# A tutorial on principal component analysis

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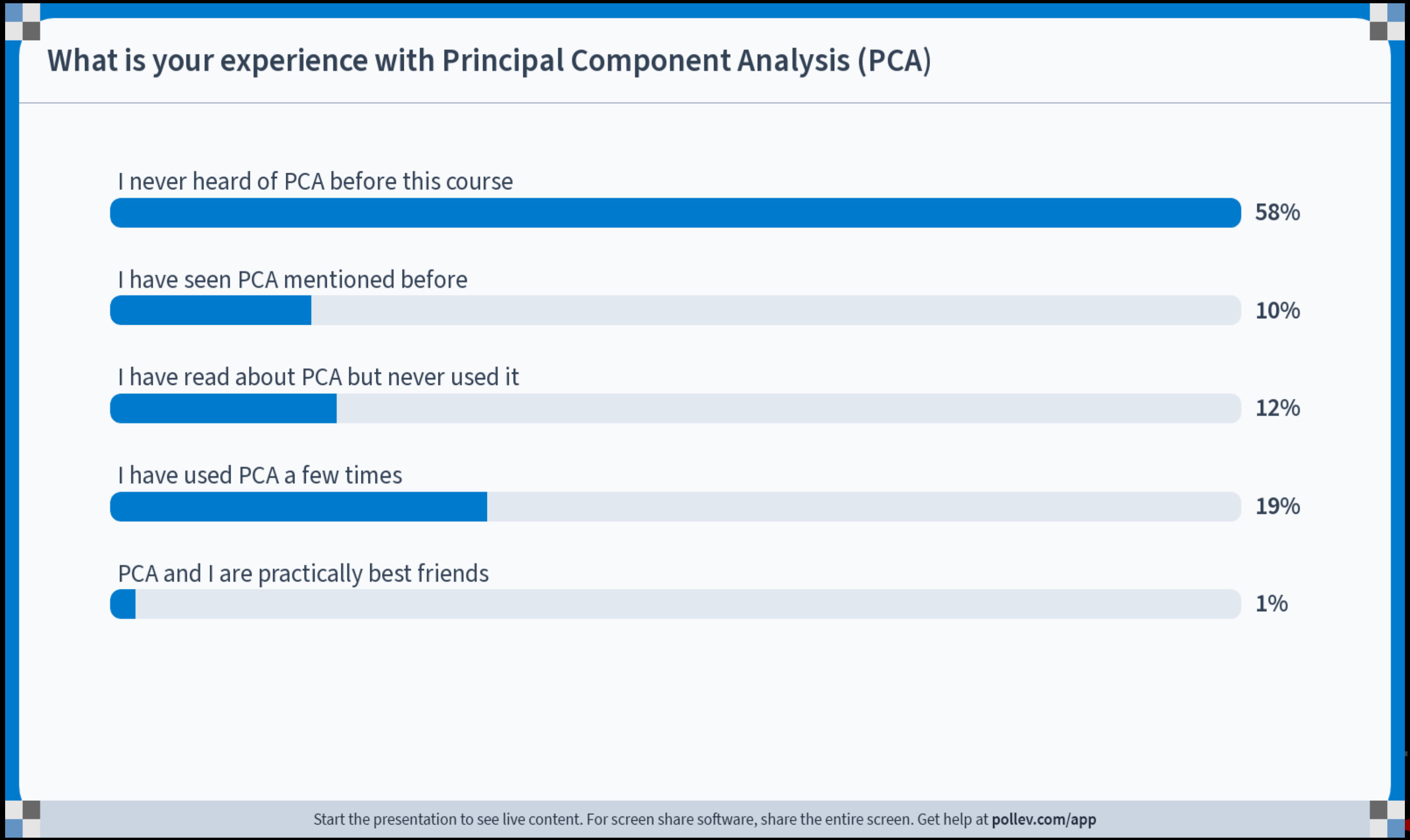
DTU Compute

Based on

Jonathan Shlens: A tutorial on Principal Component Analysis (version 3.02 – April 7, 2014)

