

# MAF Visualization of somatic mutations in cell lines

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THIS IS AN UNREFINED DATA JUST TO SHOW THE GENERAL IDEA OF WHAT THESE RESULTS WILL LOOK LIKE IN A COUPLE DAYS

## 1. LOADING DATA (#anchor1)

Needed libraries:

```
library(readr)
library(rstudioapi)
library(maftools)
```

```
## Loading required package: BiocManager
```

```
## Bioconductor version 3.10 (BiocManager 1.30.4), R 3.6.0 (2019-04-26)
```

```
## Installing package(s) 'maftools'
```

```
## Warning: package 'maftools' is in use and will not be installed
```

```
## installation path not writeable, unable to update packages: boot, cluster,
## nlme
```

```
## Update old packages: 'BiocGenerics', 'DESeq2', 'edgeR', 'limma',
## 'maftools', 'quantreg', 'RcppArmadillo'
```

Reading the data

```
Untreated <- readRDS(paste0(wd, "/data/NCI_TPW_gep_untreated.rds"))
Treated <- readRDS(paste0(wd, "/data/NCI_TPW_gep_treated.rds"))

Metadata = read.table(paste0(wd, "/data/NCI_TPW_metadata.tsv"),
                      header = TRUE, sep = "\t", stringsAsFactors = TRUE)

Sensitivity <- readRDS(paste0(wd, "/data/NegLogGI50.rds"))

Basal <- readRDS(paste0(wd, "/data/CCLE_basalexpression.rds"))
Copynumber <- readRDS(paste0(wd, "/data/CCLE_copynumber.rds"))
Mutations <- readRDS(paste0(wd, "/data/CCLE_mutations.rds"))

Cellline_annotation = read.table(paste0(wd, "/data/cellline_annotation.tsv"),
                                header = TRUE, sep = "\t", stringsAsFactors = TRUE)
Drug_annotation = read.table(paste0(wd, "/data/drug_annotation.tsv"),
                             header = TRUE, sep = "\t", stringsAsFactors = TRUE)
```

Transforming the data

```
Treated <- as.data.frame(Treated)
Untreated <- as.data.frame(Untreated)
Sensitivity<- as.data.frame(Sensitivity)
```

Data normalization

```
Untreated_norm <- apply(Untreated, 2, function(x){
  (x - mean(x)) / sd(x)
})
```

```
Treated_norm <- apply(Treated, 2, function(x){
  (x - mean(x)) / sd(x)
})
```

```
FC <- Treated - Untreated
FC_norm <- apply(FC, 2, function(x){
  (x - mean(x)) / sd(x)
})
```

## 1.1 Biomarkers (#anchor2)

### (1) Creating Vorinostat

```
#Untreated matrix
UntreatedVorinostatcolumns <- grep(pattern = "vorinostat",colnames(Untreated))

#Same with treated matrix
TreatedVorinostatcolumns <- grep(pattern = "vorinostat",colnames(Treated))

#Define Vorinostat-data:
UntreatedVorinostat <- Untreated[,UntreatedVorinostatcolumns]
TreatedVorinostat <- Treated[,TreatedVorinostatcolumns]

#fold change matrix
FC <- TreatedVorinostat - UntreatedVorinostat

#Sensitivity
vorinostat_Sensitivity_alleZeilen= grep ('vorinostat', rownames(Sensitivity))
vorinostat_Sensitivity_data= Sensitivity[vorinostat_Sensitivity_alleZeilen,]
```

### (2) Creating FC Data - Finding the Biomarkers

```
FC <- TreatedVorinostat - UntreatedVorinostat

#We work with mean of the rows because we only want to compare the genes
FC_meanrow= rowMeans(FC)
```

```

## Sorting the data
#We work with absolute value to find the highest values,
#because we want to have the most up and down regulated genes.
FC_abs= abs(FC_meanrow)

#We sort the values to get the 100 largest values
sortedFC_abs <- sort(FC_abs, decreasing = TRUE)
sortedFC_abs <- as.matrix(sortedFC_abs)

#We select the first n for biomarkers
biomarkers_FC30 = sortedFC_abs[1:30,]
biomarkers_FC30 <- as.matrix(biomarkers_FC30)

biomarkers_FC100 = sortedFC_abs[1:100,]
biomarkers_FC100 <- as.matrix(biomarkers_FC100)

## Creating a matrix with FC values, that are both positive and negative
FC_both= cbind(FC_meanrow,FC_abs)
FC_both=as.data.frame(FC_both)

#Ordering this matrix
FC_both_sorted <- FC_both[order(FC_both$FC_abs, decreasing = TRUE),]

#FC values of biomarkers: We select the first 100 of the sorted matrix.
biomarkers_FC_values30 = FC_both_sorted[1:30,]

biomarkers_FC_values100 = FC_both_sorted[1:100,]

#Removing the absolute values
biomarkers_FC_values30 <- subset( biomarkers_FC_values30, select = -FC_abs)
biomarkers_FC_values30 = as.matrix(biomarkers_FC_values30)

biomarkers_FC_values100 <- subset( biomarkers_FC_values100, select = -FC_abs)
biomarkers_FC_values100 = as.matrix(biomarkers_FC_values100)

```

## Creating a polished MAF file

Editing the original mutation file, so that the table has all the columns that are needed so that it can be read with the package

```

Mutations <- readRDS(paste0(wd,"/data/CCLE_mutations.rds"))

names(Mutations)[names(Mutations) == "Tumor_Seq_Allele1"] <- "Tumor_Seq_Allele2"
names(Mutations)[names(Mutations) == "Start_position"] <- "Start_Position"
names(Mutations)[names(Mutations) == "End_position"] <- "End_Position"
names(Mutations)[names(Mutations) == "Hugo_Symbol"] <- "Hugo_Symbol"
rownames(Mutations) <- c()
MutationsT <- Mutations[,c(1,4,5,6,10,11,8,9,16,2,3,7,12,13,14,15,17,18)]

```

Create a file with all genes

```
write.table(MutationsT, file = "MutationsT.csv", row.names = F, sep = "\t")
```

Creating a MAF file

```
lam1 <- read.maf(maf = "C:/GitHub/project-02-group-05/MutationsT.csv", useAll = T, verbose = T)
```

```
## -Reading
## -Validating
## --Removed 12 duplicated variants
## --Non MAF specific values in Variant_Classification column:
##   Stop_Codon_Ins
##   Start_Codon_Del
## -Silent variants: 18801
## -Summarizing
## --Possible FLAGS among top ten genes:
##   TTN
##   MUC16
##   NEB
##   OBSCN
## -Processing clinical data
## --Missing clinical data
## -Finished in 7.890s elapsed (6.310s cpu)
```

```
lam1
```

```
## An object of class  MAF
##
##           ID summary      Mean Median
## 1:      NCBI_Build      37      NA    NA
## 2:         Center      NA      NA    NA
## 3:        Samples      58      NA    NA
## 4:         nGenes 15286      NA    NA
## 5:  Frame_Shift_Del   2936  50.621  10.0
## 6:  Frame_Shift_Ins   1376  23.724  14.0
## 7:    In_Frame_Del    335   5.776   4.0
## 8:    In_Frame_Ins    158   2.724   2.0
## 9: Missense_Mutation 43449 749.121 325.5
##10: Nonsense_Mutation  2934  50.586  19.0
##11: Nonstop_Mutation    67   1.155   0.5
##12:    Splice_Site   2704  46.621  19.5
##13:          total  53959 930.328 387.0
```

Create a File with 100 Biomarkers

```
BM_mut = MutationsT[ which((MutationsT$Hugo_Symbol)
                           %in% rownames(biomarkers_FC_values100)), ]
```

```
write.table(BM_mut, file = "BM_mut.csv", row.names = F, sep = "\t")

BM_laml <- read.maf(maf = "C:/GitHub/project-02-group-05/BM_mut.csv", useAll = T, verbose = T)

## -Reading
## -Validating
## -Silent variants: 78
## -Summarizing
## -Processing clinical data
## --Missing clinical data
## -Finished in 0.210s elapsed (0.110s cpu)
```

## Mutations in all genes

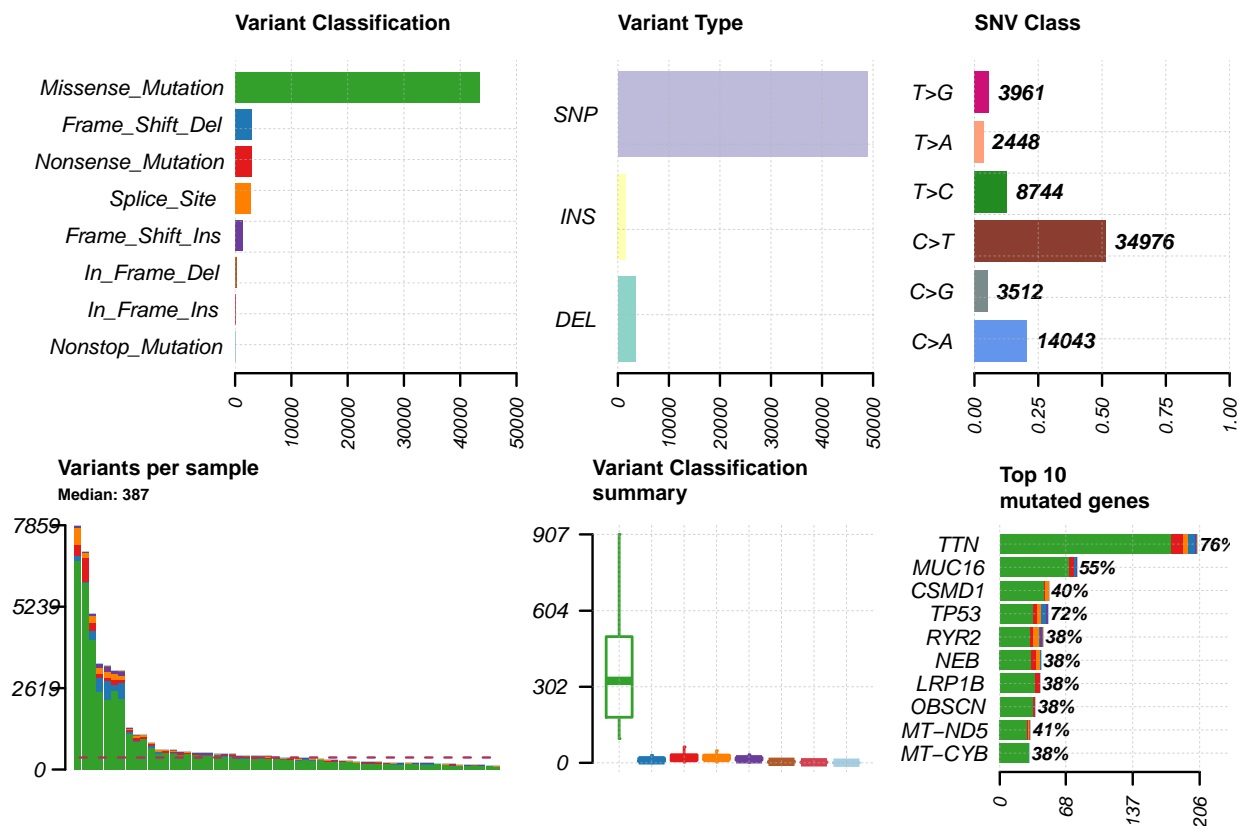
### Generating summaries

```
write.mafSummary(maf = laml, basename = 'laml')
```

