

# **lab\_08**

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## **Background**

something

## **Libraries**

```
library(ggplot2)
```

## **Data import**

Remove patient id and diagnosis from the dataset.

```
cancer_raw_df <- read.csv("WisconsinCancer.csv", row.names=1)
new_samples <- read.csv("new_samples.csv")
```

## Data Cleaning

Remove diagnosis column from the dataset

```
diagnosis <- as.factor(cancer_raw_df$diagnosis)
cancer_df <- cancer_raw_df[,-1]
```

## Data summary

```
obsvs <- nrow(cancer_df)
vars <- ncol(cancer_df)
vars_w_mean <- length(grep("_mean$", names(cancer_df), value=TRUE))
n_malignant <- sum(diagnosis=="M")
sprintf("Q1. There are %s observations in the dataset", obsvs)
```

[1] "Q1. There are 569 observations in the dataset"

```
sprintf("Q2. There are %s malignant diagnosis", n_malignant)
```

[1] "Q2. There are 212 malignant diagnosis"

```
sprintf("Q3. There are %s vars with suffix _mean", vars_w_mean)
```

[1] "Q3. There are 10 vars with suffix \_mean"

## PCA

```
round(colMeans(cancer_df), 4)
```

radius_mean	texture_mean	perimeter_mean
14.1273	19.2896	91.9690
area_mean	smoothness_mean	compactness_mean
654.8891	0.0964	0.1043
concavity_mean	concave.points_mean	symmetry_mean
0.0888	0.0489	0.1812
fractal_dimension_mean	radius_se	texture_se

	0.0628	0.4052	1.2169
perimeter_se		area_se	smoothness_se
	2.8661	40.3371	0.0070
compactness_se		concavity_se	concave.points_se
	0.0255	0.0319	0.0118
symmetry_se		fractal_dimension_se	radius_worst
	0.0205	0.0038	16.2692
texture_worst		perimeter_worst	area_worst
	25.6772	107.2612	880.5831
smoothness_worst		compactness_worst	concavity_worst
	0.1324	0.2543	0.2722
concave.points_worst		symmetry_worst	fractal_dimension_worst
	0.1146	0.2901	0.0839

```
apply(cancer_df, 2, sd)
```

radius_mean	texture_mean	perimeter_mean
3.524049e+00	4.301036e+00	2.429898e+01
area_mean	smoothness_mean	compactness_mean
3.519141e+02	1.406413e-02	5.281276e-02
concavity_mean	concave.points_mean	symmetry_mean
7.971981e-02	3.880284e-02	2.741428e-02
fractal_dimension_mean	radius_se	texture_se
7.060363e-03	2.773127e-01	5.516484e-01
perimeter_se	area_se	smoothness_se
2.021855e+00	4.549101e+01	3.002518e-03
compactness_se	concavity_se	concave.points_se
1.790818e-02	3.018606e-02	6.170285e-03
symmetry_se	fractal_dimension_se	radius_worst
8.266372e-03	2.646071e-03	4.833242e+00
texture_worst	perimeter_worst	area_worst
6.146258e+00	3.360254e+01	5.693570e+02
smoothness_worst	compactness_worst	concavity_worst
2.283243e-02	1.573365e-01	2.086243e-01
concave.points_worst	symmetry_worst	fractal_dimension_worst
6.573234e-02	6.186747e-02	1.806127e-02

```
cancer_pca <- prcomp(cancer_df, scale=TRUE)
cancer_pca_summary <- summary(cancer_pca)
pc1_var <- cancer_pca_summary$importance[2, 1]
sprintf("Q4. PC1 explains %s of the variance", pc1_var)
```

```
[1] "Q4. PC1 explains 0.44272 of the variance"

# Get the PCs that explain 70% of the variance
sum_var <- 0
pc_n <- 0
while(sum_var<=0.7) {
  pc_n <- pc_n + 1
  sum_var <- sum_var + cancer_pca_summary$importance[2, pc_n]
}
sprintf("Q5. The first %s PCs explain %s of the variance", pc_n, sum_var)
```

