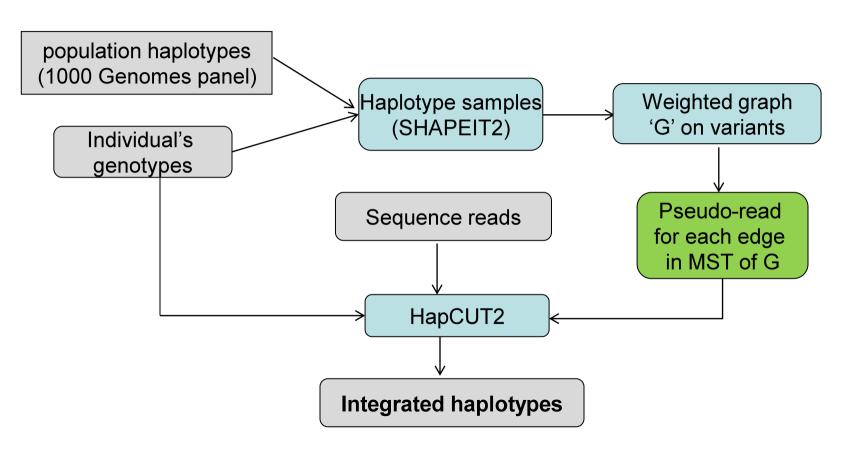


$$P(H|H^p) \approx P(H_{x_1}) \prod_{i=1}^{n-1} P(H_{x_{i+1}}|H_{x_i}),$$

- x<sub>1</sub>, x<sub>2</sub>,...,x<sub>n</sub> is a permutation of the variants
- Select permutation that has minimum KL distance to full distribution
- Chow-Liu (1968): maximum spanning tree of graph with edge weights equal to mutual information gives optimal permutation

Each term can be encoded as a pseudo-read 'r' s.t.  $P(H_x|H_y) = P(r|H_{xy}, q_x, q_y)$ 

### Integrated phasing method



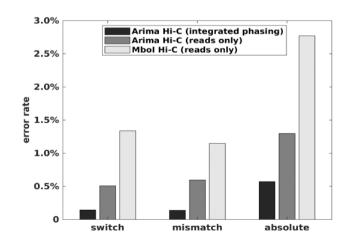
### Results: Hi-C data

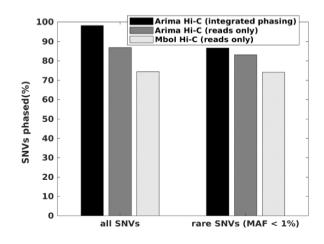
- data for NA19240 from 1KG project (30x coverage)
- Aligned reads to reference genome using BWA-mem
- Phasing accuracy measured using 1KG trio haplotypes

Method	SNVs phased (%)	Absolute error rate (%)	Switch error rate (%)	Mismatch rate (%)	Run time
Reads only	51.30	0.49	0.20	0.365	02:43
Integrated phasing	97.32	0.31	0.034	0.266	08:57
SHAPEIT2	98.67	42.1	0.27	0.76	04:57

### Results: Hi-C data

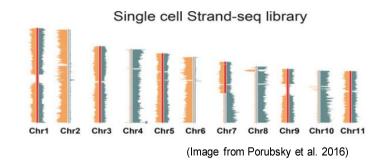
- Data for NA12878 generated using two different Hi-C protocols
  - Mbol RE
  - multi-enzyme chemistry (Arima Genomics)
- Aligned reads to reference genome using BWA-mem
- Phasing accuracy measured using Platinum Genomes haplotypes





### Results: Strand-seq data

- Single-cell sequencing method that provides sparse haplotype information across entire chromosomes
- Strand-seq enables phasing of 70-80% of variants for human genomes (Porubsky et al. 2016)



NA12878 data for 133 cells

Method	SNVs phased (%)	Switch error rate (%)	Mismatch error rate (%)
Reads only	71.38	0.091	0.268
Integrated phasing	94.56	0.0364	0.134

### Conclusions

 Novel likelihood based method that can integrate phase information from sequence reads and population haplotype panel

 Significantly improves completeness and accuracy of phasing using two different sparse sequencing methods

 Multi-enzyme Hi-C sequencing (30-40x WGS) enables highly accurate and dense whole-genome haplotyping

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