# Dimensionality Reduction

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## PCA and LDA, How do they work and What's their importance?

PCA (Principal Component Analysis) is a type of unsupervised learning, which removes correlation between independent variable and looks for hidden latent variable, and reduces noise.

LDA (Linear Discriminant Analysis) is a supervised algorithm that performs classification and dimensionality reduction at the same time. The key to LDA is that when classification is performed, the variance within the class is minimized, but the variance between classes is maximized.

The difference in these two comes from PCA finding a new axis that allows the data to be widely distributed, while the LDA finds a new axis that best classifies data.

PCA performs better when the difference in class comes from the difference in variance, and LDA performs better when the difference in class of data comes from the difference in mean. Also, When data is represented in a 3-dimensional plot, LDA shows a better performance than PCA as well in classification.

## Data Introduction

https://archive-beta.ics.uci.edu/ml/datasets/motion+capture+hand+postures Motion capsure of Hand postures has been selected to perform dimensionality reduction The Dataset contains 5 classes of hand postures, and 11 points of tracking on the hand, the markings on hand have a 3d position corresponding to them, from X0, Y0, Z0, up to X11, Y11, Z11 having fewer variables here would mean we would have to guess the hand posture by looking at fewer fingers

```
pos <- read.csv("postures.csv", na.strings = c("?"), header=FALSE)
i <- c(1:17)
pos <- pos[-c(1), i]
pos <- na.omit(pos)
pos[ , i] <- apply(pos[ , i], 2, function(j) as.numeric(as.character(j)))
```

```
set.seed(1234)
i <- sample(1:nrow(pos), nrow(pos)*0.8, replace=FALSE)
train <- pos[i,]
test <- pos[-i,]

str(train)
```

```
## 'data.frame':    59980 obs. of  17 variables:
##  $ V1 : num  2 3 5 5 5 1 2 5 2 5 ...
##  $ V2 : num  10 2 8 13 12 14 4 8 11 2 ...
##  $ V3 : num  59.7 108.1 78 13 -16.4 ...
##  $ V4 : num  141.6 45.9 77.5 106.4 87.3 ...
##  $ V5 : num  33.79 -68.84 -95.29 3.22 10.11 ...
##  $ V6 : num  71 71.5 75.6 -20.2 50.3 ...
```

```
##  $ V7 : num  85.8 129 53.3 86.3 87.8 ...
##  $ V8 : num  -1.39 -38.49 -95.1 -31.21 10.81 ...
##  $ V9 : num  100.96 69.36 62.94 7.47 15.39 ...
##  $ V10: num  133.4 80.5 17 130.8 89.5 ...
##  $ V11: num  10.9 -26.7 -82.6 -51.8 19.2 ...
##  $ V12: num  90.5 17.6 89 23.4 76.4 ...
##  $ V13: num  76.9 78.5 83.5 134.1 79.4 ...
##  $ V14: num  -22.8 -50.8 -11.9 -35.9 -10.8 ...
##  $ V15: num  120.7 98 -10.4 51.3 14.5 ...
##  $ V16: num  111.3 26.2 129.8 131.6 140 ...
##  $ V17: num  -15.46 -66.37 3.61 -26.19 -23.79 ...
##  - attr(*, "na.action")= 'omit' Named int [1:3120] 9 42 43 44 51 55 80 87 88 89 ...
##   ..- attr(*, "names")= chr [1:3120] "10" "43" "44" "45" ...
```

