2015 EBI Cancer Genomics workshop - CNV analysis

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Introduction

This workshop will show you how to proceed when to detect Copy Number Variants (CNV) using either Next Generation Sequencing (NGS) or SNParray data

The initial structure of your folders should look like this:

Data

in this hands-on two types of data are available: SNParray and NGS data

NGS data

approximately 1M of Illumina paired-end 100 reads covering the region chr19:50500375-52501256 from a whole genome experiment for germline and matched tumor samples.

For each sample:

 $\bullet\,$ 1 alignment file (.bam generated in the previous hands-on) on the human reference sequence

SNParray data

Illumina data for more than $650000~\mathrm{SNPs}$ located genome wide for germline and matched tumor samples

For each sample:

- 1 file containing the LogRatio (LRR) mesurement of each probe: the signal intensities compared to a collection of reference hybridizations
- 1 file containing the B Allele Frequency (BAF) mesurement of each probe: the proportion of the total allele signal (A + B) explained by a single allele (A)

What are the advantages and limitations of using each type of technology? solution technology

NGS data analysis

We will start from two alignment files of the tumor and germline samples form the same individual and we will apply a manual read depth procedure to estimate the tumoral copy number.

What are the steps to proceed this analysis? solution NgsAnalysisSummary

NGS data analysis for CNV detection

Starting from a fastq files (1-9) or from BAM files (4-9):

1. Sequence trimming

Removing low quality bases

2. Genome alignment

Locate individual reads to the reference genome

3. Alignment refinement

Realign around INDELs, remove duplicates, etc...

4. Bin creation and count

The choice of the bin size has a major importance (moving or overlaping windows)

We use the software BVAtools to run this sep of the analysis.

Environment setup Open a terminal and set-up the environment in order to be able running BVAtools:

```
export BVATOOLS_JAR=/home/training/Applications/bvatools-1.6/bvatools-1.6-full.jar
```

BVAtools overview Take a look at the BVAtools usage:

```
java -jar $BVATOOLS_JAR
java -jar $BVATOOLS_JAR bincounter
```

Which parameters should we used?

 $solution\ BinCount$

Feel free to test different sets of parameters.

```
cd /home/training/ebicancerworkshop201507/NGS_CNV
java -jar $BVATOOLS_JAR bincounter \
    --minMapQ 35 \
    --refbam ../alignment/normal/normal.sorted.dup.bam \
    --bam ../alignment/tumor/tumor.sorted.dup.bam \
    --norm chr \
    --windows 1000 \
> sample_binCount_1kb.tsv
```

The output file should looks like:

```
$ head sample_binCount_1kb.tsv
chr start end sample_raw ref_raw sample_normalized ref_normalized ln(sample/ref)
chr1     0     1999     0     0     0.0     0.0     NaN
```

Why first lines show no coverage data?

solution BinCount 2

5. Bin count correction (optional)

Two different type of correction are usually applied to the dat:

- 1. GC content
- 2. Mappability

It won't be done today because it needs a whole genome data to properly work

6. Computing LRR

The analysis of binned data and CNV calls will be don eusing the R tool and the DNAcopy package from Bioconductor

Open R

cd \$HOME/ebicancerworkshop201507/CNV/NGSR

Load DNAcopy

library("DNAcopy")

A short presentation DnaCopy Here is the minimal list of functions in the DNAcopy package that are used to run a basic CNV calling algorithm

Function	Explanation
CNA	Creates a Copy Number Array data object
TONI A	D 1: () () ()
DNAcopy	R object resulting of the segmentation step
I COLA	
smooth.CNA	Smooth the signal to reduce outliers points
an man and	Find appropriate harbonium aincilar ainmal using the CDC almonithm
segment	Find segments harboring similar signal using the CBS algorithm
mlat DMA asma	antional, plot the popult of the commentation
plot.DNAcopy	optional: plot the result of the segmentation
acam enta aummanami	entional provides statistics from secoments
segments.summary	optional: provides statistics from segements

Load binned Data

data=read.table("sample_binCount_1kb.tsv",header=T)

head(data)

```
chr start end sample_raw ref_raw sample_normalized ref_normalized
1
          0
             199
                            0
        200
              399
                            0
                                     0
                                                         0
                                                                         0
    1
        400 599
                                     0
                                                        0
                                                                         0
                            0
                                                        0
                                                                         0
    1
        600
             799
                                     0
5
        800 999
                                                                         0
                            0
    1 1000 1199
                                     0
                                                        0
                                                                         0
6
  ln.sample.ref.
1
2
              NaN
3
              NaN
4
              {\tt NaN}
5
              {\tt NaN}
6
              NaN
```

Clean data to remove region with no coverage

dataClean=data[data[,4] > 0 | data[,5] > 0,1:5]
head(dataClean)

	chr	start	end	sample_raw	ref_raw
13549734	19	50500200	50500399	70	120
13549735	19	50500400	50500599	185	328
13549736	19	50500600	50500799	188	349
13549737	19	50500800	50500999	174	363
13549738	19	50501000	50501199	146	312
13549739	19	50501200	50501399	198	341