### Visualizations

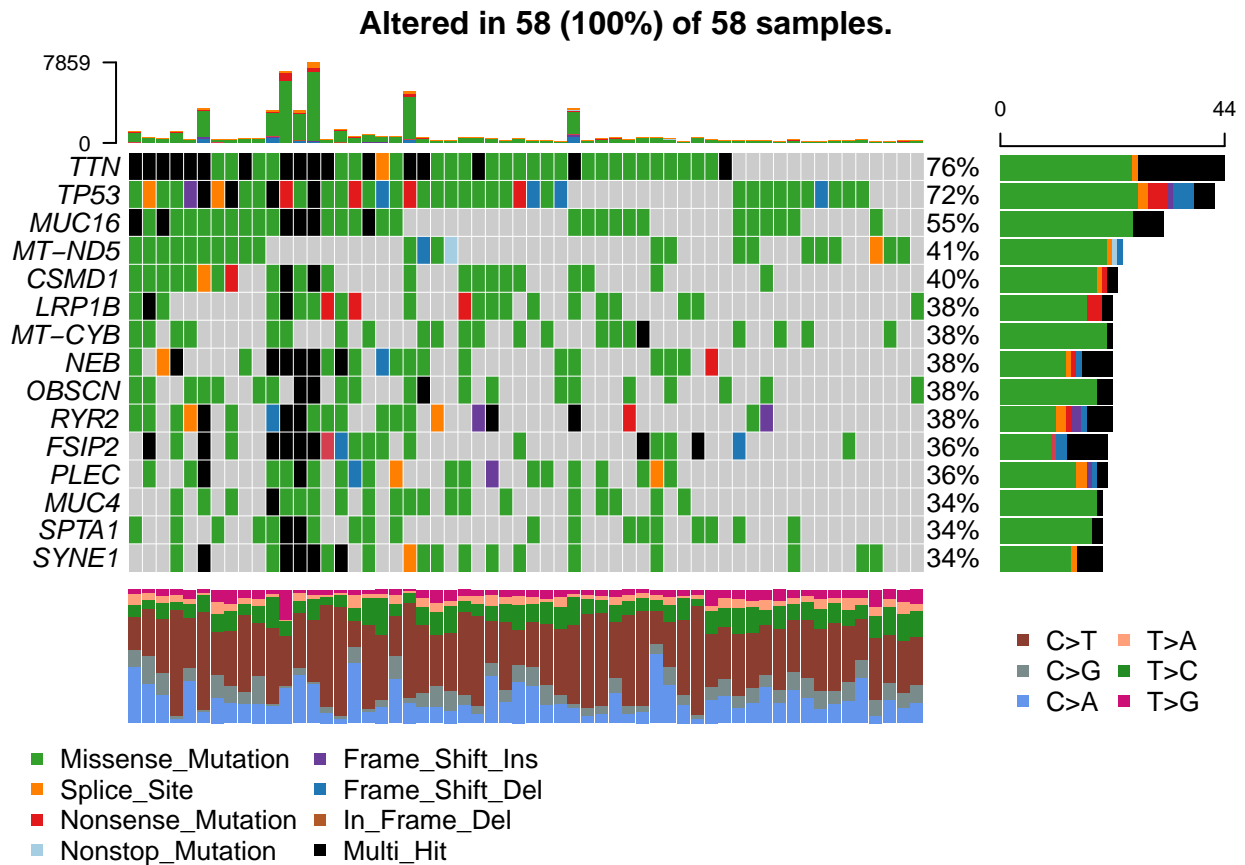
#### Plotting MAF summary

```
plotmafSummary(maf = laml, rmOutlier = TRUE, addStat = 'median', dashboard = TRUE, titvRaw = FALSE)
```



## Plotting oncoplot with Transversions/Transitions

```
oncoplot(maf = lam1, top = 15, draw_titv = TRUE)
```



```
oncoplot(maf = lam1, top = 15, draw_titv = TRUE, additionalFeature = c("Tumor_Sample_Barcode", "MALME-3M"))
```

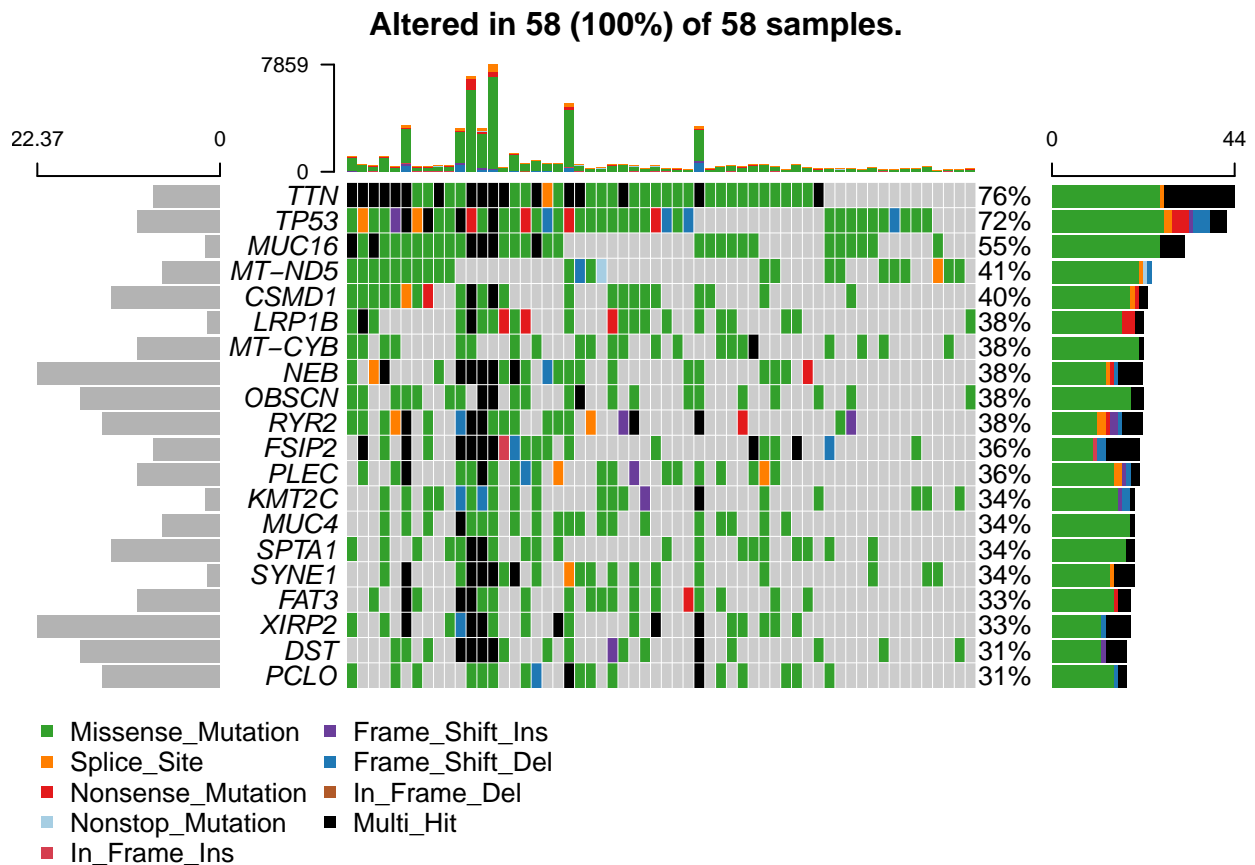
#Altered in all samples as this are all cancer cell lines

## Oncoplot expression values

```
set.seed(seed = 1024)
exprs_tbl = data.frame(genes = getGeneSummary(x = lam1)[1:20, Hugo_Symbol],
                        exprn = rnorm(n = 10, mean = 12, sd = 5))
head(exprs_tbl)
```

```
##      genes      exprn
## 1      TTN  8.106686
## 2     TP53 10.052618
## 3     MUC16  1.831008
## 4    MT-ND5  7.088134
## 5     CSMD1 13.239450
## 6      RYR2  1.480677
```

```
oncoplot(maf = lam1, exprsTbl = exprs_tbl)
```



## CHANGE EXPRESSION VALUES

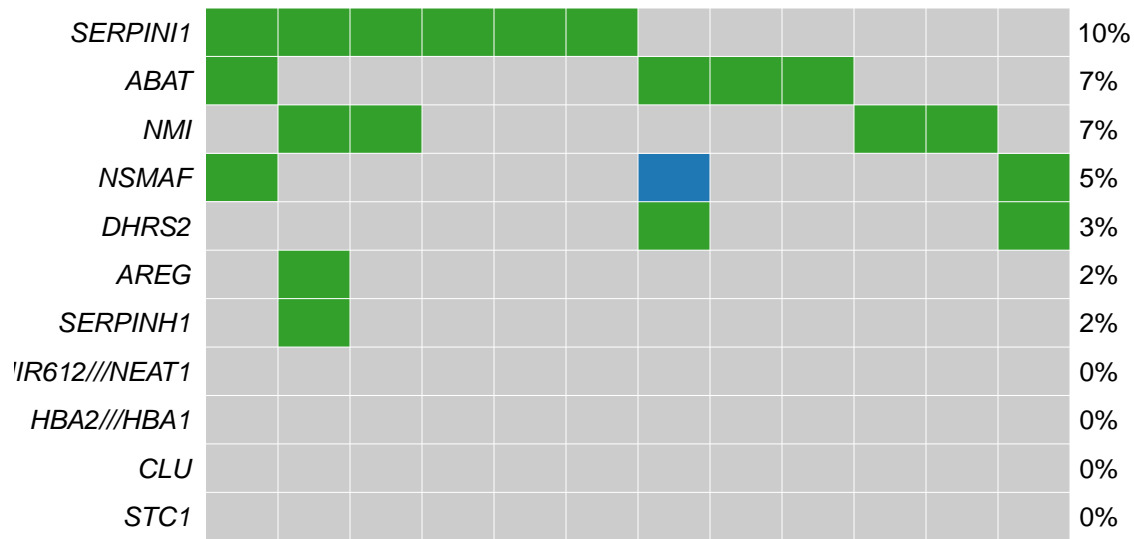
### Oncostrips for the top10 biomarkers

```
oncostrip(maf = lam1, genes = c('DHR2',
                                'ABAT',
                                'SERPINI1',
                                'MIR612//NEAT1 ',
                                'HBA2//HBA1 ',
                                'CLU',
                                'NMI',
                                'STC1',
                                'AREG',
                                'NSMAF',
                                'SERPINH1'))
```

```
## Warning in mtext(text = colnames(nm), side = 2, at = 1:ncol(nm), font =
## 3, : font width unknown for character 0x9
```

```
## Warning in mtext(text = colnames(nm), side = 2, at = 1:ncol(nm), font =
## 3, : font width unknown for character 0x9
```

**Altered in 12 (20.69%) of 58 samples.**



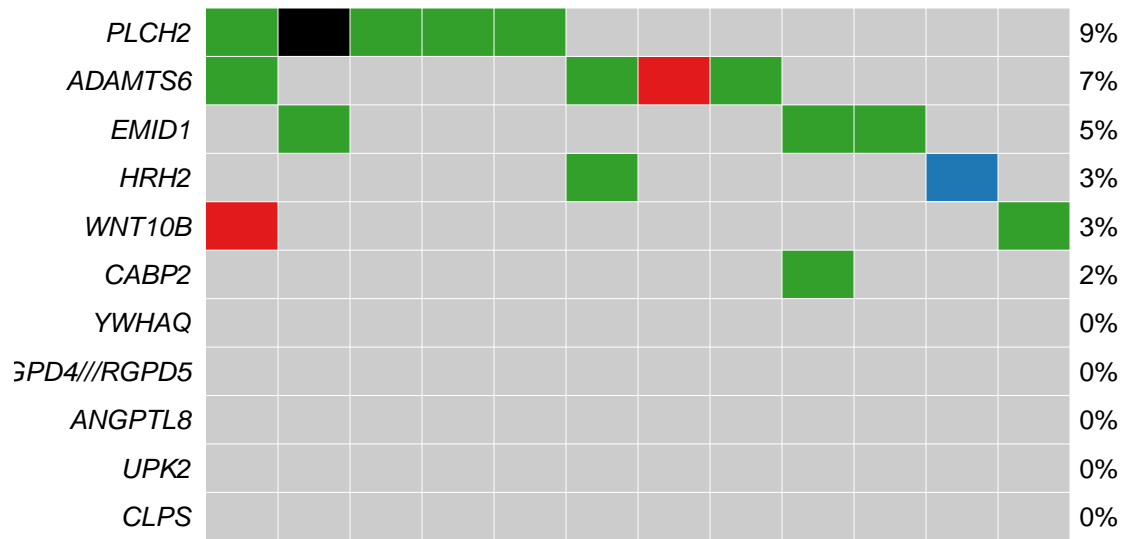
■ Missense\_Mutation 
 ■ Multi\_Hit  
■ Frame\_Shift\_Del

Oncostrrips for the 10 genes with the least change in expression

```
oncostrip(maf = lam1, genes = c('ADAMTS6',
                                'YWHAQ',
                                'EMID1',
                                'PLCH2',
                                'HRH2',
                                'WNT10B',
                                'RGPD6///RGPD8///RGPD3///RGPD4///RGPD5',
                                'ANGPTL8',
                                'CABP2',
                                'UPK2',
                                'CLPS'))
```