http://compute.dtu.dk/courses/02502


What is your experience with Principal Component Analysis (PCA)
I never heard of PCA before this course
58%
I have seen PCA mentioned before
10%
I have read about PCA but never used it
12%
I have used PCA a few times
19%
PCA and I are practically best friends
1%
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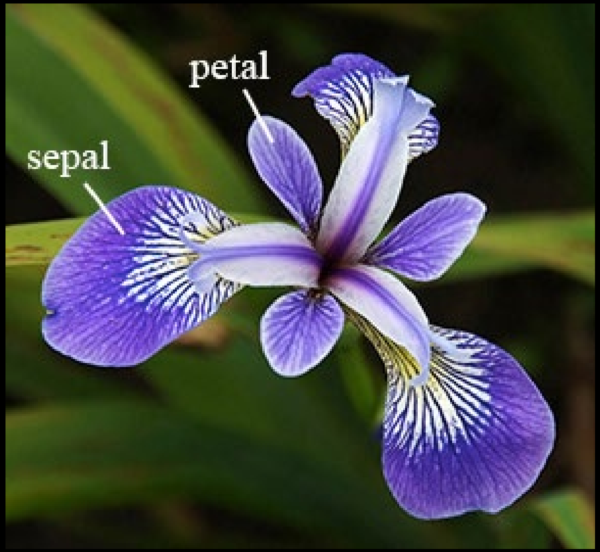
# Principal Component Analysis (PCA) learning objectives

- Describe the concept of principal component analysis
- Explain why principal component analysis can be beneficial when there is high data redundancy
- Arrange a set of multivariate measurements into a matrix that is suitable for PCA analysis
- Compute the covariance of two sets of measurements
- Compute the covariance matrix from a set of multivariate measurements
- Compute the principal components of a data set using Eigenvector decomposition
- Describe how much of the total variation in the data set that is explained by each principal component

# Iris data

The **Iris flower data**
set or Fisher's Iris data set is a data set introduced by Ronald Fisher in his 1936 paper *The use of multiple measurements in taxonomic problems*

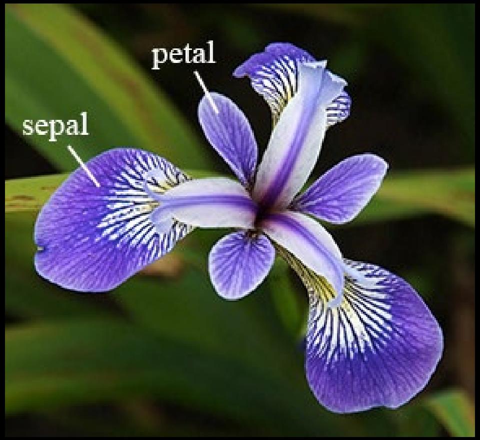
# Iris data




- 3 Iris types
  - 50 flowers of each type
- For each flower
  - Sepal length
  - Sepal width
  - Petal length
  - Petal width
- We use one type as example
  - 50 measured flowers

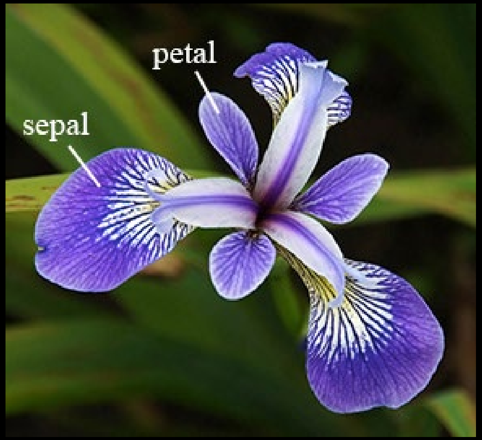
# Iris Data Matrix

- One column is one flower
- One row is all measurements of one type




$$\mathbf{X} = \begin{array}{c} \begin{array}{ccc} 1 & \qquad\qquad\qquad & 50 \end{array} \\ \begin{bmatrix} \text{Sepal length}_1 & \cdots & \text{Sepal length}_{50} \\ \text{Sepal width}_1 & \cdots & \text{Sepal width}_{50} \\ \text{Petal length}_1 & \cdots & \text{Petal length}_{50} \\ \text{Petal width}_1 & \cdots & \text{Petal width}_{50} \end{bmatrix} \end{array}$$

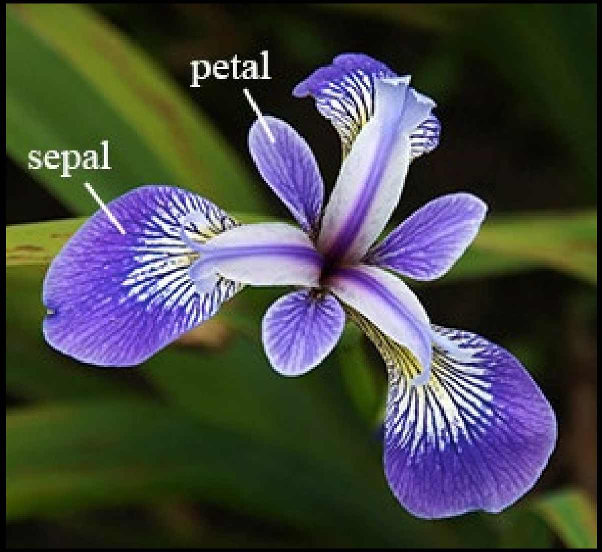
# What can we use these data for?