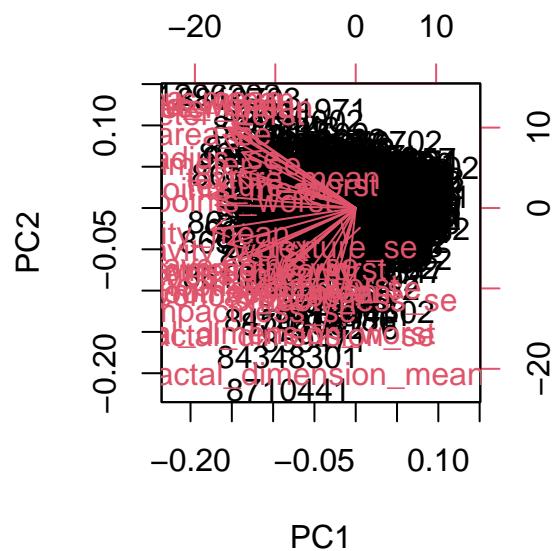
```
[1] "Q5. The first 3 PCs explain 0.72636 of the variance"
```

```
# Get the PCs that explain 90% of the variance
sum_var <- 0
pc_n <- 0
while(sum_var<=0.9) {
  pc_n <- pc_n + 1
  sum_var <- sum_var + cancer_pca_summary$importance[2, pc_n]
}
sprintf("Q6. The first %s PCs explain %s of the variance", pc_n, sum_var)
```

```
[1] "Q6. The first 7 PCs explain 0.9101 of the variance"
```