**Altered in 12 (20.69%) of 58 samples.**



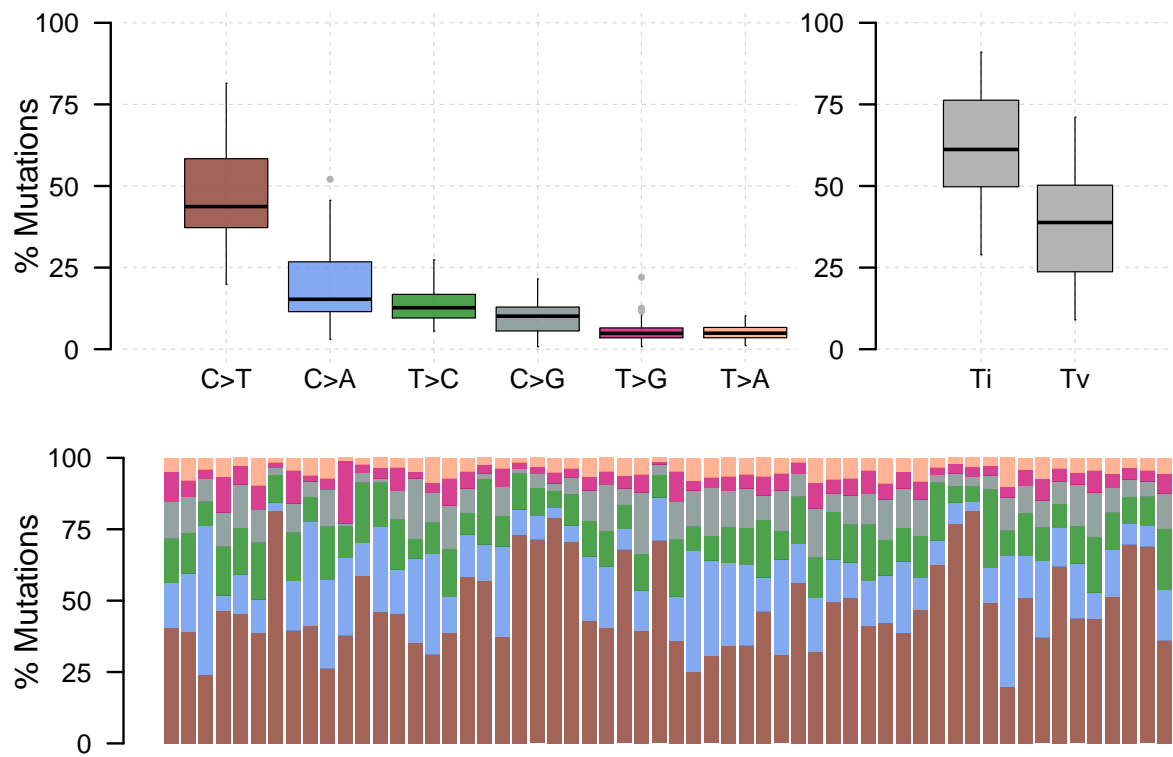
■ Missense\_Mutation    ■ Frame\_Shift\_Del  
■ Nonsense\_Mutation    ■ Multi\_Hit

#### Transitions and Transversion

```

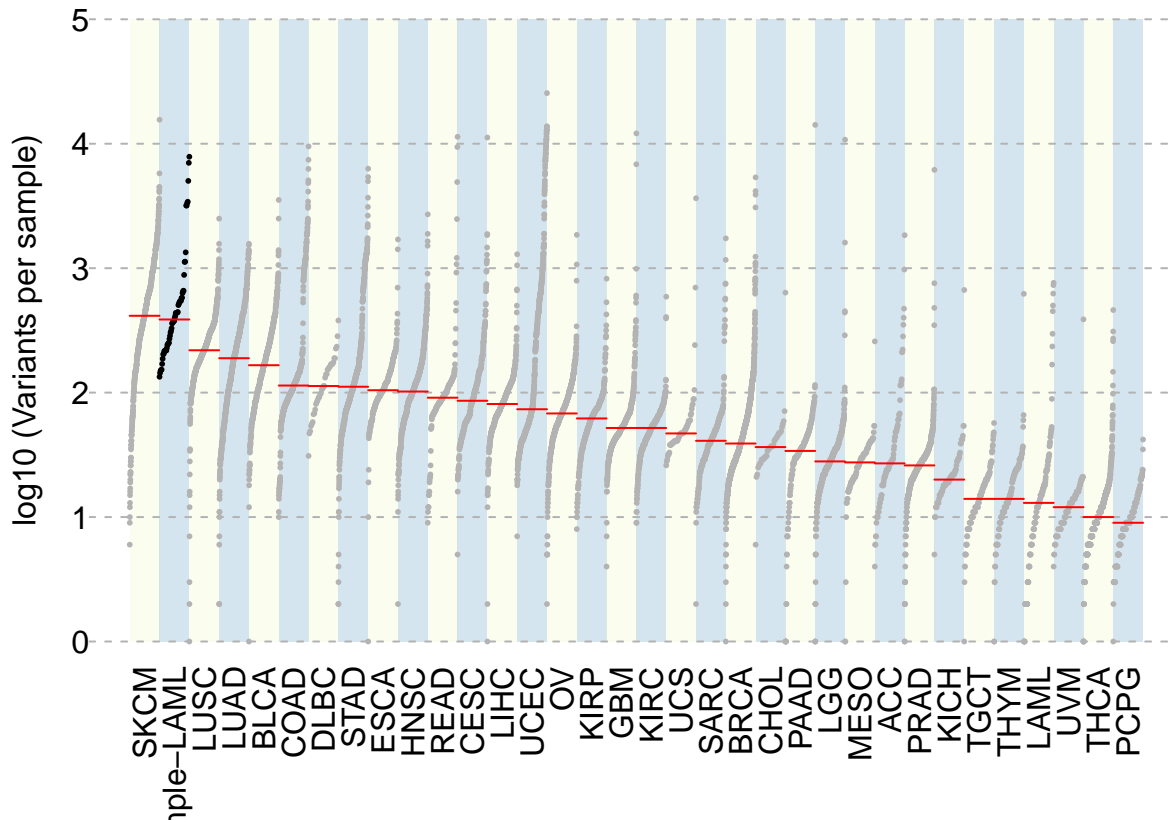
laml.titv = titv(maf = laml, plot = FALSE, useSyn = TRUE)

#plot titv summary
plotTiTv(res = laml.titv)
  
```



#### Mutation load vs TCGA cohorts

```
laml.mutload = tcgaCompare(maf = laml, cohortName = 'Example-LAML')
```



### Somatic interactions

```
somaticInteractions(maf = lam1, top = 30, pvalue = c(0.05, 0.1))
```

```
## Checking for Gene sets
```

```
## -----
```

```
## genes: 5
```

```
## geneset size: 3
```

```
## 10 combinations
```

```
## Significantly altered gene-sets: 1
```

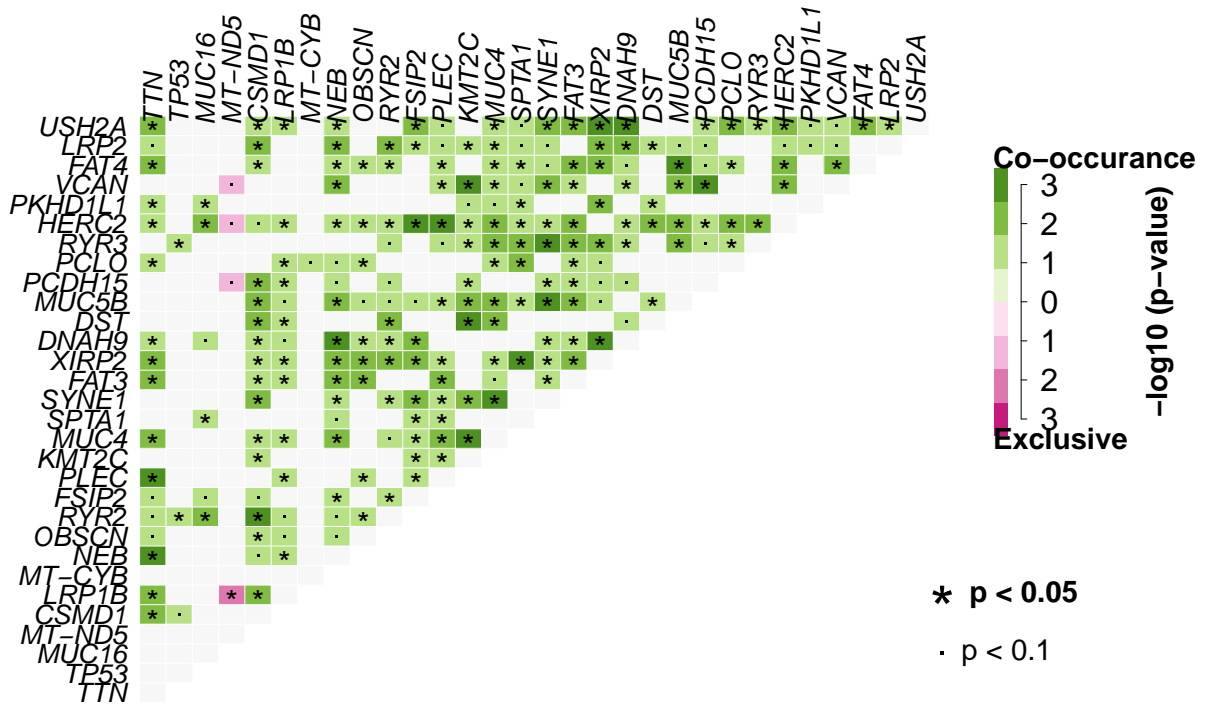
```
## -----
```

```
## $pairs
```

##	gene1	gene2	pValue	oddsRatio	00	11	01	10	Event
## 1:	USH2A	XIRP2	5.504229e-05	14.0423124	35	12	7	4	Co_Occurance
## 2:	VCAN	PCDH15	6.595420e-05	13.1259785	35	12	6	5	Co_Occurance
## 3:	MUC4	KMT2C	8.051493e-05	11.7362366	32	14	6	6	Co_Occurance
## 4:	RYR2	CSMD1	8.669148e-05	10.4728993	29	16	7	6	Co_Occurance
## 5:	RYR3	SYNE1	1.677523e-04	11.5616537	33	13	7	5	Co_Occurance
## ---									
## 224:	MT-ND5	HERC2	8.850156e-02	0.3292542	21	4	13	20	Mutually_Exclusive
## 225:	MT-ND5	VCAN	8.850156e-02	0.3292542	21	4	13	20	Mutually_Exclusive
## 226:	DNAH9	MUC16	9.514840e-02	2.8219382	21	13	19	5	Co_Occurance
## 227:	NEB	CSMD1	9.834834e-02	2.6777301	25	12	11	10	Co_Occurance

```
## 228:  MUC16  FSIP2 9.862900e-02  2.8861297 20 15  6 17      Co_Occurance
##
## $gene_sets
##          gene_set      pvalue
## 1: LRP1B, PCDH15, MT-ND5 0.04964611
```

