08 PCA

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4/20/2022

Load required packages

```
library(tidyverse)
```

```
## -- Attaching packages ---------------------------------
```

```
## v ggplot2 3.3.3     v purrr   0.3.4
## v tibble  3.1.1     v dplyr   1.0.5
## v tidyr   1.1.3     v stringr 1.4.0
## v readr   1.4.0     v forcats 0.5.1
```

```
# if you're using macOS, you can run: library(dplyr)
library(skimr)
library(broom)
library(modelr)
```

Introduction

- A data table is a space of information
  - Each column/variable is a feature/`dimension` that adds more information to our understanding about a problem
- When data is bigger and bigger, the information set gets bigger and bigger
- For example, data can have more than 1,000 variables
  - We need to analyze statistics of each variable and do some tests like t-test to understand the data
  - But very exhausted

Dimension reduction

- That's why in data science, people think out a way to reduce the dimension of data
- Say, how to combine 1,000 variables into a few variables that can capture most of information in the data
- It is similar to news summary by the end of the day:
  - Instead of reading all 1,000 news articles, we just need to read 2-3 news summary by the end and understand most of things happen in today
- Today's lecture will introduce to you that skill: Principal component analysis or PCA

An overview of PCA

- Combine features into a smaller set of principal component:
  - Each component has `score`: which is linear combination of features
- Each component aims to explain the highest variance/variation in the data
  - The first component explains most of variance
  - The second component continues to explain a bit
  - and so on

An example

- We have a data of crime in 50 US states with 4 variables:
  - `Assault`: the number of assault arrests/100,000 residents
  - `Murder`: the number of murder arrests/100,000 residents
  - `Rape`: the number of rape arrests/100,000 residents
  - `UrbanPop`: the percent of population in each state living in urban areas

Import data

```
Crime = USArrests
head(Crime)
```

```
##             Murder Assault UrbanPop Rape
## Alabama       13.2     236       58 21.2
## Alaska        10.0     263       48 44.5
## Arizona        8.1     294       80 31.0
## Arkansas       8.8     190       50 19.5
## California     9.0     276       91 40.6
## Colorado       7.9     204       78 38.7
```

Skim statistics

```
skim_without_charts(Crime) %>%
  as.data.frame() %>%
  select(var=skim_variable, mean=numeric.mean,
         sd=numeric.sd)
```

```
##         var    mean         sd
## 1    Murder   7.788  4.355510
## 2   Assault 170.760 83.337661
## 3 UrbanPop  65.540 14.474763
## 4      Rape  21.232  9.366385
```

Discussion

- `Assault` has the highest variance and mean
- `UrbanPop` has different units with other variables

To run PCA in R

- Pretty simple:

```
pca_out = prcomp(Crime)
names(pca_out)
```

```
## [1] "sdev"     "rotation" "center"   "scale"    "x"
```

Output of PCA

- `center` and `scale` show means and standard deviations of the variables that were used for scaling prior to implementing PCA
- `rotation`: provides the principal component `loadings`, which is how each variables contribute to a principal component
- `x`: principal component scores, which is linear combination of all variables
- `sdev`: standard deviation of each principal component

rotation: principal component loadings

```
pca_out$rotation
```

```
##                PC1        PC2        PC3         PC4
## Murder   0.04170432 -0.04482166  0.07989066 -0.99492173
## Assault  0.99522128 -0.05876003 -0.06756974  0.03893830
## UrbanPop 0.04633575  0.97685748 -0.20054629 -0.05816914
## Rape     0.07515550  0.20071807  0.97408059  0.07232502
```

- `Assault` contributes mostly to `PC1`
- It just simply ignore the other variables' information
- It may raise concern that we lose so much money
  - Units and each variable variance is very important and can affect our PCA analysis
  - It is better to scale data before running PCA, let's do again

Scaled PCA

```
pca_out = prcomp(Crime, scale. = TRUE)
pca_out$rotation
```

```
##                   PC1        PC2        PC3         PC4
## Murder   -0.5358995  0.4181809 -0.3412327  0.64922780
## Assault  -0.5831836  0.1879856 -0.2681484 -0.74340748
## UrbanPop -0.2781909 -0.8728062 -0.3780158  0.13387773
## Rape     -0.5434321 -0.1673186  0.8177779  0.08902432
```

- Now PC1 contains information from each variable

How good is a PCA?