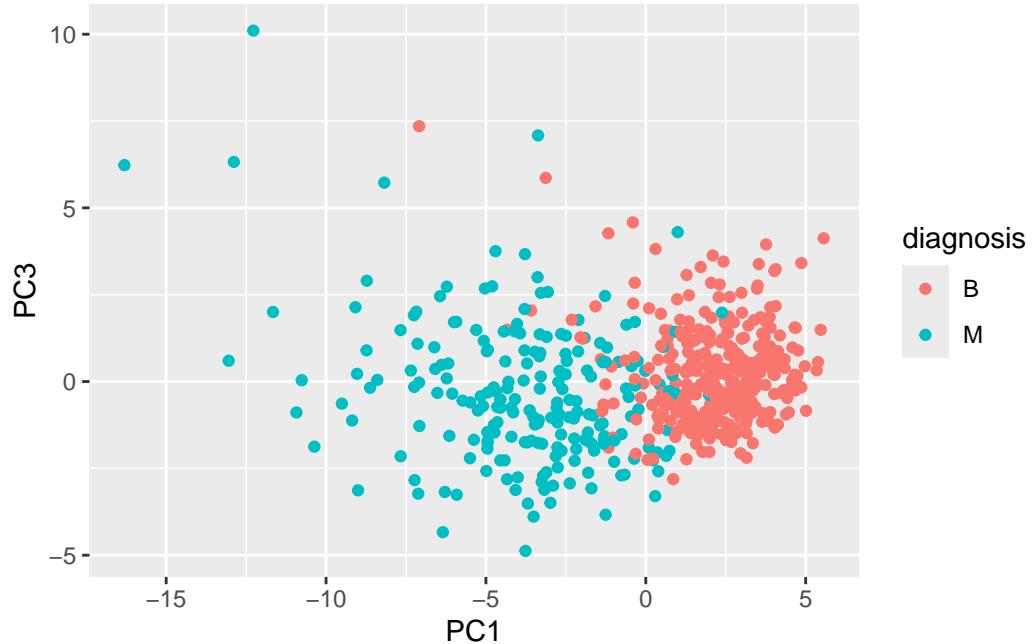
Q7.

```
biplot(cancer_pca)
```

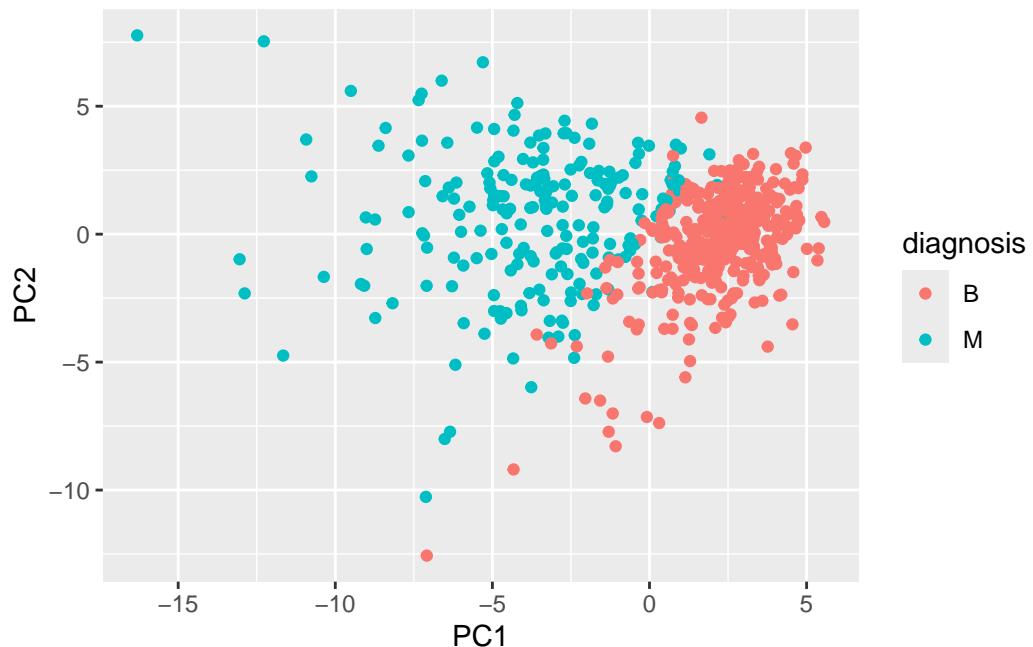


Q8.

```
ggplot(cancer_pca$x) +  
  aes(PC1, PC3, col=diagnosis) +  
  geom_point()
```



```
ggplot(cancer_pca$x) +  
  aes(PC1, PC2, col=diagnosis) +  
  geom_point()
```



```
lo <- cancer_pca$rotation["concave.points_mean", 1]
sprintf("Q9. The contribution of concave.points_mean to PC1 is %s", round(lo,2))
```

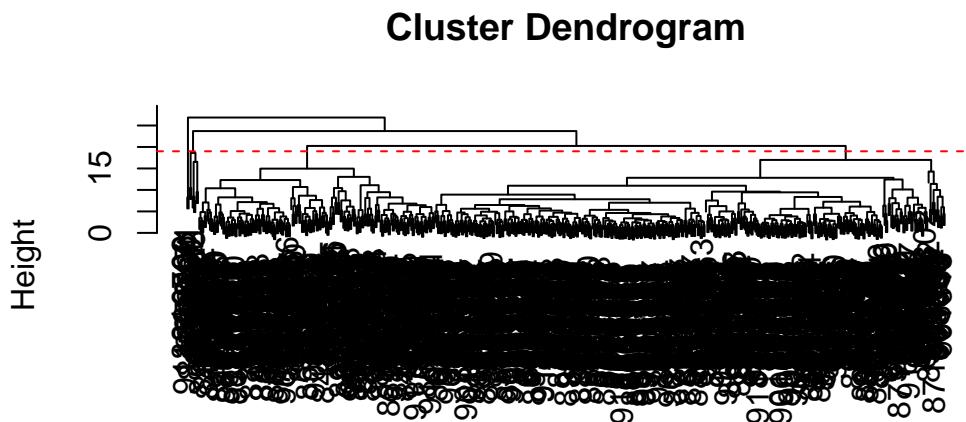
```
[1] "Q9. The contribution of concave.points_mean to PC1 is -0.26"
```

## Hierarchical Clustering

Q10. what is the height at which the clustering model has 4 clusters?

19

```
cancer_df_scaled <- scale(cancer_df)
cancer_dist <- dist(cancer_df_scaled, method="euclidean")
cancer_hclust <- hclust(cancer_dist, method="complete")
plot(cancer_hclust)
abline(19, 0, col="red", lty=2)
```



cancer\_dist  
hclust (\*, "complete")

```
cancer_hclust_cut <- cutree(cancer_hclust, 2)
table(cancer_hclust_cut, diagnosis)
```

```

diagnosis
cancer_hclust_cut   B   M
      1 357 210
      2   0   2

cancer_dist <- dist(cancer_df_scaled, method="euclidian")
cancer_hclust <- hclust(cancer_dist, method="ward.D2")
cancer_hclust_cut <- cutree(cancer_hclust, 2)
table(cancer_hclust_cut, diagnosis)

```

```

diagnosis
cancer_hclust_cut   B   M
      1 20 164
      2 337 48

```

Q12. Which method gives your favorite results for the same data.dist dataset?  
Explain your reasoning.

Ward.D2, because it split the largest number of B and M diagnosis into different clusters.