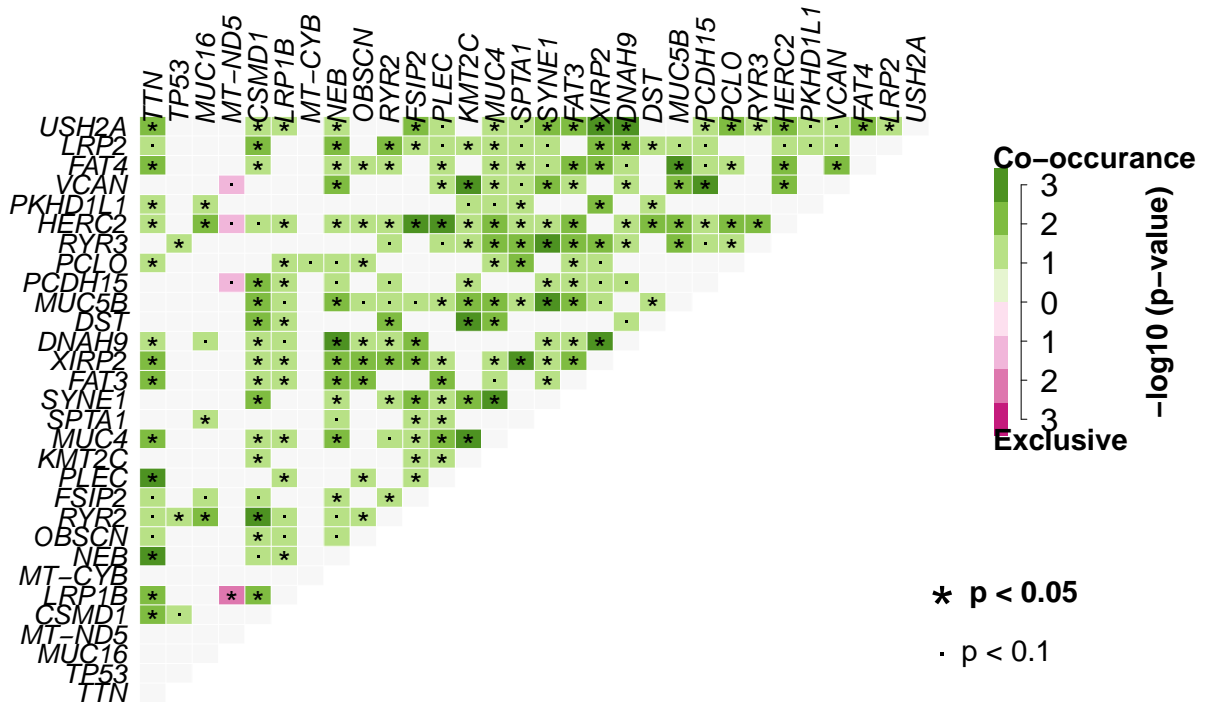
```
summary(somaticInteractions(maf = lam1, top = 30, pvalue = c(0.05, 0.1)))
```



```
## Checking for Gene sets
## -----
## genes: 5
## geneset size: 3
## 10 combinations
## Significantly altered gene-sets: 1
## -----
```

```
##          Length Class      Mode
## pairs      9      data.table list
## gene_sets  2      data.table list
```

```
pairlist(somaticInteractions(maf = lam1, top = 30, pvalue = c(0.05, 0.1)))
```



```
## Checking for Gene sets
```

```
## -----
```

```
## genes: 5
```

```
## geneset size: 3
```

```
## 10 combinations
```

```
## Significantly altered gene-sets: 1
```

```
## -----
```

```
## [[1]]
```

```
## [[1]]$pairs
```

##	gene1	gene2	pValue	oddsRatio	00	11	01	10	Event
## 1:	USH2A	XIRP2	5.504229e-05	14.0423124	35	12	7	4	Co_Occurance
## 2:	VCAN	PCDH15	6.595420e-05	13.1259785	35	12	6	5	Co_Occurance
## 3:	MUC4	KMT2C	8.051493e-05	11.7362366	32	14	6	6	Co_Occurance
## 4:	RYR2	CSMD1	8.669148e-05	10.4728993	29	16	7	6	Co_Occurance
## 5:	RYR3	SYNE1	1.677523e-04	11.5616537	33	13	7	5	Co_Occurance

```
## ---
```

## 224:	MT-ND5	HERC2	8.850156e-02	0.3292542	21	4	13	20	Mutually_Exclusive
## 225:	MT-ND5	VCAN	8.850156e-02	0.3292542	21	4	13	20	Mutually_Exclusive
## 226:	DNAH9	MUC16	9.514840e-02	2.8219382	21	13	19	5	Co_Occurance
## 227:	NEB	CSMD1	9.834834e-02	2.6777301	25	12	11	10	Co_Occurance
## 228:	MUC16	FSIP2	9.862900e-02	2.8861297	20	15	6	17	Co_Occurance

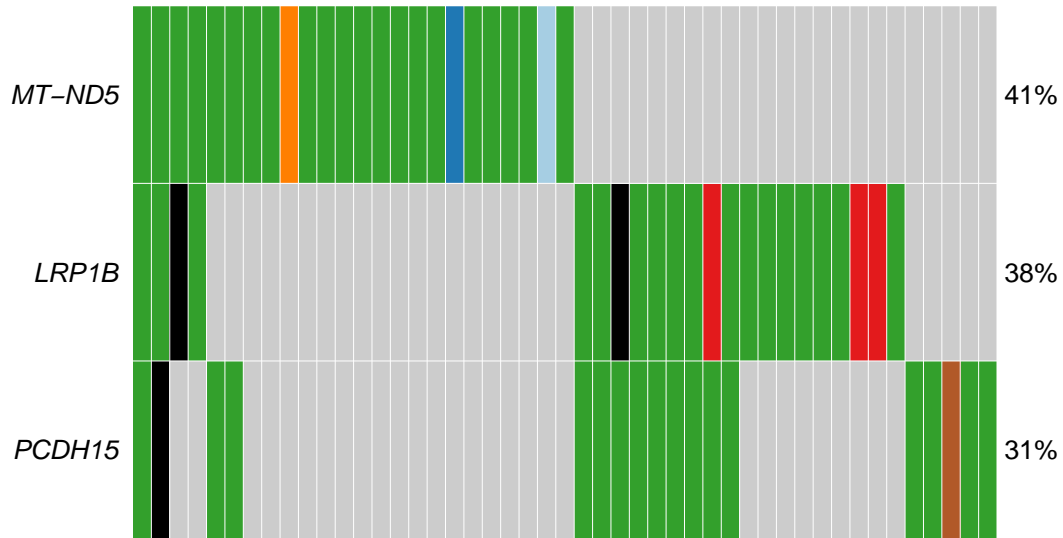
```
##
```

```
## [[1]]$gene_sets
```

##	gene_set	pvalue
## 1:	LRP1B, PCDH15, MT-ND5	0.04964611

```
oncostrip(maf = lam1, genes = c('LRP1B', 'PCDH15', 'MT-ND5'))
```

**Altered in 47 (81.03%) of 58 samples.**

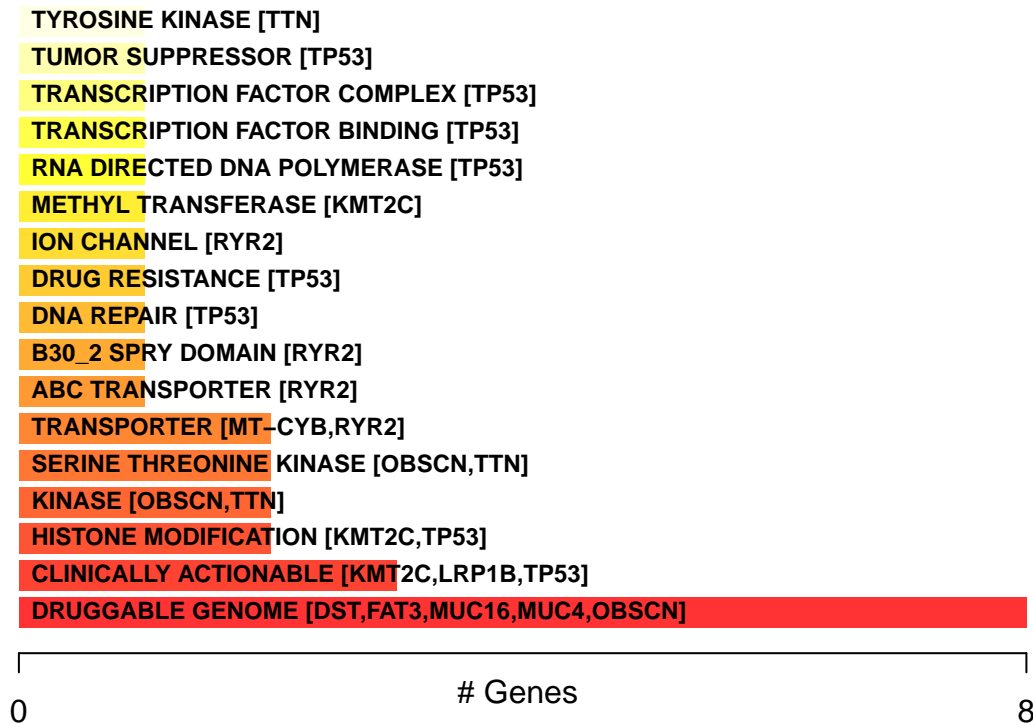


- Missense\_Mutation      ■ In\_Frame\_Del
- Nonsense\_Mutation    ■ Frame\_Shift\_Del
- Splice\_Site            ■ Multi\_Hit
- Nonstop\_Mutation

## Drug Gene interactions

```
dgi = drugInteractions(maf = lam1, fontSize = 0.75)
```

## Druggable categories



```
dnmt3a.dgi = drugInteractions(genes = "MUC16", drugs = TRUE)
```

```
## Number of claimed drugs for given genes:
```

```
##   Gene  N
```

```
## 1: MUC16 15
```

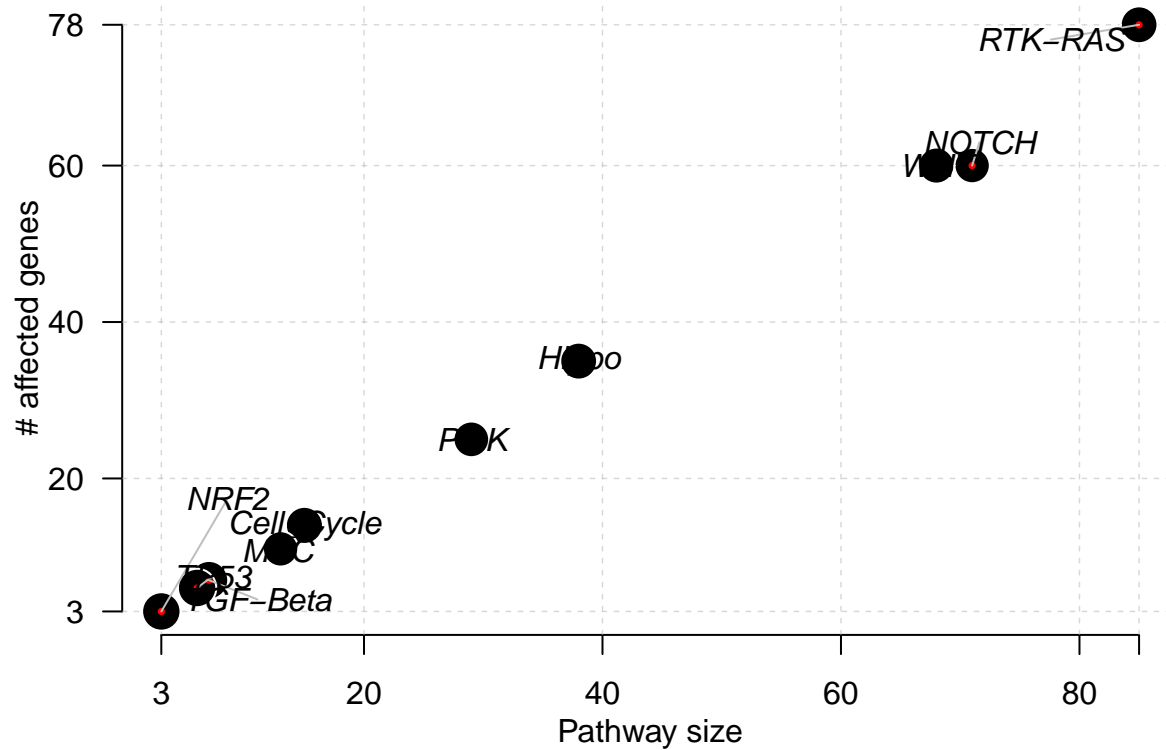
```
dnmt3a.dgi[,.(Gene, interaction_types, drug_name, drug_claim_name)]
```

##	Gene	interaction_types	drug_name	drug_claim_name
## 1:	MUC16		ABAGOVOMAB	CHEMBL1742981
## 2:	MUC16		DIFFERENTIATING AGENTS	
## 3:	MUC16		DOCETAXEL	DOCETAXEL
## 4:	MUC16		CYCLOSPORINE	CYCLOSPORINE
## 5:	MUC16			N/A
## 6:	MUC16		TOPOTECAN	TOPOTECAN
## 7:	MUC16		OREGOVOMAB	B43.13
## 8:	MUC16		ABAGOVOMAB	ABAGOVOMAB
## 9:	MUC16		OREGOVOMAB	CHEMBL2107917
## 10:	MUC16		OREGOVOMAB	OREGOVOMAB
## 11:	MUC16		SODIUM BUTYRATE	SODIUM BUTYRATE
## 12:	MUC16		TAMOXIFEN	TAMOXIFEN
## 13:	MUC16		BUSERELIN ACETATE	BUSERELIN ACETATE
## 14:	MUC16		ETOPOSIDE	ETOPOSIDE
## 15:	MUC16			IFN

```
OncogenicPathways(maf = laml)
```

```
## Pathway alteration fractions
```

