### BCC pre-processing

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#### Data

Read in the data and check the format:

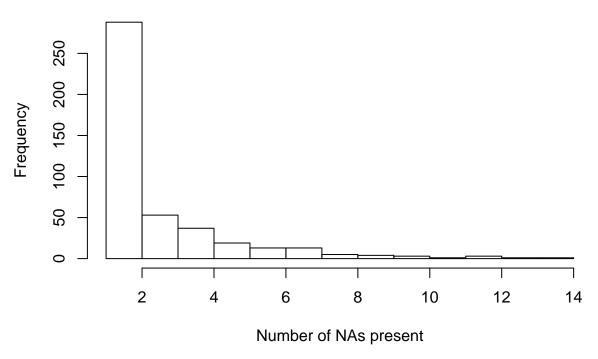
```
data loc <- "../Raw data/"
filenames <- c(
  "BRCA.exp.348.med.csv",
  "BRCA.348.precursor.txt",
  "rppaData-403Samp-171Ab-Trimmed.txt",
  "BRCA.Methylation.574probes.802.txt"
GE <- read.csv(paste0(data_loc, "BRCA.exp.348.med.csv"), header = TRUE)
miRNA <- read.csv(paste0(data_loc, "BRCA.348.precursor.txt"), header = TRUE)
Protein <- read.table(paste0(data_loc, "rppaData-403Samp-171Ab-Trimmed.txt"), header = TRUE)
Meth <- read.table(paste0(data_loc, "BRCA.Methylation.574probes.802.txt"), header = TRUE)
orig_datafiles <- list(GE, miRNA, Protein, Meth) %>%
 magrittr::set_names(c("GE", "miRNA", "Protein", "Meth"))
dim(GE)
## [1] 17814
               349
dim(miRNA)
## [1] 1046 349
dim(Protein)
## [1] 171 404
dim(Meth)
## [1] 574 802
# View the head of the data
head(GE[, 1:5])
         NAME TCGA.A1.A0SH.O1A.11R.A084.07 TCGA.A1.A0SJ.O1A.11R.A084.07
##
## 1
       ELM02
                                  0.162208
                                                                0.577708
## 2 CREB3L1
                                  1.338000
                                                               -0.483500
                                  0.044063
## 3
       RPS11
                                                               -0.258062
## 4
        PNMA1
                                  0.249500
                                                                0.682250
## 5
        MMP2
                                  1.843833
                                                               -0.531000
## 6 C10orf90
                                  0.184500
                                                                0.127500
```

```
TCGA.A1.A0SK.01A.12R.A084.07 TCGA.A1.A0S0.01A.22R.A084.07
## 1
                                                       -0.375208
                         1.113042
                                                       -1.628750
## 2
                        -1.558500
## 3
                         0.119813
                                                       -0.542063
## 4
                         0.867750
                                                       -0.139750
## 5
                        -1.674833
                                                       -1.838167
## 6
                         -0.843750
                                                       -0.363750
head(miRNA[, 1:5])
             Gene TCGA.A8.A07E.01A.11R TCGA.A8.A09C.01A.11R TCGA.A8.A084.01A.21R
##
## 1 hsa-let-7a-1
                              4629.4498
                                                   5437.9616
                                                                          7340.861
## 2 hsa-let-7a-2
                              9384.9411
                                                  10872.5343
                                                                         14676.347
## 3 hsa-let-7a-3
                              4742.0152
                                                   5596.5660
                                                                          7457.106
## 4
      hsa-let-7b
                             31208.3577
                                                  25291.9778
                                                                         71135.465
                                                  1250.5346
## 5
       hsa-let-7c
                              2414.6069
                                                                          1003.195
## 6
                              537.4601
                                                                           606.083
       hsa-let-7d
                                                   597.8165
##
    TCGA.A8.A091.01A.11R
## 1
                9232.1420
## 2
               18276.1584
## 3
                9207.9908
## 4
               85803.7544
## 5
                1438.2719
## 6
                 419.4695
# head(Protein[, 1:5])
# head(Meth[, 1:5])
For integrative clutstering we need common samples across datasets. Find these.
# Match columns (samples) between sources
namesExp <- names(GE)[2:349]</pre>
namesmiRNA <- names(miRNA)[2:349]
namesProtein <- names(Protein)[2:404]
namesMeth <- names(Meth)</pre>
head(namesExp)
## [1] "TCGA.A1.AOSH.O1A.11R.AO84.O7" "TCGA.A1.AOSJ.O1A.11R.AO84.O7"
## [3] "TCGA.A1.A0SK.O1A.12R.A084.07" "TCGA.A1.A0SO.01A.22R.A084.07"
## [5] "TCGA.A2.A04N.01A.11R.A115.07" "TCGA.A2.A04P.01A.31R.A034.07"
head(namesProtein)
## [1] "TCGA.C8.A138.01A.21.A13D.20" "TCGA.AO.A03L.01A.31.A13A.20"
## [3] "TCGA.A2.AOSV.O1A.21.A13A.20" "TCGA.A2.AOSW.O1A.21.A13A.20"
## [5] "TCGA.BH.AOCO.O1A.11.A13B.20" "TCGA.AN.AOAK.O1A.11.A13B.20"
# Matching samples present
namesExp <- substr(namesExp, 1, 16)</pre>
namesmiRNA <- substr(namesmiRNA, 1, 16)
namesProtein <- substr(namesProtein, 1, 16)
MatchProt <- match(namesExp, namesProtein, nomatch = 0)</pre>
MatchMeth <- match(namesExp, namesMeth, nomatch = 0)</pre>
```