Normalize count between tumor and germaline

dataNorm=cbind(dataClean,dataClean[,4]/sum(dataClean[,4]),dataClean[,5]/sum(dataClean[,5]))
head(dataNorm)

```
chr
           start
                   end sample_raw ref_raw
13549734
      19 50500200 50500399
                            70
                                 120
328
                           185
188
                                 349
13549737 19 50500800 50500999
                           174
                                 363
13549738 19 50501000 50501199
                           146
                                 312
198
                                 341
      dataClean[, 4]/sum(dataClean[, 4]) dataClean[, 5]/sum(dataClean[, 5])
```

13549734	4.080481e-05	3.686617e-05
13549735	1.078413e-04	1.007675e-04
13549736	1.095901e-04	1.072191e-04
13549737	1.014291e-04	1.115202e-04
13549738	8.510718e-05	9.585203e-05
13549739	1.154193e-04	1.047614e-04

Estimate the logRatio in each bin

```
Chr=dataNorm[,1]
Pos=dataNorm[,2]
logR=log2((dataNorm[,6]+0.00001)/(dataNorm[,7]+0.000001))
logR[1:6]
```

$[1] \quad 0.14275958 \quad 0.09694868 \quad 0.03126659 \quad -0.13555779 \quad -0.16964886 \quad 0.13851792$

7. LRR signal smoothing (optional)

the purpose of this step is to reduce the impact og each single point outliers before doing the analysis

First create a CNA object

```
CNA.object=CNA(logR,Chr,Pos, data.type="logratio",sampleid="TNratio")
CNA.object

Number of Samples 1
Number of Probes 9818
Data Type logratio
```

Then smooth the data

```
smoothed.CNA.object=smooth.CNA(CNA.object)
smoothed.CNA.object

Number of Samples 1
Number of Probes 9818
Data Type logratio
```

8. LRR signal segmentation

Copy number aberrations (CNA) occur in contiguous regions of the chromosome that often cover multiple bins up to whole chromosome arms or chromosomes. The segmentation split the chromosomes into regions of equal copy number that accounts for the noise in the data

Non-exhaustive available methods:

- Circular Binary Segmentation
- Mean Shift-Based
- Shifting Level Model
- Expectation Maximization
- Hidden Markov Model
- Etc...

There is actually no gold standard for the cancer data

Generate segments using Circular Binary Segmentation

segment1=segment(smoothed.CNA.object, verbose=1)
head(segment1\$output)

	ID	${\tt chrom}$	<pre>loc.start</pre>	loc.end	${\tt num.mark}$	seg.mean
1	TNratio	19	50500200	50595200	476	0.0082
2	TNratio	19	50596400	50598600	7	-0.7104
3	TNratio	19	50598800	50609200	9	0.4972
4	TNratio	19	50609400	50636000	15	-0.7169
5	TNratio	19	50636600	50637600	6	-0.0457
6	TNratio	19	50637800	50638800	6	0.5814

9. CNV calling from segments

There is many method that can differenciate the copy number of each segments each

Non-exhaustive available methods:

- Thresholds
- Sd deviation
- Poisson distribution
- Z-score
- Event-Wise Testing

• Etc...

As for segmentation there is non perfect method design for cancer data yet because each cancer sample is different

Call CNA for segment using threshold approach

Output your result in a file

```
CNAtype=rep(".",dim(CNAcall)[1])
names(CNAtype)="CNA_type
CNAtype[CNAcall[,6] >= duplicationTh]="DUP"
CNAtype[CNAcall[,6] <= deletionTh]="DEL"
CNAcallfinal=cbind(CNAcall,CNAtype)
write.table(CNAcallfinal,"sampleCNAcall.tsv",sep="\t",quote=F,col.names=T,row.names=F)
q(save="yes")</pre>
```

You can then look at the call file using this command:

```
head sampleCNAcall.tsv
```

```
ID chrom loc.start loc.end num.mark seg.mean CNAtype
TNratio 19 52133600 52149400 80 -5.6947 DEL
```

This file shows the presence of large deleton event in the chr19 region (19 52133600 52149400).

If you reduce the threshold value you will start to see many region that will pop-up all along the candidat region. In fact one of the major issue of most of the CNV caller from NGS data: due to not so uniform coverage, local variation occurs in the read depth which can produce noise in the resulls:

- 1. scattered calls
- 2. false positive calls
- 3. false negative calls

For your information, here is a non-exhaustive list of available softwares for calling CNV using whole genome NGS Data:

Tool	URL
SegSeq	http://www.broad.mit.edu/cancer/pub/solexa_copy_numbers/
$\operatorname{CNV-seq}$	$\rm http://tiger.dbs.nus.edu.sg/cnv-seq$
RDXplorer	${\rm http://rdxplorer.source forge.net}$
$\operatorname{BIC-seq}$	http://compbio.med.harvard.edu/Supplements/PNAS11.html
CNAsega	http://www.compbio.group.cam.ac.uk/software/cnaseg
${\rm cn.MOPS}$	http://www.bioinf.jku.at/software/cnmops/
${\rm JointSLMb}$	$http://nar.oxfordjournals.org/content/suppl/2011/02/16/gkr068.DC1/JointSLM_R_Package.2011/02/16/gkr068.DC1/JointSLM_R_Package.2011/02/16/gkr068.DC1/JointSLM_R_Package.2011/02/16/gkr068.DC1/JointSLM_R_Package.2011/02/16/gkr068.DC1/JointSLM_R_Package.2011/02/16/gkr068.DC1/JointSLM_R_Package.2011/02/16/gkr068.DC1/JointSLM_R_Package.2011/D01/D01/D01/D01/D01/D01/D01/D01/D01/$
ReadDepth	$\rm http://code.google.com/p/readdepth$
rSW-seqa	http://compbio.med.harvard.edu/Supplements/BMCBioinfo 10-2.html
CNVnator	http://sv.gersteinlab.org
CNVnorma	http://www.precancer.leeds.ac.uk/cnanorm
CMDS	https://dsgweb.wustl.edu/qunyuan/software/cmds
${\rm mrCaNaVar}$	http://mrcanavar.sourceforge.net
${\rm cnvHMM}$	http://genome.wustl.edu/software/cnvhmm
PopSV	$\rm https://github.com/jmonlong/PopSV$
SCoNEs	https://bitbucket.org/mugqic/scones

SNParray data analysis

SNParray analysis are very similar to NGS data analysis while incorporating the additional information bring by the SNP: the BAF. In this analysis we will start from one LRR signal file and one BAF signal file for each of the germline and matched tumor samples from an individul.

Many software are available for doing CNV call from SNParray. Here is a non-exhaustive list of softaware that could be used:

- 1. Proprietary softwares
- 2. GenomeStudio/CNVpartition Illumina
- 3. Genotyping Console/Birdsuite Affymetrix
- 4. Affymetrix oriented softwares
- 5. Genome Alteration Detection Algorithm (GADA)
- 6. Cokgen
- 7. Commercial softwares
- 8. Partek Genomics Suite
- 9. Golden Helix SNP
- 10. Freely available general software
- 11. PennCNV
- 12. QuantiSNP
- 13. Freely available cancer oriented software
- 14. Allele-Specific Copy number Analysis of Tumors (ASCAT)
- 15. OncoSNP

What are the major cancer factors that could biais a CNV analysis?

 $solution\ cancer Challenge$

In this practical I choose to use ASCAT because it handles samples with aneuploidy and the presence of normal cells contamination. Moreover ASCAT facilitates detection of tumor cell heterogeneity.

Here is a video showing how the ASCAT software works:

What are the steps to proceed this analysis?

solution 6.SnpAnalysisSummary

SNParray analysis

we start from filtered LRR and BAF files

during the anlalysis we will need to estimate 3 parrameters in order to have confident CNV calling

- 1. aberrant cell fraction
- 2. tumor ploidy
- 3. absolute all ele-specific copy number calls (for each allelic probes of the $\operatorname{SNP})$

Open R

```
cd ../SNP_CNV/
```

```
Load ASCAT
```

```
source("../src/ascat-2.2.R")
Load data
ascat.raw = ascat.loadData("../SNParray/tumor2.LRR.tsv",
  "../SNParray/tumor2.BAF.tsv",
  "../SNParray/normal2.LRR.tsv",
  "../SNParray/normal2.BAF.tsv")
Plot raw data
ascat.plotRawData(ascat.raw)
Perform segmentation
ascat.seg = ascat.aspcf(ascat.raw)
sPlot segments
ascat.plotSegmentedData(ascat.seg)
Estimate model parameters
ascat.output = ascat.runAscat(ascat.seg)
Ouput model parameters
params.estimate=data.frame(Sample=names(ascat.output$aberrantcellfraction),
 Aberrant_cell_fraction=round(ascat.output$aberrantcellfraction,2),
 Ploidy=round(ascat.output$ploidy,2))
write.table(params.estimate,
  "sample.Param_estimate.tsv",
  sep="\t",
 quote=F,
  col.names=T,row.names=F)
```

Call CNA

determine the copy number by simply counting the total number of allele reported to the sample ploidy

```
CNA=rep(".",dim(ascat.output$segments)[1])
CNA[rowSums(output.table[,5:6]) > round(ascat.output$ploidy)]="DUP"
CNA[rowSums(output.table[,5:6]) < round(ascat.output$ploidy)]="DEL"
output.table=data.frame(ascat.output$segments,CNA=CNA)</pre>
```

Save CNA calls

```
write.table(output.table[output.table$CNA != ".",],
    "sample_CNVcalls.tsv",
    quote=F,
    sep="\t",
    col.names=T,
    row.names=F)
```

These files shows the presence of large deletion and duplication evenet all along the genome of this individuals.

Particularly in the chromosome 12 a very impressive duplication can be observed.

The only limitation of this approach is the size of event that could be detected. Few kb events or less will be missed.

Aknowledgments

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