**PCA**

```
library(caret)
```

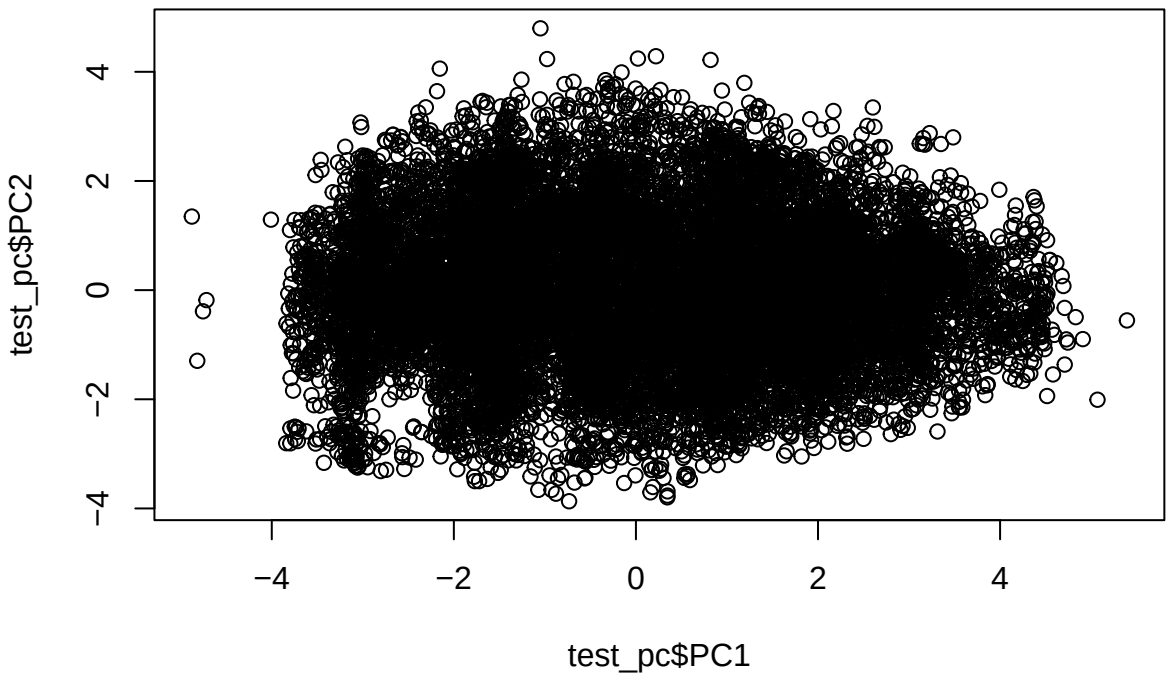
```
## Loading required package: ggplot2
```

```
## Loading required package: lattice
```

```
pca_out <- preProcess(train[,1:17], method=c("center", "scale", "pca"))
pca_out
```

```
## Created from 59980 samples and 17 variables
##
## Pre-processing:
##   - centered (17)
##   - ignored (0)
##   - principal component signal extraction (17)
##   - scaled (17)
##
## PCA needed 14 components to capture 95 percent of the variance
```

```
train_pc <- predict(pca_out, train[,])
test_pc <- predict(pca_out, test[,])
plot(test_pc$PC1, test_pc$PC2, pch=c(23,22)[unclass(test_pc$v1)])
```

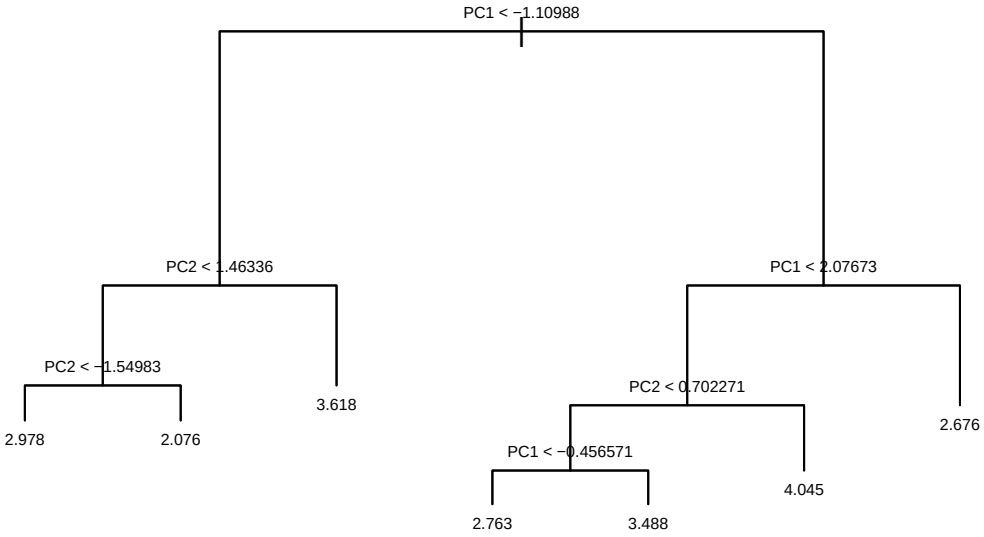



PCA Accuracy

```
train_df <- data.frame(train_pc$PC1, train_pc$PC2, train$V1)
test_df <- data.frame(test_pc$PC1, test_pc$PC2, test$V1)
library(class)
set.seed(1234)
pred <- knn(train=train_df[,1:2], test=test_df[,1:2], cl=train_df[,3], k=17)
mean(pred==test$V1)
```

```
## [1] 0.5514137
```

```
library(tree)
colnames(train_df) <- c("PC1", "PC2", "Class")
colnames(test_df) <- c("PC1", "PC2", "Class")
set.seed(1234)
tree1 <- tree(Class~., data=train_df)
plot(tree1)
text(tree1, cex=0.5, pretty=0)
```




```
pred <- predict(tree1, newdata=test_df, type="vector")
```