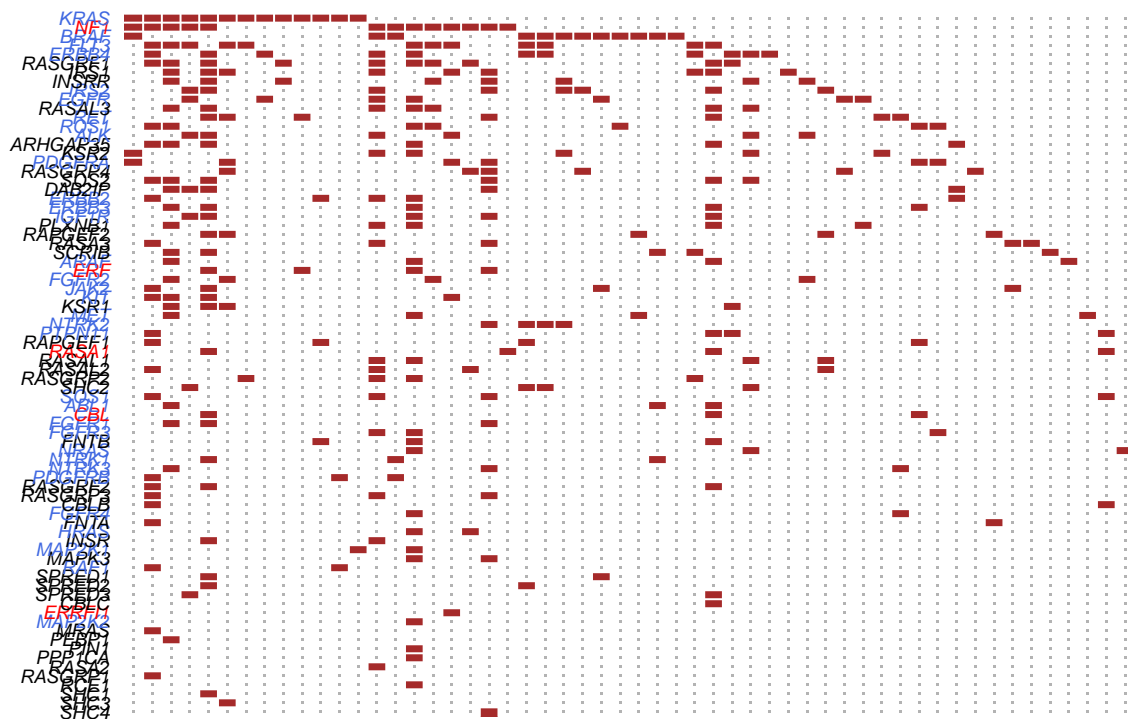
##	Pathway	N	n_affected_genes	fraction_affected
## 1:	RTK-RAS	85	78	0.9176471
## 2:	WNT	68	60	0.8823529
## 3:	NOTCH	71	60	0.8450704
## 4:	Hippo	38	35	0.9210526
## 5:	PI3K	29	25	0.8620690
## 6:	Cell_Cycle	15	14	0.9333333
## 7:	MYC	13	11	0.8461538
## 8:	TGF-Beta	7	7	1.0000000
## 9:	TP53	6	6	1.0000000
## 10:	NRF2	3	3	1.0000000



```
PlotOncogenicPathways(maf = laml, pathways = "RTK-RAS")
```

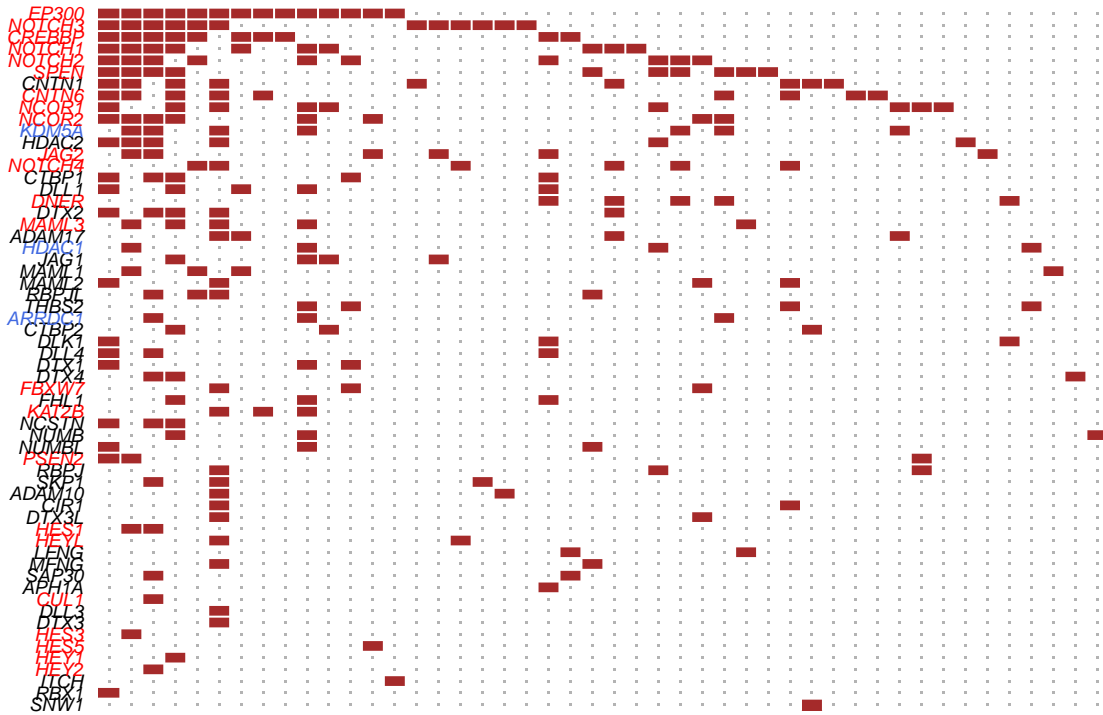


## RTK-RAS pathway



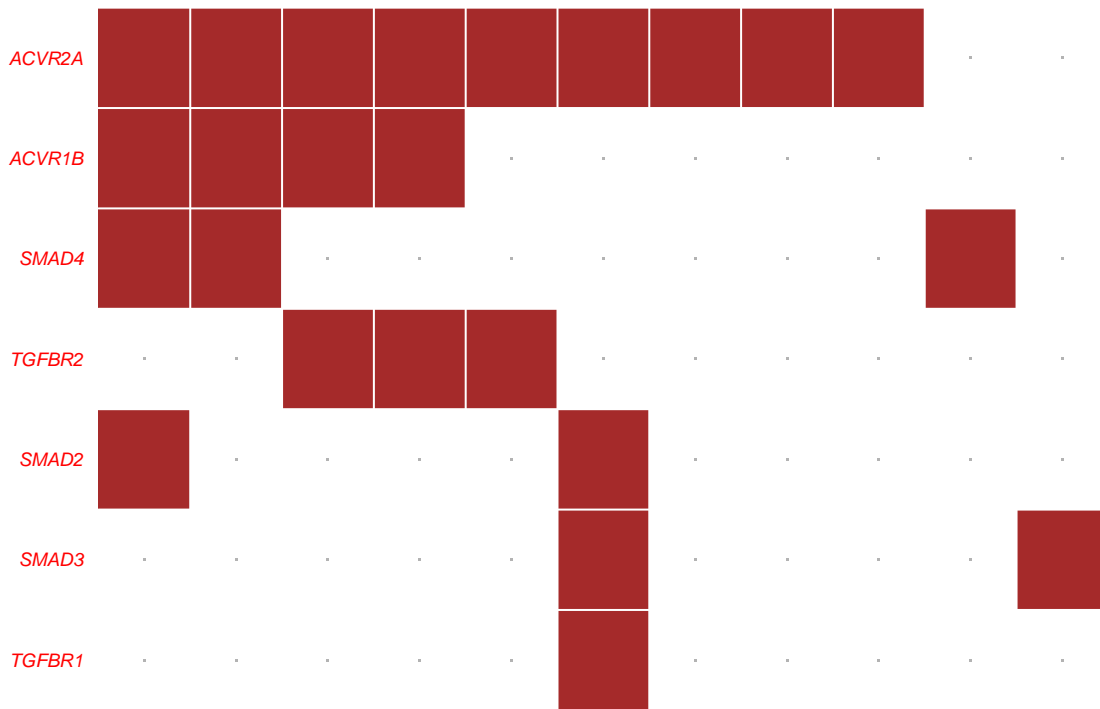
```
PlotOncogenicPathways(maf = laml, pathways = "NOTCH")
```

## NOTCH pathway



```
PlotOncogenicPathways(maf = laml, pathways = "TGF-Beta")
```

## TGF-Beta pathway



## Mutational signatures

```
if (!requireNamespace("BiocManager", quietly = TRUE)) install.packages("BiocManager")
BiocManager::install("BSgenome.Hsapiens.UCSC.hg19")
library(BSgenome.Hsapiens.UCSC.hg19, quietly = TRUE)
if (!requireNamespace("BiocManager", quietly = TRUE)) install.packages("BiocManager") BiocManager::install()
BiocInstaller::biocValid()
biocLite("stringi") biocLite("TxDb.Hsapiens.UCSC.hg19.knownGene")
library(BiocManager)
library(BSgenome.Hsapiens.UCSC.hg19)
laml.tnm = trinucleotideMatrix(maf = laml, prefix = 'chr', add = TRUE, ref_genome = "BSgenome.Hsapiens.UCSC.hg19")
plotApobecDiff(tnm = laml.tnm, maf = laml, pVal = 0.2)
```

## Mutations in the biomarkers

```
BM_laml
```

```
## An object of class  MAF
##
##      ID summary  Mean Median
## 1:   NCBI_Build    37    NA    NA
## 2:     Center     NA    NA    NA
## 3:    Samples     50    NA    NA
## 4:     nGenes     67    NA    NA
## 5: Frame_Shift_Del    21 0.477  0.0
## 6: Frame_Shift_Ins     6 0.136  0.0
## 7: Missense_Mutation   151 3.432  1.5
## 8: Nonsense_Mutation    5 0.114  0.0
## 9: Nonstop_Mutation    1 0.023  0.0
## 10: Splice_Site        8 0.182  0.0
## 11:      total     192 4.364  2.0
```

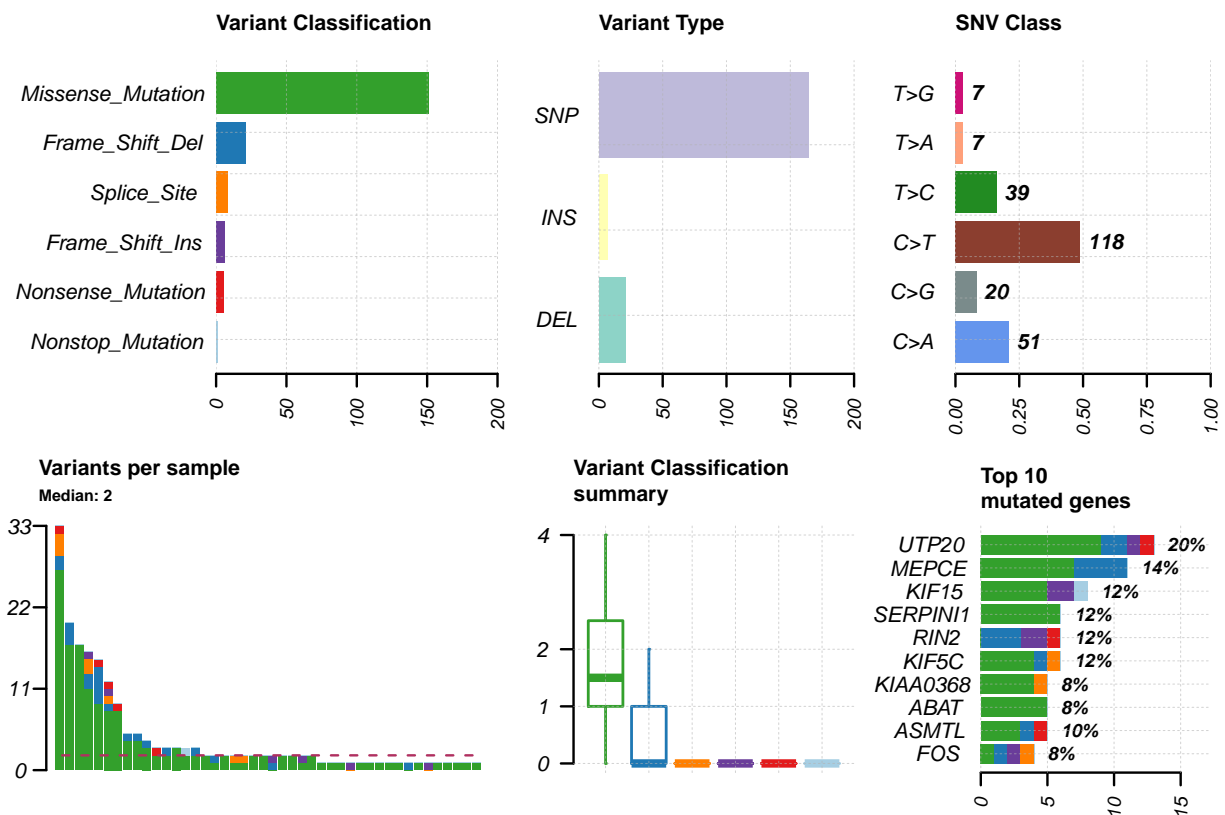
## Summaries

```
write.mafSummary(maf = BM_laml, basename = 'laml')
```