Convert to matrix format and set row names

```
miRNA_names <- miRNA[, 1]
miRNA <- miRNA[, 2:349]
miRNA.mat <- as.matrix(miRNA[, order(namesmiRNA)]) %>%
  set_rownames(miRNA_names)
Protein.mat <- Protein[, 2:404]</pre>
Protein.mat <- as.matrix(Protein.mat[, MatchProt]) %>%
  set_rownames(Protein[, 1])
Meth.mat <- as.matrix(Meth[, MatchMeth]) %>%
  set_rownames(row.names(Meth))
             <- as.matrix(GE[,2:349])
Exp.mat
reduced_matrix_data <- list(Exp.mat, miRNA.mat, Protein.mat, Meth.mat) %%
  magrittr::set_names(c("GE", "miRNA", "Protein", "Meth"))
How much missingness is present?
# How many missing entries in our data
print(lapply(reduced_matrix_data, function(x){
  sum(is.na(x))
}
))
## $GE
## [1] 1119
## $miRNA
## [1] 0
##
## $Protein
## [1] 0
##
## $Meth
## [1] 0
\hbox{\it\# The only dataset with NAs is the Gene expression data}\\
dim(reduced_matrix_data$GE)
## [1] 17814
ge_missingness <- rowSums(is.na(reduced_matrix_data$GE))</pre>
ge_missingness[ge_missingness > 0] %>%
 hist(main = "Count of NAs in each gene in GE data (0's excluded)",
       xlab = "Number of NAs present")
```

### Count of NAs in each gene in GE data (0's excluded)



As the Gene Expression contains actual NA's we will impute missing values using knn with k = 10 (the default setting).

```
# Impute missing values via KNN (K=10) for the Gene expression data
Exp.mat <- impute.knn(Exp.mat)
Exp.mat <- Exp.mat$data %>%
    set_rownames(GE[,1])

reduced_matrix_data$GE <- Exp.mat</pre>
```

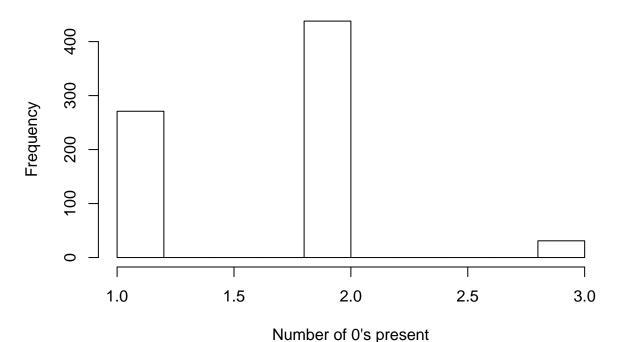
We might also be interested in the number of 0's present in the datasets as this could represent missing data.

```
# Check how many 0's there are in the datasets (possibly these are missing points too!)
print(lapply(reduced_matrix_data, function(x){
    sum(x == 0)
}
))
```

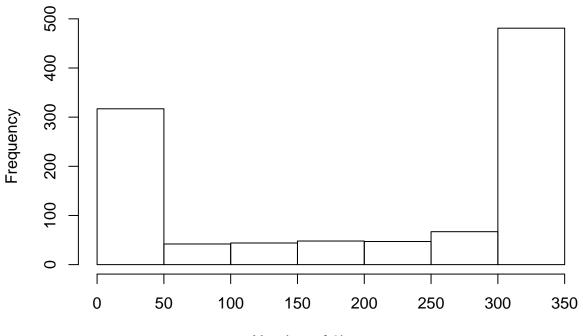
```
## $GE
## [1] 1240
##
## $miRNA
## [1] 211498
##
## $Protein
## [1] 0
##
## $Meth
## [1] 0
```

```
\# The GE and miRNA datasets both have 0 entries, check how many genes have 0's
print(lapply(reduced_matrix_data, function(x){
  sum(rowSums(x == 0) > 0)
}
))
## $GE
## [1] 740
##
## $miRNA
## [1] 840
## $Protein
## [1] 0
##
## $Meth
## [1] 0
ge_zeroness <- rowSums(reduced_matrix_data$GE == 0)</pre>
ge_zeroness[ge_zeroness > 0] %>%
  hist(main = "Count of 0's in each gene in GE data (0's excluded)",
       xlab = "Number of 0's present")
```