- How much variance of dataset can be explained by PC?
  - If PC can explain much of variance of dataset, it means that we do capture much of information in the data
- In R, we need to calculate the variance explained by each principal component and draw the `scree plot`

Variance explained by each component

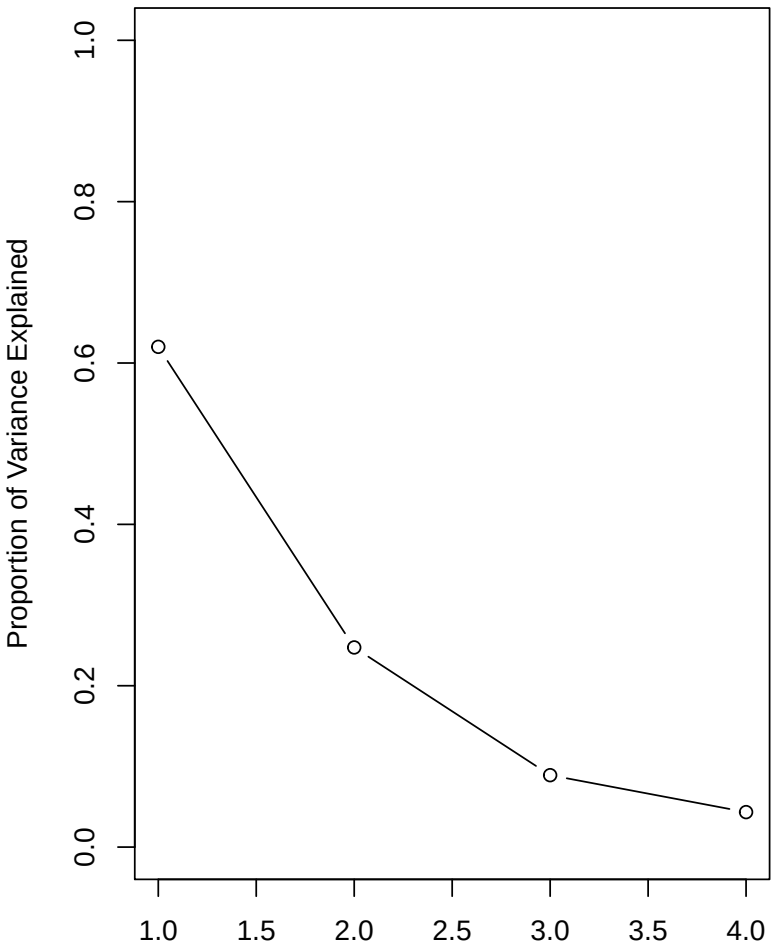
```
pca_var = pca_out$sdev^2
pve = pca_var/sum(pca_var)
pve
```

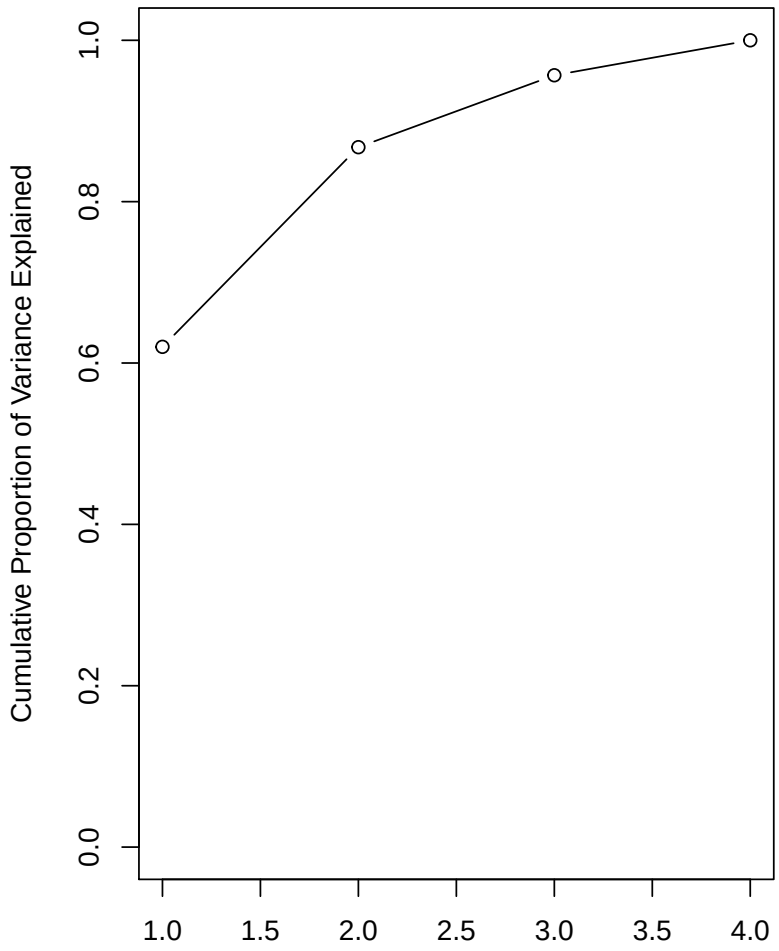
```
## [1] 0.62006039 0.24744129 0.08914080 0.04335752
```

- So PC1 explains 62% of data variance
- PC2 explains 24.7% of data variance
- So only two PC we can explain around 87% of data variance

Scree plot

```
par(mfrow = c(1, 2))
plot(pve, xlab = "Principal Component", ylab = "Proportion
plot(cumsum(pve), xlab = "Principal Component", ylab = "Cu
```





Practice time

- In class, we will practice more
- We will do PCA for our university ranking data to see if we can combine variables to explain the ranking of a university