## Visualization

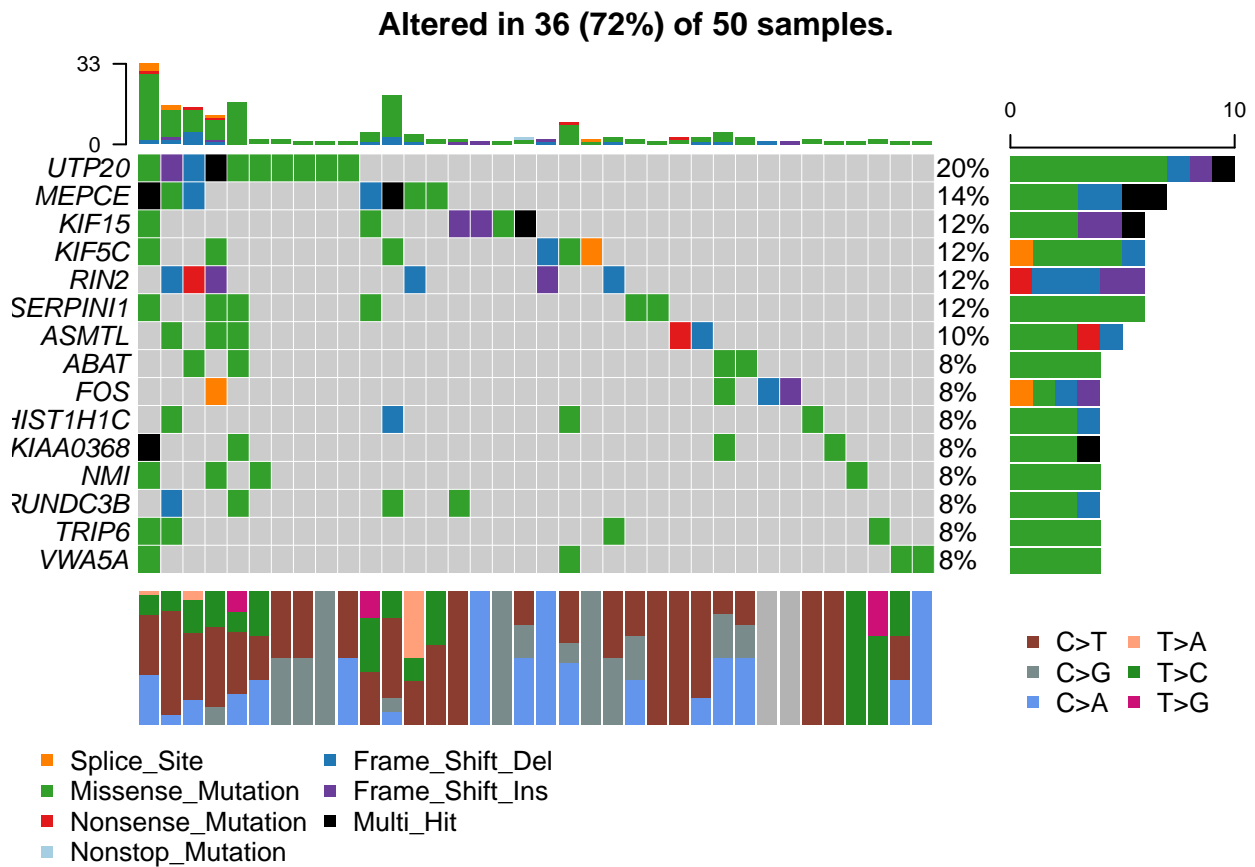
### Plotting MAF summary

```
plotmafSummary(maf = BM_laml, rmOutlier = TRUE, addStat = 'median', dashboard = TRUE, titvRaw = FALSE)
```



## Plotting oncoplot

```
oncoplot(maf = BM_laml, top = 15, draw_titv = TRUE)
```



#Altered in all samples as this are all cancer cell lines

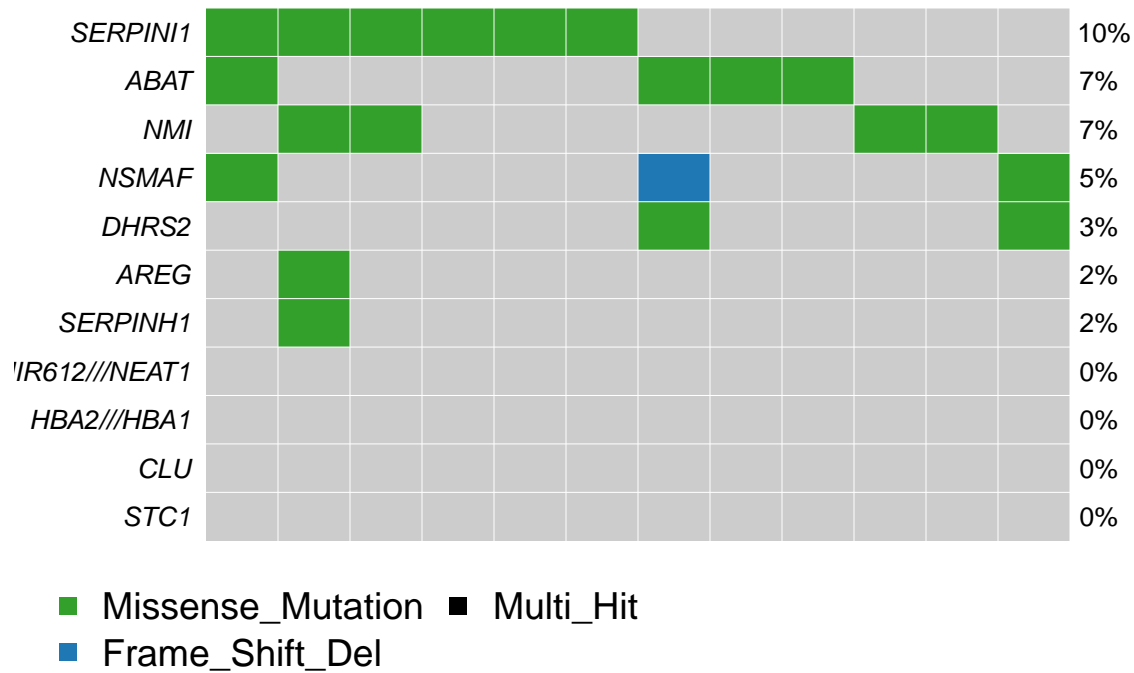
## Oncostrips for the top10 biomarkers

```
oncostrip(maf = laml, genes = c('DHRS2',
                                'ABAT',
                                'SERPINI1',
                                'MIR612//NEAT1 ',
                                'HBA2//HBA1 ',
                                'CLU',
                                'NMI',
                                'STC1',
                                'AREG',
                                'NSMAF',
                                'SERPINH1'))
)
```

```
## Warning in mtext(text = colnames(nm), side = 2, at = 1:ncol(nm), font =
## 3, : font width unknown for character 0x9
```

```
## Warning in mtext(text = colnames(nm), side = 2, at = 1:ncol(nm), font =
## 3, : font width unknown for character 0x9
```

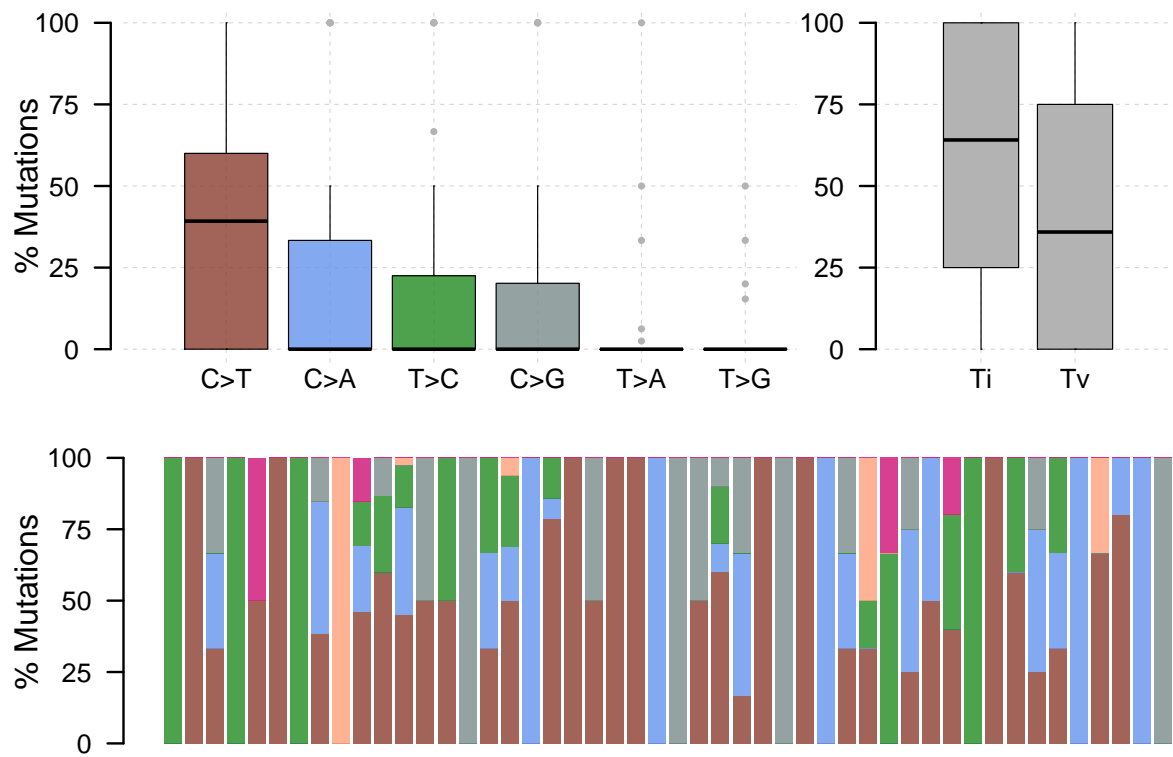
**Altered in 12 (20.69%) of 58 samples.**