### Count of 0's in each gene in GE data (0's excluded)

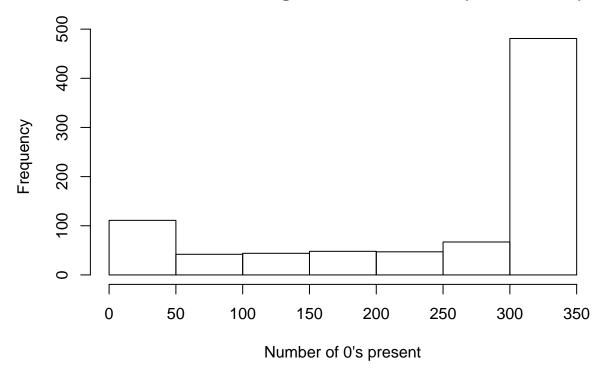


### Count of 0's in each gene in miRNA data



Number of 0's present

### Count of 0's in each gene in miRNA data (0's excluded)



```
# There's a far greater number of 0 entries in the miRNA compared to the GE;
# also, no gene in the GE dataset has more than 3 associated 0 entries
```

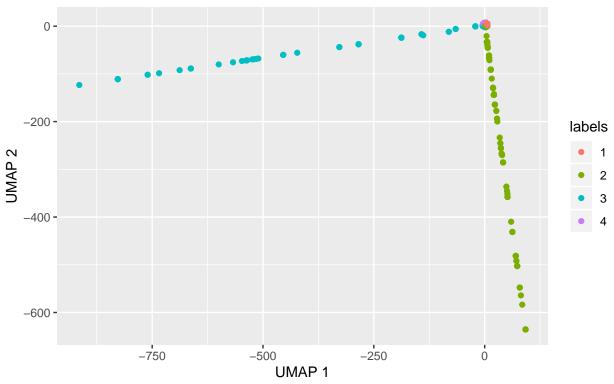
Now we visualise the effect of the preprocessing steps by mapping the points to a 2D UMAP; colouring based upon their UMAP coordinates. We split the points based upon the median of the points in each direction, so points are assigned values based upon:

Table 1: Labels defined by UMAP coordinates.

Condition.in.UMAP.1	Condition.in.UMAP.2	Label
Greater than median	Greater than median	1
Greater than median	Less than median	2
Less than median	Greater than median	3
Less than median	Less than median	4

First consider the

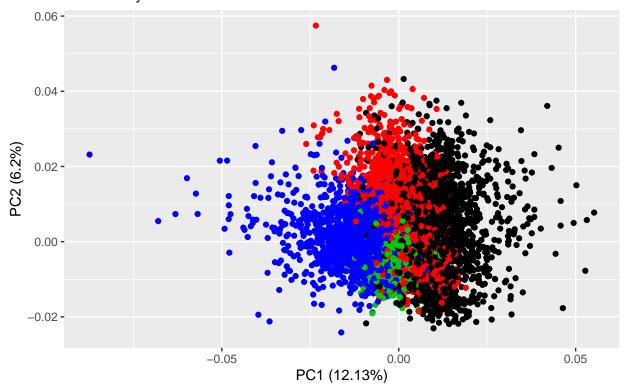
## Gene expression: pre-processing UMAP Coloured by UMAP coordinates



```
# Save UMAP plot
# ggsave(umap_file_names[1])

# Plot PCA with UMAP defined labels
autoplot(ge_pca, data = Exp.mat, colour = ge_labels) +
    labs(title = "Gene expression: pre-processing",
        subtitle = "Coloured by UMAP coordinates")
```