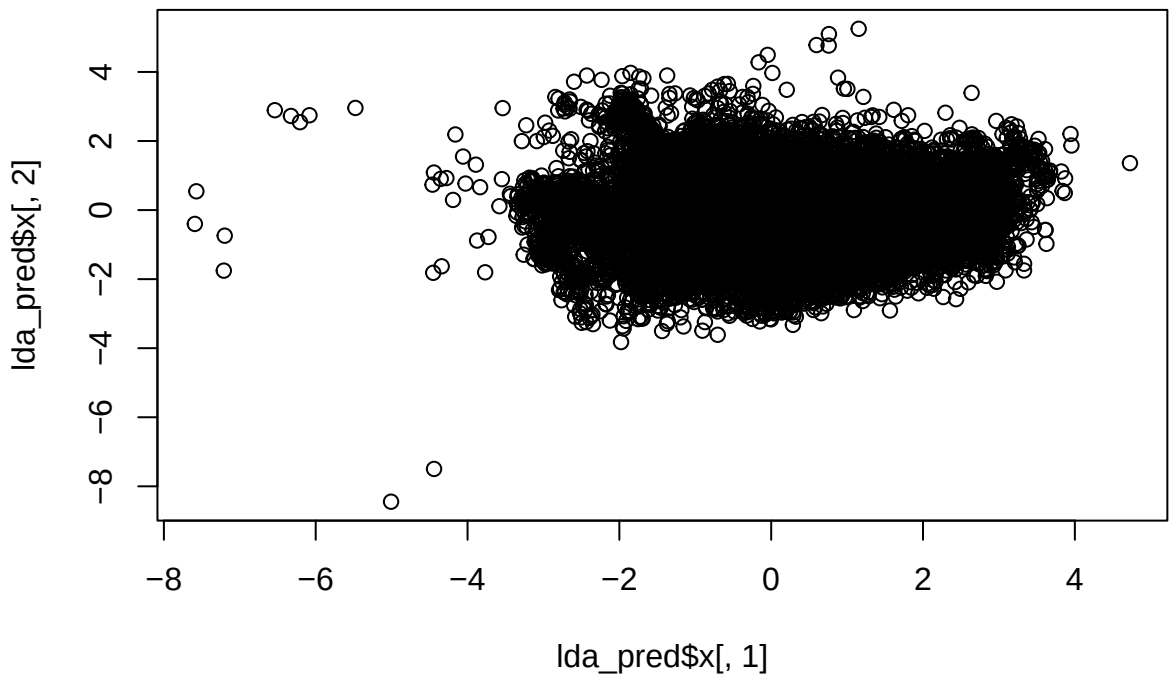
```
glm1 <- glm(PC1~., data=train_pc, family="gaussian")
summary(glm1)
```

```
##
## Call:
## glm(formula = PC1 ~ ., family = "gaussian", data = train_pc)
##
## Deviance Residuals:
##    Min      1Q  Median      3Q     Max
## -5.937  -1.535  -0.077   1.546   5.472
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) -1.115e-16  7.780e-03       0        1
## PC2         -2.966e-15  5.947e-03       0        1
## PC3          1.831e-15  6.399e-03       0        1
## PC4          1.983e-15  6.501e-03       0        1
## PC5          1.693e-15  6.578e-03       0        1
## PC6          5.760e-16  6.679e-03       0        1
## PC7          3.034e-14  7.438e-03       0        1
## PC8         -5.477e-14  8.139e-03       0        1
## PC9          1.292e-14  9.772e-03       0        1
## PC10        -4.305e-15  9.936e-03       0        1
```

```
## PC11          8.142e-15  1.011e-02       0        1
## PC12         -2.125e-15  1.017e-02       0        1
## PC13          7.870e-14  1.123e-02       0        1
## PC14          2.561e-14  1.384e-02       0        1
##
## (Dispersion parameter for gaussian family taken to be 3.63018)
##
##     Null deviance: 217687  on 59979  degrees of freedom
## Residual deviance: 217687  on 59966  degrees of freedom
## AIC: 247563
##
## Number of Fisher Scoring iterations: 2
```

**LDA**

```
library(MASS)
lda1 <- lda(V1~., data=train)
lda_pred <- predict(lda1, newdata=test, type="class")
plot(lda_pred$x[,1], lda_pred$x[,2], pch=c(23,21,22)[unclass(lda_pred$V1)])
```




LDA Accuracy

```
mean(lda_pred$class==test$V1)
```

```
## [1] 0.6192318
```

## Analysis

As seen above, the accuracy of PCA logistic regression was 0.55, while LDA method had an accuracy of 0.62. Since PCA is unsupervised and LDA is supervised, we can see that the results are more accurate on LDA since the classes are known