#### Transitions and Transversion

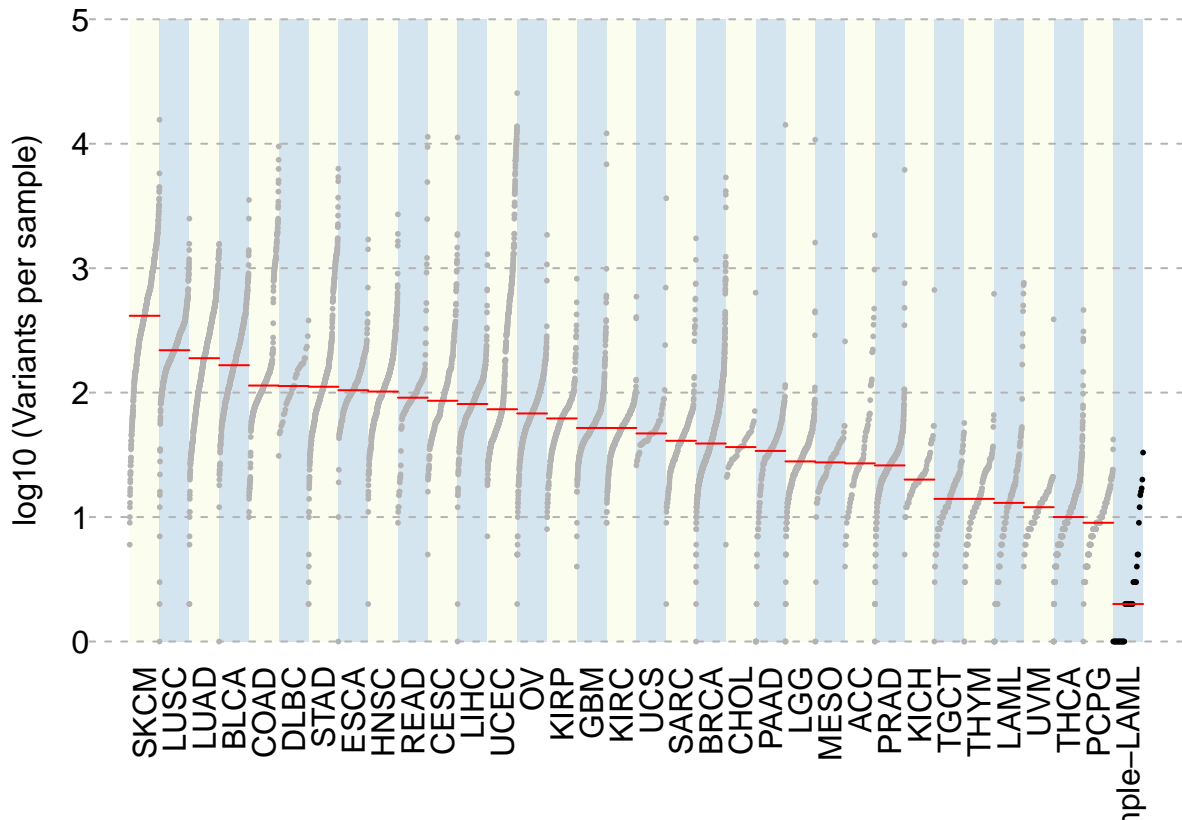
```
BM_laml.titv = titv(maf = BM_laml, plot = FALSE, useSyn = TRUE)

#plot titv summary
plotTiTv(res = BM_laml.titv)
```



#### Mutation load vs TCGA cohorts

```
laml.mutload = tcgaCompare(maf = BM_laml, cohortName = 'Example-LAML')
```



## Somatic interactions

```
somaticInteractions(maf = BM_laml, top = 30, pvalue = c(0.05, 0.1))
```

```
## $pairs
##      gene1      gene2      pValue oddsRatio 00 11 01 10      Event
## 1:      RIN2      GTF2I 0.001020408      Inf 44  3 NA  3 Co_Occurance
## 2:     KIF5C HIST1H2BD 0.001020408      Inf 44  3 NA  3 Co_Occurance
## 3:     VWA5A      PRPH 0.004897959      Inf 46  2 NA  2 Co_Occurance
## 4:     UTP20      GTF2I 0.006122449      Inf 40  3 NA  7 Co_Occurance
## 5:      PHF2      GTF2I 0.007244898 61.358137 46  2  1  1 Co_Occurance
## 6:    SLC17A7 HIST1H2BD 0.007244898 61.358137 46  2  1  1 Co_Occurance
## 7:      ASMTL      TYMS 0.008163265      Inf 45  2 NA  3 Co_Occurance
## 8:     KIF5C      PRPH 0.012244898      Inf 44  2 NA  4 Co_Occurance
## 9:    SERPINI1      TYMS 0.012244898      Inf 44  2 NA  4 Co_Occurance
## 10:     NSMAF      ABAT 0.014285714 35.351222 45  2  2  1 Co_Occurance
## 11: HIST1H2BD HIST1H1C 0.014285714 35.351222 45  2  2  1 Co_Occurance
## 12:     NSMAF KIAA0368 0.014285714 35.351222 45  2  2  1 Co_Occurance
## 13:      MCM5     RUNDC3B 0.014285714 35.351222 45  2  2  1 Co_Occurance
## 14:    COR01A     TRIP6 0.014285714 35.351222 45  2  2  1 Co_Occurance
## 15:    FOXM1     TRIP6 0.014285714 35.351222 45  2  2  1 Co_Occurance
## 16:      ADI1     MEPCE 0.017142857      Inf 43  2  5 NA Co_Occurance
## 17:    UTP20      NMI 0.021754234 15.303464 39  3  1  7 Co_Occurance
## 18:    ASMTL      GTF2I 0.023469388 24.693763 44  2  1  3 Co_Occurance
## 19:    ASMTL      PHF2 0.023469388 24.693763 44  2  1  3 Co_Occurance
```