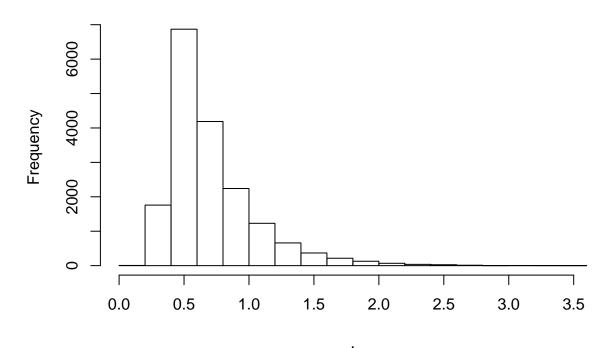
## Gene expression: pre-processing Coloured by UMAP coordinates



```
# ggsave(file_names[[1]][1])

Exp.mat %>%
   apply(1, sd) %>%
   hist(main = "Standard deviation of genes in GE data (before processing)")
```

### Standard deviation of genes in GE data (before processing)

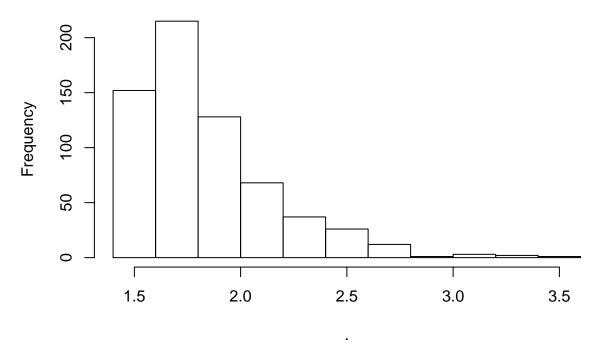


processedExpression <- Exp.mat[apply(Exp.mat,1,sd)>1.5,] ###Filter to select only most variable genes
print(ncol(Exp.mat) - ncol(processedExpression))

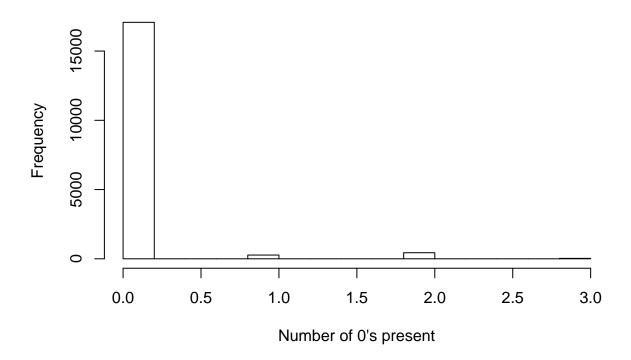
```
## [1] 0
```

```
processedExpression %>%
  apply(1, sd) %>%
  hist(main = "Standard deviation of genes in GE data (post processing)")
```