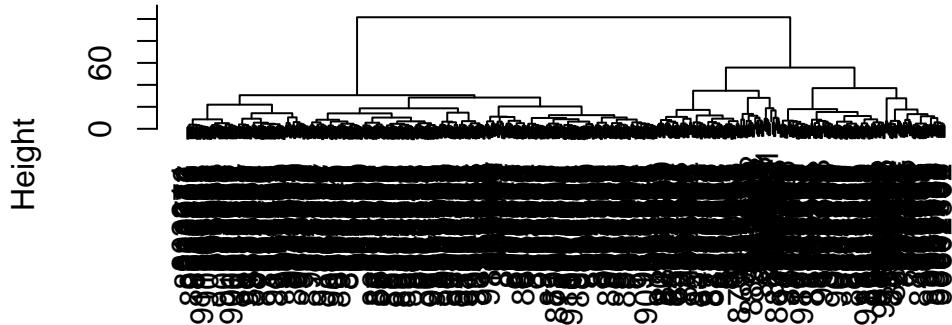
## Clustering PCA

```

pca_dist <- dist(cancer_pca$x[,1:7], method="euclidian")
pca_hclust <- hclust(pca_dist, method="ward.D2")
plot(pca_hclust)

```

## Cluster Dendrogram



```
pca_dist  
hclust (*, "ward.D2")
```

Q13. How well does the newly created model with four clusters separate out the two diagnoses?

This model has a higher True positive value

```
pca_hclust_cut <- cutree(pca_hclust, 2)  
table(pca_hclust_cut, diagnosis)
```

		diagnosis
		B    M
pca_hclust_cut	1	28 188
	2	329 24

```
sensitivity <- round(188 / (188 + 28), 2)  
specificity <- round(324 / (324 + 24), 2)  
sprintf("sensitivity: %s, specificity: %s", sensitivity, specificity)
```

```
[1] "sensitivity: 0.87, specificity: 0.93"
```

Q14. How well do the hierarchical clustering models you created in previous sections (i.e. before PCA) do in terms of separating the diagnoses?

This model has less True positive but also less false positives

```
cancer_dist <- dist(cancer_df_scaled, method="euclidian")
cancer_hclust <- hclust(cancer_dist, method="ward.D2")
cancer_hclust_cut <- cutree(cancer_hclust, 2)
table(cancer_hclust_cut, diagnosis)
```

	diagnosis	
cancer_hclust_cut	B	M
1	20	164
2	337	48

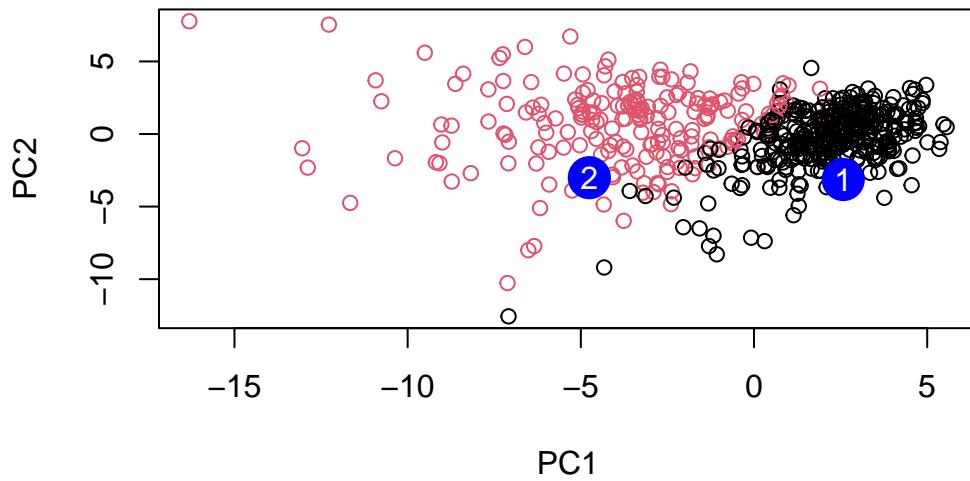
```
sensitivity <- round(164 / (164 + 20), 2)
specificity <- round(337 / (337 + 48), 2)
sprintf("sensitivity: %s, specificity: %s", sensitivity, specificity)
```

[1] "sensitivity: 0.89, specificity: 0.88"

## Prediction

```
url <- "https://tinyurl.com/new-samples-CSV"
new <- read.csv(url)
npc <- predict(cancer_pca, newdata=new)
```

```
plot(cancer_pca$x[,1:2], col=diagnosis)
points(npc[,1], npc[,2], col="blue", pch=16, cex=3)
text(npc[,1], npc[,2], c(1,2), col="white")
```



Q16. Which of these new patients should we prioritize for follow up based on your results?

Patient 2 should be prioritized.