De novo whole genome assembly

Lecture 1

Qi Sun

Bioinformatics Facility Cornell University

Data generation

Sequencing Platforms

- Short reads: Illumina
- Long reads: PacBio; Oxford Nanopore

Contiging/Scaffolding Platforms

- Linked-Reads: 10X Chromium
- Optical Mapping: BioNano
- Hi-C: Dovetail; Phase Genomics

DNA fragment length

Sequencing read length

DNA fragment





Short-read Sequencing Platform: Illumina

Paired-end

Fragment: <500bp fragment Read: 100-250 bp

Mate pair reads

Fragment: 5kb, 8kb or 15kb Read: 50 bp





Illumina Reads Assembly Strategy



Long-read Sequencing Platform: PacBio

Fragment: >>10kb Read: 10-20 kb



PacBio: Long read (>10kb); High error rate (>10%)



Chin et al. (2013) Nature Methods 10:563

Oxford Nanopore



Error rate is catching up to PacBio but much much cheaper

MinION

Software for short-read assembly

SOAP de novo: easy to run; relatively fast

Discovar: require longer reads (>=250bp);

MaSuRCA: high quality assembly; slow and memory

intensive



Two categories of contiging strategies

Long reads overlap-layout-consensus

Short reads de-bruijn-graph



Canu, Falcon, Celera et al.

Velvet, Soap-denovo, Abyss, Trinity et al

source: http://www.homolog.us/Tutorials/index.php

de-bruijn-graph for contiging short reads



source: http://www.homolog.us/Tutorials/index.php

Kmer Paths in paralogous regions





Sequencing errors and Tips, bubbles and crosslinks



Deal with sequencing errors and repetitive regions

- 1. Sequencing errors
 - Remove low depth kmers in a bubble;
 - Too long kmers would cause coverage problem;
- 2. Repetitive region
 - Longer kmers



Tiny repeat: Separate the path Break boundary between low and high copy regions

Read depth vs Kmer depth



Impact of kmer-length (2) Read depth vs Kmer depth



Longer kmers could results in too little kmer depth

Kmer counting from sequencing reads

AATTTGTGAATGGCT	1
ATGCAAGACCAATTG	128
ACAAATAGGGGTAGT	1
ΑΑCACAAAATAATAA	1
GCTGTAAGCTTTAAC	1
AACCTATGAGTGAAA	1
ATTCGTAGATCTTCC	101
CAGGTATCAGGCATG	146
TATCAGCTGGAGTCA	60
ACCAGAGATATAAAA	1
GGTCCATTTTGTTTA	1
GTCAAAAAATTACGA	1
ACATTCCCTCGGTAA	1
AGCATTTCTTAACAC	1
ΤΑΑΑΑΑCCATCTTTA	137
ATTCGATTTGTCAAG	62
ACATTGGAAAAAACT	1
AATGGAAATACAATA	2
•••	
CATTCGTTAGATCAA	1
CATTCGT G AGATCAA	128
•••	
CCTTGTCATTAACTC	667

Kmer depth distribution plots



(15mers)

Heterozygous genomes

Experimentally:

- Create inbred lines or haploid cell culture.
- Assembly of clonal fragments, merging allelic regions.

Assembly

- SNP: merge bubbles
- Highly polymorphic regions



Kmer coverage distribution



Examine an assembly software 1. Soap denovo



Scaffolding strategies 1. Mate-pair reads



Software: Soap denovo, et al



Scaffolding strategies 2. Illumina Moleculo and 10X



Illumina Moleculo

- Scaffolding contigs
- Phasing

Scaffolding strategies 3. Physical maps

BioNano:

Generating high-quality genome maps by labeling specific 7-mer nickase recognition sites in a genome with a single-color fluorophore



Sequence cross-linked and ligated DNA fragments





Eucaryotic genome assembly of in 2016



Exercise: Estimate genome size based on kmer distribution



Exercise: Estimate genome size based on kmer distribution



Peak kmer depth: 112

Estimate genome size based on kmer distribution



75 mer Read depth = 3 Kmer depth = 2



Step 1: convert read depth to kmer depth

 $N = M^* L/(L-K+1)$

M: kmer depth = 112 L: read length = 101 bp K: Kmer size =21 bp N: read depth =140

Step 2: genome size is total sequenced basepairs devided by read depth

Genome size = T/N

T: total base pairs = 0.505 gb N: read depth = 140 Genome size: 3.6 mb

Estimate genome size based on kmer distribution



Total kmer bases: 387 mb Kmer depth: 113 Genome size: 3.4 mb

R code to fit Poisson distribution

```
data <- read.table(file="histogram",header=F)</pre>
poisson expeact K=function(file,start=3,end=200,step=0.1){
diff<-1e20
min < -1e20
pos<-0
total<-sum(as.numeric(file[start:dim(file)[1],1]*file[start:dim(file)[1],2]))
singleCopy total <- sum(as.numeric(file[10:500,1]*file[10:500,2]))</pre>
for (i in seq(start,end,step))
  singleC <- singleCopy total/i</pre>
  a<-sum((dpois(start:end, i)*singleC-file[start:end,2])^2)
  if (a < diff){
               pos<-i
               diff<-a
  }
 ļ
 print(paste("Total kmer bases: ", total))
 print(paste("Kmer depth: ", pos))
 print(paste("Genome size: ", total/pos))
 pdf("kmerplot.pdf")
 plot(1:200,dpois(1:200, pos)*singleC, type = "l", col=3, lwd=2, lty=2,
ylim=c(0,150000), xlab="K-mer coverage", ylab="K-mer counts frequency")
 lines(file[1:200,],type="l",lwd=2)
 dev.off()
poisson expeact K(data)
```

Using short kmer could underestimate genome size (<20) Low kmer depth could overestimate genome size (<20) - Minghui Wang



Exercise: Run kmer analysis tools to estimate genome size

You will be provided with a Fastq file. Using Jellyfish to get the kmer count, then estimate the kmer depth

/programs/jellyfish-2.2.3/bin/jellyfish count -s 1G -m 21 -t 4 -o kmer -C SRR1554178.fastq

/programs/jellyfish-2.2.3/bin/jellyfish dump -c -t kmer > kmer21.txt