### Standard deviation of genes in GE data (post processing)

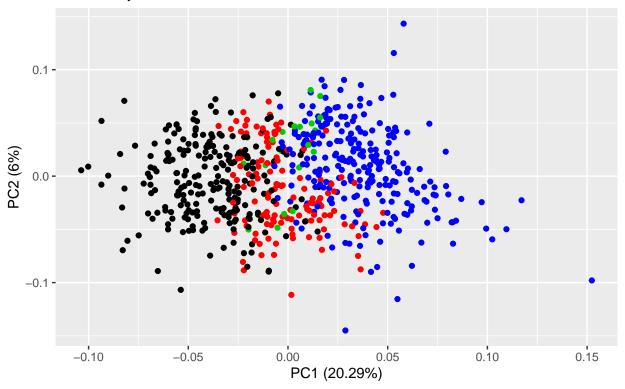


### Count of 0's in each gene in GE data post-processing

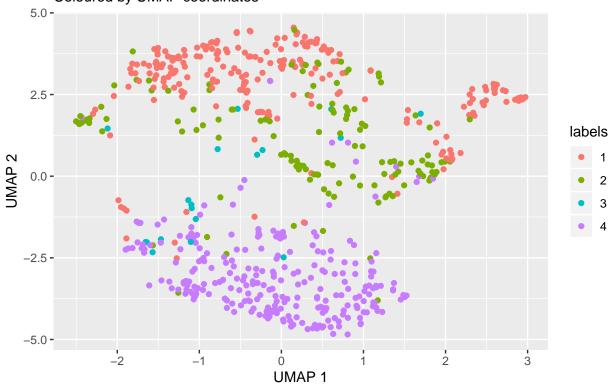


## Warning in if (value %in% columns) {: the condition has length > 1 and only the ## first element will be used

## Gene expression: post–processing Coloured by UMAP coordinates

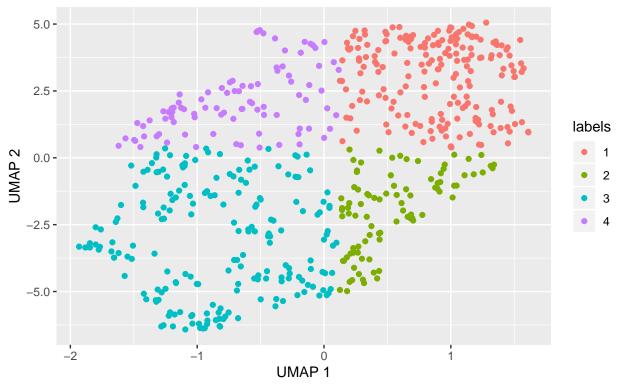


## Gene expression: post–processing UMAP Coloured by UMAP coordinates

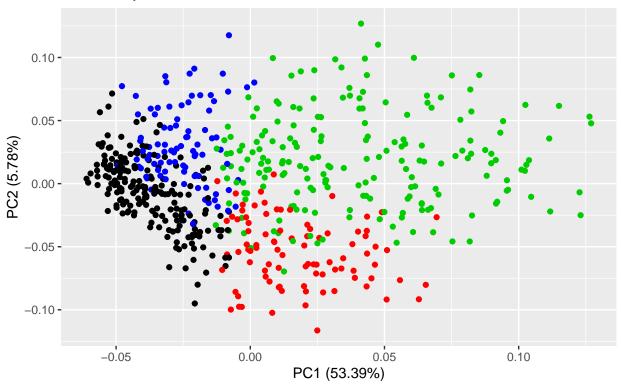


 $\#\ ggs ave ("~/Documents/PhD/Year\_1/Consensus\_clustering/Analysis/BCC\_TCGA\_data/Data/gene\_expression\_umap\_instantial for the property of the$ 

# Methylation: pre-processing UMAP Coloured by UMAP coordinates



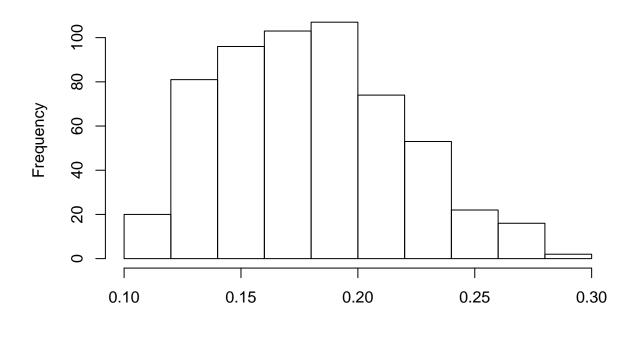
# Methylation: pre-processing Coloured by UMAP coordinates



```
# ggsave(file_names[[1]][2])

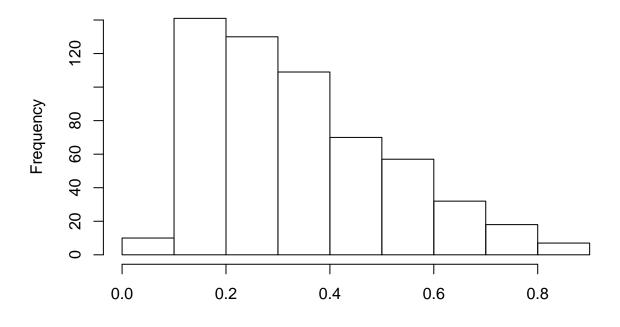
Meth.mat %>%
    apply(1, sd) %>%
    hist(main = "Methylation: Gene standard deviation (before processing)")
```

### Methylation: Gene standard deviation (before processing)



```
Meth.mat %>%
  apply(1, mean) %>%
  hist(main = "Methylation: Gene mean (after processing)")
```

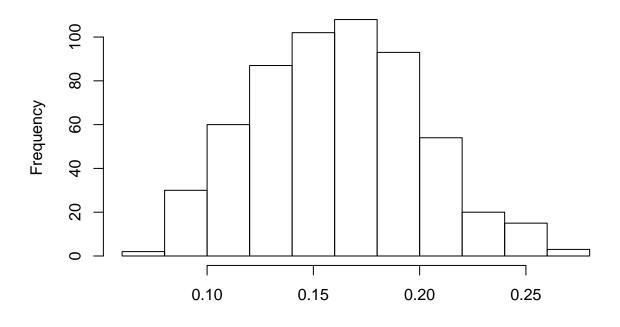
### **Methylation: Gene mean (after processing)**



processedMethylation <- sqrt(Meth.mat) ##take square root of methylation data
p\_meth\_pca <- prcomp(processedMethylation)</pre>