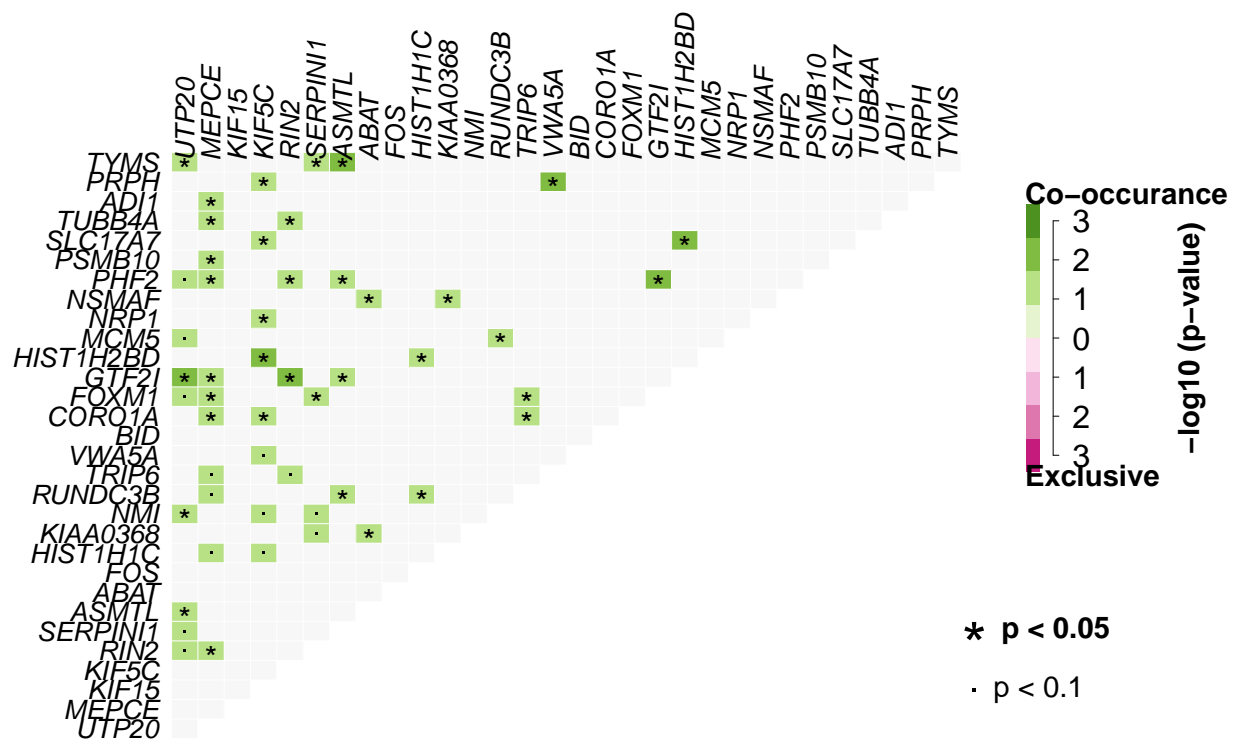


```

## 20: KIAA0368 ABAT 0.027768129 18.766900 44 2 2 2 Co_Occurance
## 21: RUNDC3B HIST1H1C 0.027768129 18.766900 44 2 2 2 Co_Occurance
## 22: MEPCE RIN2 0.029227787 9.230996 40 3 3 4 Co_Occurance
## 23: CORO1A KIF5C 0.034693878 18.823979 43 2 4 1 Co_Occurance
## 24: NRP1 KIF5C 0.034693878 18.823979 43 2 4 1 Co_Occurance
## 25: SLC17A7 KIF5C 0.034693878 18.823979 43 2 4 1 Co_Occurance
## 26: PHF2 RIN2 0.034693878 18.823979 43 2 4 1 Co_Occurance
## 27: TUBB4A RIN2 0.034693878 18.823979 43 2 4 1 Co_Occurance
## 28: FOXM1 SERPINI1 0.034693878 18.823979 43 2 4 1 Co_Occurance
## 29: TYMS UTP20 0.036734694 Inf 40 2 8 NA Co_Occurance
## 30: RUNDC3B ASMTL 0.044963092 12.774305 43 2 3 2 Co_Occurance
## 31: MEPCE CORO1A 0.047857143 15.078757 42 2 1 5 Co_Occurance
## 32: MEPCE FOXM1 0.047857143 15.078757 42 2 1 5 Co_Occurance
## 33: MEPCE GTF2I 0.047857143 15.078757 42 2 1 5 Co_Occurance
## 34: MEPCE PHF2 0.047857143 15.078757 42 2 1 5 Co_Occurance
## 35: MEPCE PSMB10 0.047857143 15.078757 42 2 1 5 Co_Occurance
## 36: MEPCE TUBB4A 0.047857143 15.078757 42 2 1 5 Co_Occurance
## 37: ASMTL UTP20 0.048260303 7.651420 38 3 7 2 Co_Occurance
## 38: HIST1H1C KIF5C 0.065501520 9.603657 42 2 4 2 Co_Occurance
## 39: NMI KIF5C 0.065501520 9.603657 42 2 4 2 Co_Occurance
## 40: VWA5A KIF5C 0.065501520 9.603657 42 2 4 2 Co_Occurance
## 41: TRIP6 RIN2 0.065501520 9.603657 42 2 4 2 Co_Occurance
## 42: KIAA0368 SERPINI1 0.065501520 9.603657 42 2 4 2 Co_Occurance
## 43: NMI SERPINI1 0.065501520 9.603657 42 2 4 2 Co_Occurance
## 44: RIN2 UTP20 0.085565142 5.046913 37 3 7 3 Co_Occurance
## 45: SERPINI1 UTP20 0.085565142 5.046913 37 3 7 3 Co_Occurance
## 46: HIST1H1C MEPCE 0.089027356 7.630451 41 2 5 2 Co_Occurance
## 47: RUNDC3B MEPCE 0.089027356 7.630451 41 2 5 2 Co_Occurance
## 48: TRIP6 MEPCE 0.089027356 7.630451 41 2 5 2 Co_Occurance
## 49: UTP20 FOXM1 0.097959184 9.114104 39 2 1 8 Co_Occurance
## 50: UTP20 MCM5 0.097959184 9.114104 39 2 1 8 Co_Occurance
## 51: UTP20 PHF2 0.097959184 9.114104 39 2 1 8 Co_Occurance
## gene1 gene2 pValue oddsRatio 00 11 01 10 Event
##
## $gene_sets
## NULL

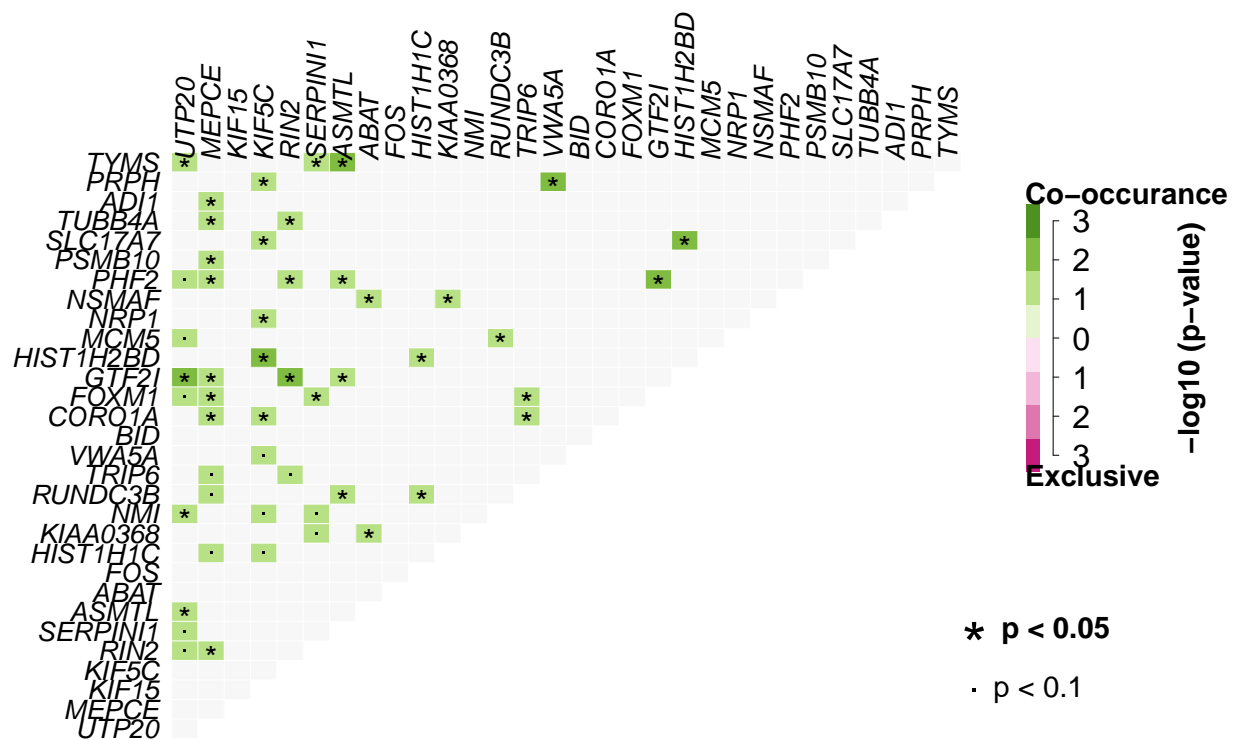
```

```
summary(somaticInteractions(maf = BM_laml, top = 30, pvalue = c(0.05, 0.1)))
```



```
##          Length Class      Mode
## pairs      9      data.table list
## gene_sets  0      -none-    NULL
```

```
pairlist(somaticInteractions(maf = BM_laml, top = 30, pvalue = c(0.05, 0.1)))
```



```
## [[1]]
## [[1]]$pairs
##      gene1      gene2      pValue oddsRatio 00 11 01 10      Event
## 1:      RIN2      GTF2I 0.001020408      Inf 44  3 NA  3 Co_Occurance
## 2:      KIF5C HIST1H2BD 0.001020408      Inf 44  3 NA  3 Co_Occurance
## 3:      VWA5A      PRPH 0.004897959      Inf 46  2 NA  2 Co_Occurance
## 4:      UTP20      GTF2I 0.006122449      Inf 40  3 NA  7 Co_Occurance
## 5:      PHF2      GTF2I 0.007244898 61.358137 46  2  1  1 Co_Occurance
## 6:      SLC17A7 HIST1H2BD 0.007244898 61.358137 46  2  1  1 Co_Occurance
## 7:      ASMTL      TYMS 0.008163265      Inf 45  2 NA  3 Co_Occurance
## 8:      KIF5C      PRPH 0.012244898      Inf 44  2 NA  4 Co_Occurance
## 9:      SERPINI1      TYMS 0.012244898      Inf 44  2 NA  4 Co_Occurance
## 10:      NSMAF      ABAT 0.014285714 35.351222 45  2  2  1 Co_Occurance
## 11: HIST1H2BD HIST1H1C 0.014285714 35.351222 45  2  2  1 Co_Occurance
## 12:      NSMAF KIAA0368 0.014285714 35.351222 45  2  2  1 Co_Occurance
## 13:      MCM5      RUNDC3B 0.014285714 35.351222 45  2  2  1 Co_Occurance
## 14:      CORO1A      TRIP6 0.014285714 35.351222 45  2  2  1 Co_Occurance
## 15:      FOXM1      TRIP6 0.014285714 35.351222 45  2  2  1 Co_Occurance
## 16:      ADI1      MEPCE 0.017142857      Inf 43  2  5 NA Co_Occurance
## 17:      UTP20      NMI 0.021754234 15.303464 39  3  1  7 Co_Occurance
## 18:      ASMTL      GTF2I 0.023469388 24.693763 44  2  1  3 Co_Occurance
## 19:      ASMTL      PHF2 0.023469388 24.693763 44  2  1  3 Co_Occurance
## 20: KIAA0368      ABAT 0.027768129 18.766900 44  2  2  2 Co_Occurance
## 21:      RUNDC3B HIST1H1C 0.027768129 18.766900 44  2  2  2 Co_Occurance
## 22:      MEPCE      RIN2 0.029227787  9.230996 40  3  3  4 Co_Occurance
## 23:      CORO1A      KIF5C 0.034693878 18.823979 43  2  4  1 Co_Occurance
```

```

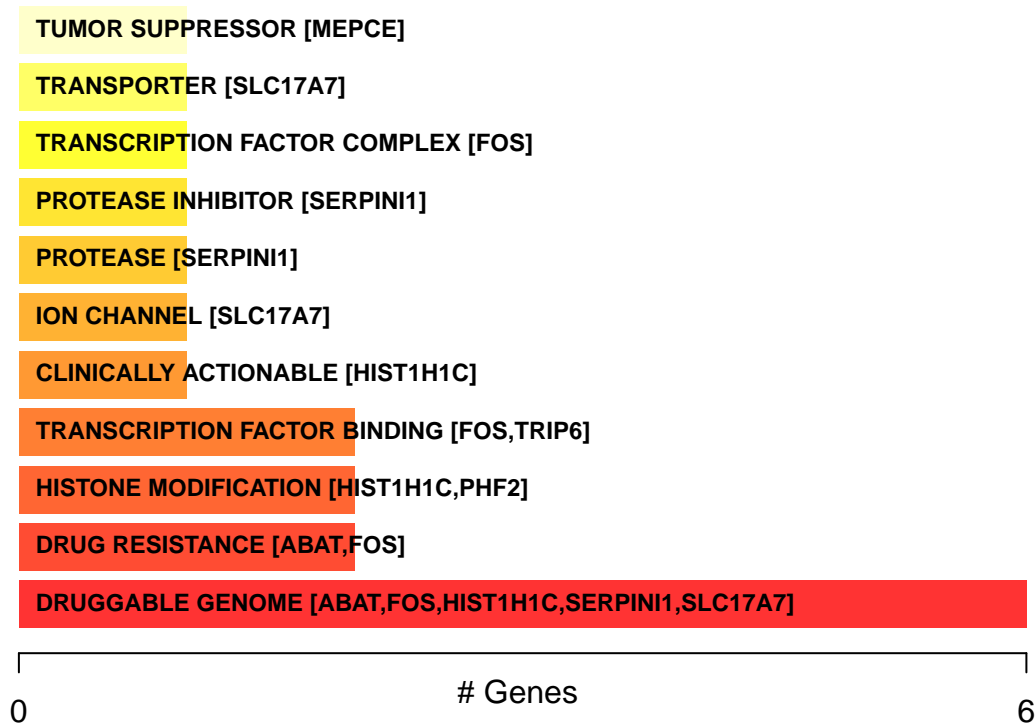
## 24:      NRP1      KIF5C 0.034693878 18.823979 43 2 4 1 Co_Occurance
## 25:    SLC17A7      KIF5C 0.034693878 18.823979 43 2 4 1 Co_Occurance
## 26:      PHF2      RIN2 0.034693878 18.823979 43 2 4 1 Co_Occurance
## 27:    TUBB4A      RIN2 0.034693878 18.823979 43 2 4 1 Co_Occurance
## 28:      FOXM1  SERPINI1 0.034693878 18.823979 43 2 4 1 Co_Occurance
## 29:      TYMS      UTP20 0.036734694      Inf 40 2 8 NA Co_Occurance
## 30:    RUNDC3B      ASMTL 0.044963092 12.774305 43 2 3 2 Co_Occurance
## 31:      MEPCE  CORO1A 0.047857143 15.078757 42 2 1 5 Co_Occurance
## 32:      MEPCE  FOXM1 0.047857143 15.078757 42 2 1 5 Co_Occurance
## 33:      MEPCE  GTF2I 0.047857143 15.078757 42 2 1 5 Co_Occurance
## 34:      MEPCE  PHF2 0.047857143 15.078757 42 2 1 5 Co_Occurance
## 35:      MEPCE  PSMB10 0.047857143 15.078757 42 2 1 5 Co_Occurance
## 36:      MEPCE  TUBB4A 0.047857143 15.078757 42 2 1 5 Co_Occurance
## 37:      ASMTL      UTP20 0.048260303 7.651420 38 3 7 2 Co_Occurance
## 38:  HIST1H1C      KIF5C 0.065501520 9.603657 42 2 4 2 Co_Occurance
## 39:      NMI      KIF5C 0.065501520 9.603657 42 2 4 2 Co_Occurance
## 40:      VWA5A      KIF5C 0.065501520 9.603657 42 2 4 2 Co_Occurance
## 41:      TRIP6      RIN2 0.065501520 9.603657 42 2 4 2 Co_Occurance
## 42:  KIAA0368  SERPINI1 0.065501520 9.603657 42 2 4 2 Co_Occurance
## 43:      NMI      SERPINI1 0.065501520 9.603657 42 2 4 2 Co_Occurance
## 44:      RIN2      UTP20 0.085565142 5.046913 37 3 7 3 Co_Occurance
## 45:  SERPINI1      UTP20 0.085565142 5.046913 37 3 7 3 Co_Occurance
## 46:  HIST1H1C      MEPCE 0.089027356 7.630451 41 2 5 2 Co_Occurance
## 47:    RUNDC3B      MEPCE 0.089027356 7.630451 41 2 5 2 Co_Occurance
## 48:      TRIP6      MEPCE 0.089027356 7.630451 41 2 5 2 Co_Occurance
## 49:      UTP20      FOXM1 0.097959184 9.114104 39 2 1 8 Co_Occurance
## 50:      UTP20      MCM5 0.097959184 9.114104 39 2 1 8 Co_Occurance
## 51:      UTP20      PHF2 0.097959184 9.114104 39 2 1 8 Co_Occurance
##      gene1      gene2      pValue oddsRatio 00 11 01 10      Event
##
## [[1]]$gene_sets
## NULL

```

## Drug Gene interactions

```
dgi = drugInteractions(maf = BM_laml, fontSize = 0.75)
```

## Druggable categories



```
dnmt3a.dgi = drugInteractions(genes = "MUC16", drugs = TRUE)
```

```
## Number of claimed drugs for given genes:
```

```
##      Gene  N
```

```
## 1: MUC16 15
```

```
dnmt3a.dgi[,.(Gene, interaction_types, drug_name, drug_claim_name)]
```

```
##      Gene interaction_types      drug_name      drug_claim_name
## 1: MUC16      ABAGOVOMAB      CHEMBL1742981
## 2: MUC16      DIFFERENTIATING AGENTS
## 3: MUC16      DOCETAXEL      DOCETAXEL
## 4: MUC16      CYCLOSPORINE      CYCLOSPORINE
## 5: MUC16      N/A
## 6: MUC16      TOPOTECAN      TOPOTECAN
## 7: MUC16      OREGOVOMAB      B43.13
## 8: MUC16      ABAGOVOMAB      ABAGOVOMAB
## 9: MUC16      OREGOVOMAB      CHEMBL2107917
## 10: MUC16      OREGOVOMAB      OREGOVAMAB
## 11: MUC16      SODIUM BUTYRATE      SODIUM BUTYRATE
## 12: MUC16      TAMOXIFEN      TAMOXIFEN
## 13: MUC16      BUSERELIN ACETATE      BUSERELIN ACETATE
## 14: MUC16      ETOPOSIDE      ETOPOSIDE
## 15: MUC16      IFN
```

```
OncogenicPathways(maf = BM_laml)
```

```
## Pathway alteration fractions
```

##	Pathway	N	n_affected_genes	fraction_affected
## 1:	Cell_Cycle	15	1	0.06666667
## 2:	Hippo	38	0	0.00000000
## 3:	MYC	13	0	0.00000000
## 4:	NOTCH	71	0	0.00000000
## 5:	NRF2	3	0	0.00000000
## 6:	PI3K	29	0	0.00000000
## 7:	RTK-RAS	85	0	0.00000000
## 8:	TGF-Beta	7	0	0.00000000
## 9:	TP53	6	0	0.00000000
## 10:	WNT	68	0	0.00000000