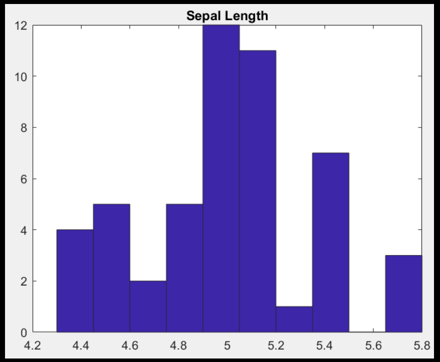


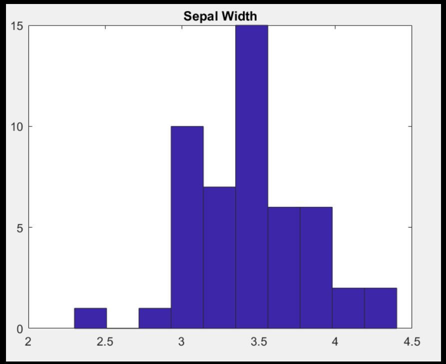

- The measurements can be used to:
  - Recognize a species of flowers
  - Classify flowers into groups
  - Describe the characteristics of the flower
  - Quantify growth rates
  - …
- Do we need all the measurements?
  - Can we *boil down* or *combine* some measurements?
- Are some measurements *redundant?*

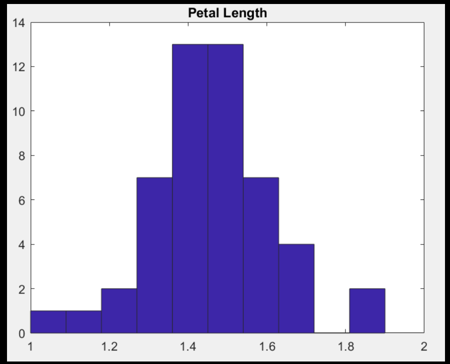
# Variance

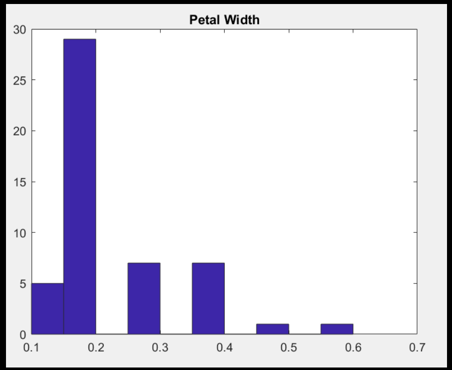
$$\sigma^2_{SL} = 0.1242$$
$$\sigma^2_{SW} = 0.1437$$
$$\sigma^2_{PL} = 0.0302$$
$$\sigma^2_{PW} = 0.0111$$