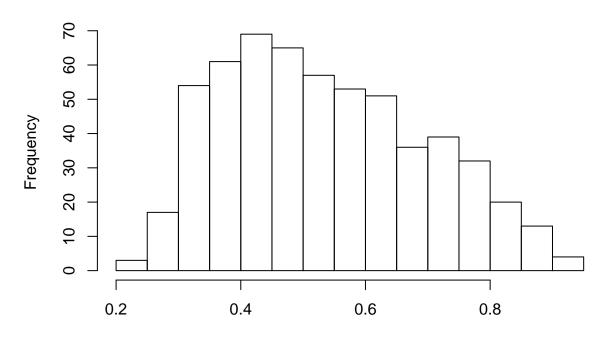
```
processedMethylation %>%
  apply(1, sd) %>%
  hist(main = "Methylation: Gene standard deviation (after processing)")
```

### Methylation: Gene standard deviation (after processing)

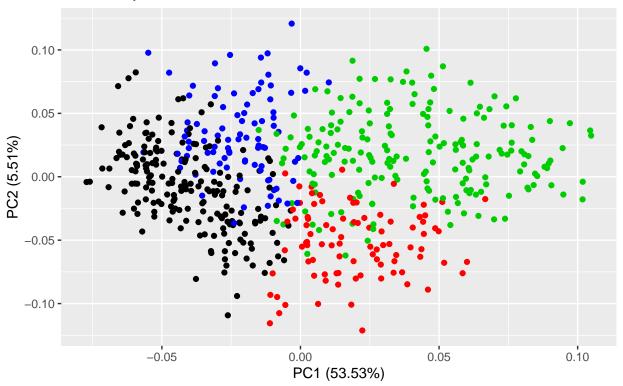


```
processedMethylation %>%
   apply(1, mean) %>%
   hist(main = "Methylation: Gene mean (after processing)")
```

### **Methylation: Gene mean (after processing)**

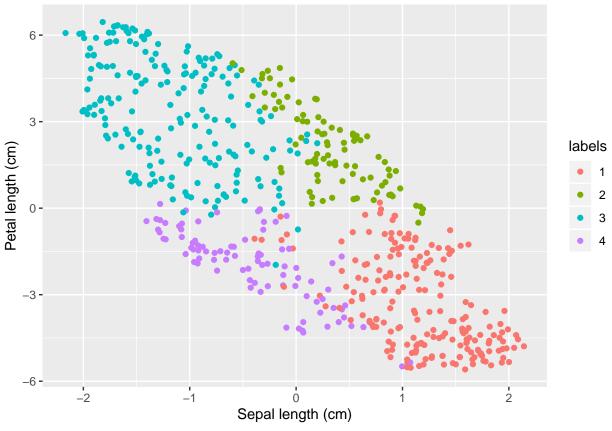


## Methylation: post-processing Coloured by UMAP coordinates

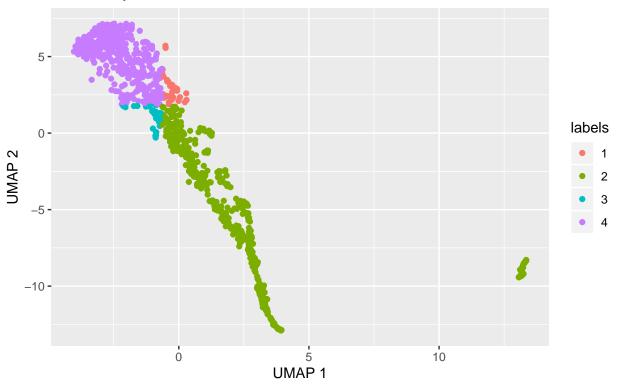


```
# ggsave(file_names[[2]][2])

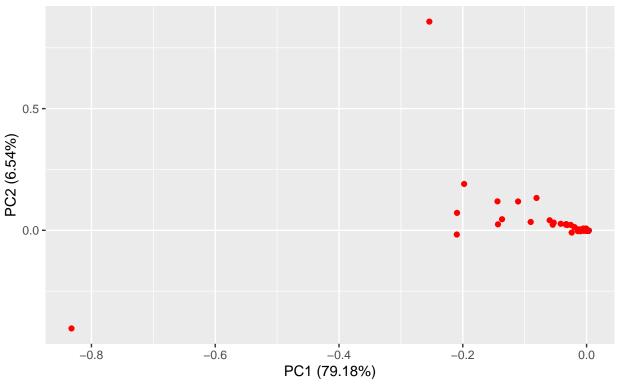
p_meth_umap <- umap(processedMethylation)
p_meth_plt_data <- makeUMAPPlotData(p_meth_umap$layout, meth_labels)
plotUMAP(p_meth_plt_data) +
   labs(y="Petal length (cm)", x = "Sepal length (cm)")</pre>
```



## miRNA: pre-processing UMAP Coloured by UMAP coordinates



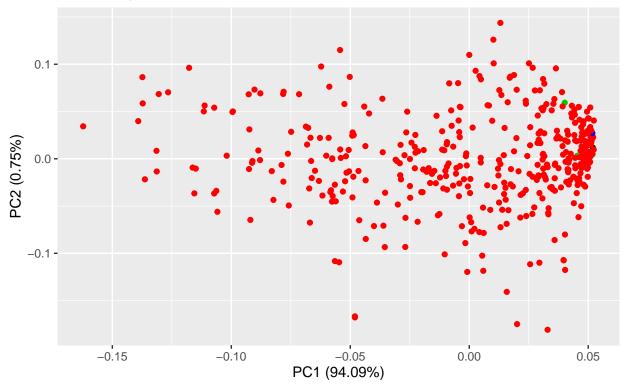
## miRNA: pre-processing Coloured by UMAP coordinates



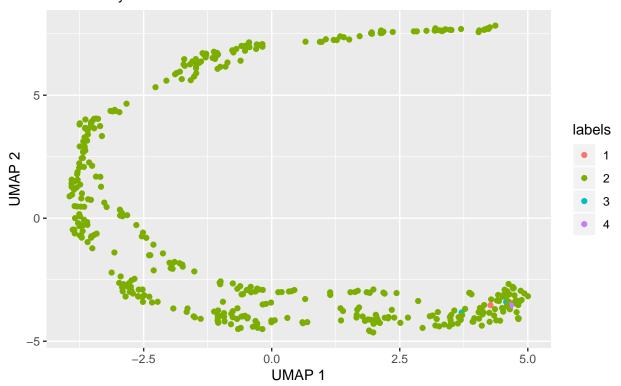
```
# xlim(4e4, 5e4) +
  # ylim(5.5e3, 6.1e3)
\# miRNA_pca$x[(miRNA_pca$x[,1] < 4e4),1:2]
# summary(miRNA_pca$x[,1:2])
# miRNA_exclude <- row.names(miRNA_pca$x)[(miRNA_pca$x[,1] < 4e4 & miRNA_pca$x[,2] < 6.1e3)]
# indices_to_drop <- ! row.names(miRNA.mat) %in% miRNA_exclude</pre>
# miRNA_reduced <- miRNA.mat[which(indices_to_drop),]</pre>
# miRNA_labels_reduced <- miRNA_labels[which(indices_to_drop)]</pre>
#
# miRNA_pca_red <- prcomp(miRNA_reduced)</pre>
# autoplot(miRNA_pca_red, data = miRNA_reduced, colour = miRNA_labels_reduced) +
    labs(title = "miRNA: pre-processing",
         subtitle = "Coloured by UMAP coordinates")
# Save the PCA plot with UMAP colouring
# ggsave(file_names[[1]][3])
# Transform the data
miRNA_to_drop <- rowSums(miRNA.mat==0) < 348*0.5
             <- miRNA.mat[which(miRNA_to_drop),]</pre>
                      <- log(1+miRNA.mat) ##take log of miRNA data
processedmiRNA
# Take the PCA of the transformed data
```

## Warning in if (value %in% columns) {: the condition has length > 1 and only the ## first element will be used

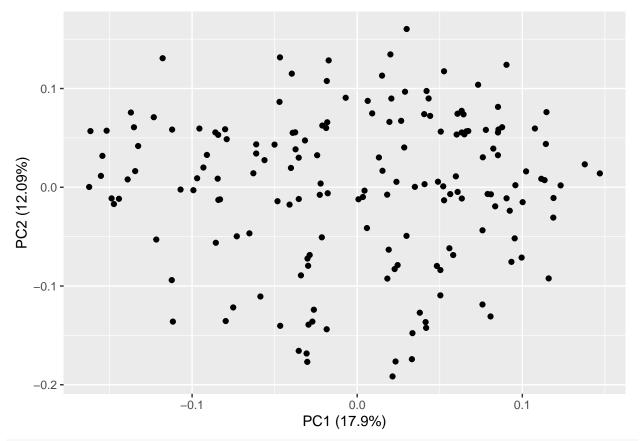
## miRNA: post–processing Coloured by UMAP coordinates



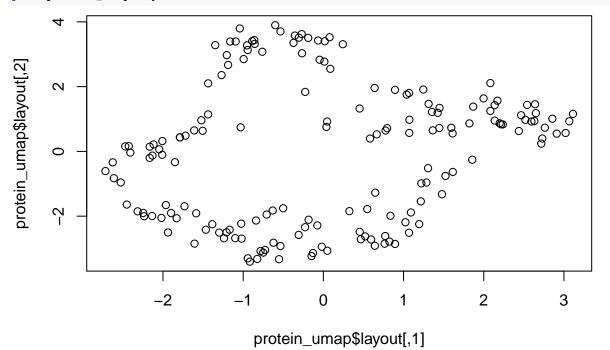
## miRNA: post–processing UMAP Coloured by UMAP coordinates



```
# ggsave("~/Documents/PhD/Year_1/Consensus_clustering/Analysis/BCC_TCGA_data/Data/miRNA_umap_post_proce
# Remove miRNAs with > 50% 0 entries
print(dim(miRNA.mat))
## [1] 423 348
miRNA.mat     <- miRNA.mat[rowSums(miRNA.mat==0) < 348*0.5,]
print(dim(miRNA.mat))
## [1] 423 348
protein_pca <- prcomp(Protein.mat)
autoplot(protein_pca)</pre>
```



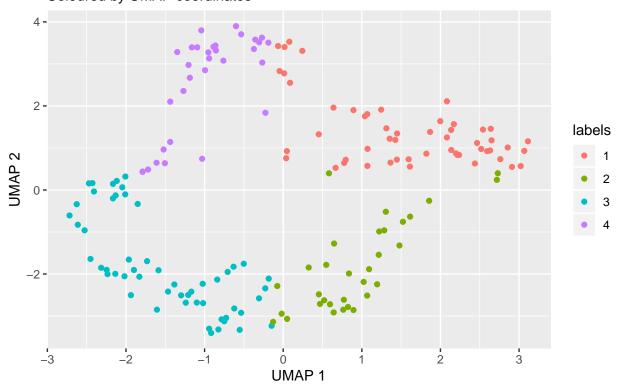
protein\_umap <- umap(Protein.mat)
plot(protein\_umap\$layout)</pre>



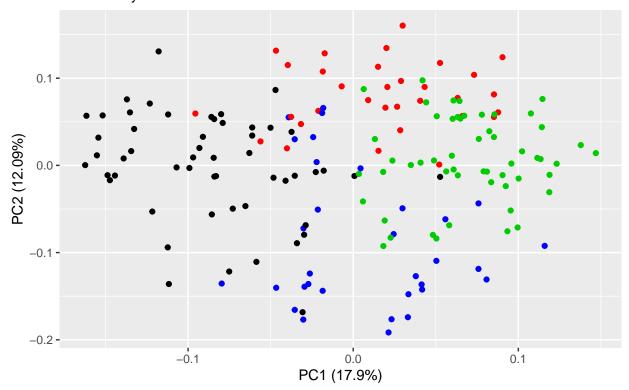
protein\_labels <- makeUMAPLabels(protein\_umap\$layout)
protein\_plt\_data <- makeUMAPPlotData(protein\_umap\$layout, protein\_labels)
plotUMAP(protein\_plt\_data) +</pre>

```
labs(title = "Protein: pre-processing UMAP",
    subtitle = "Coloured by UMAP coordinates",
    x = "UMAP 1",
    y = "UMAP 2")
```

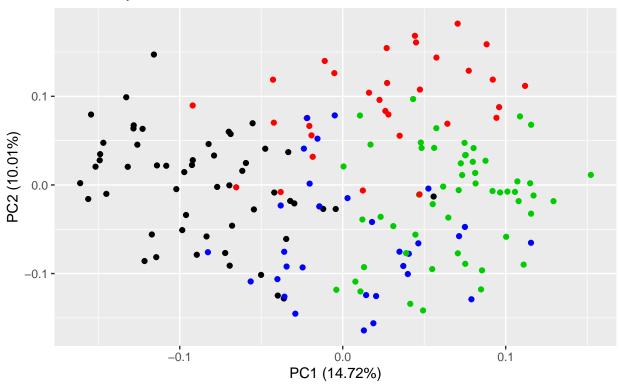
## Protein: pre-processing UMAP Coloured by UMAP coordinates



## Protein: pre-processing Coloured by UMAP coordinates



## Protein: post–processing Coloured by UMAP coordinates



```
# ggsave(file_names[[2]][4])

p_protein_umap <- umap(processedProtein)
p_protein_plt_data <- makeUMAPPlotData(p_protein_umap$layout, protein_labels)
plotUMAP(p_protein_plt_data) +
    labs(title = "Protein: post-processing UMAP",
        subtitle = "Coloured by UMAP coordinates",
        x = "UMAP 1",
        y = "UMAP 2")</pre>
```

Protein: post–processing UMAP Coloured by UMAP coordinates