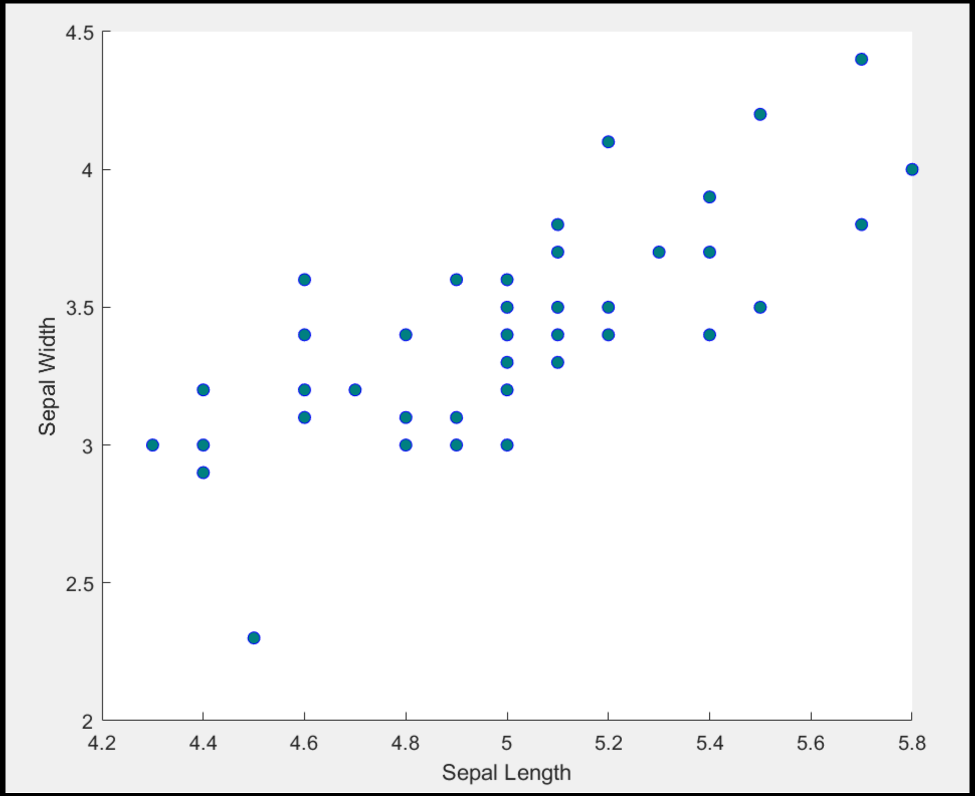



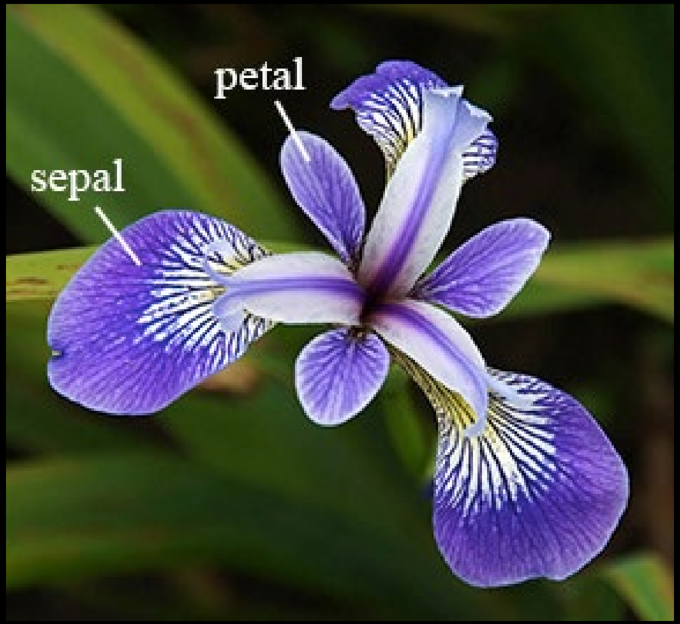



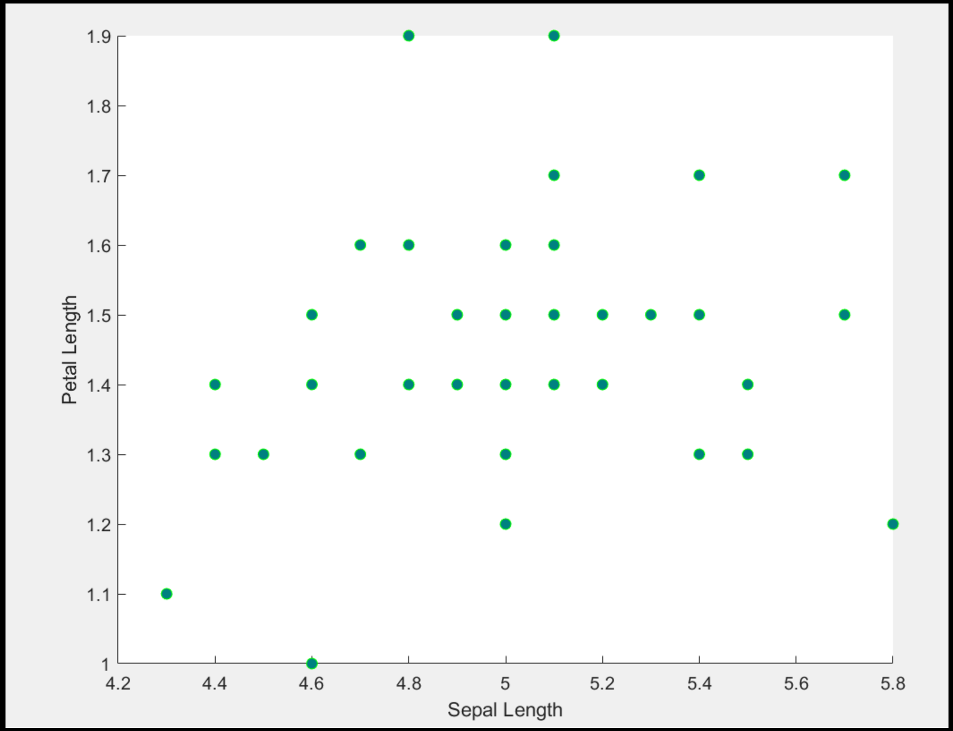
# High Redundancy



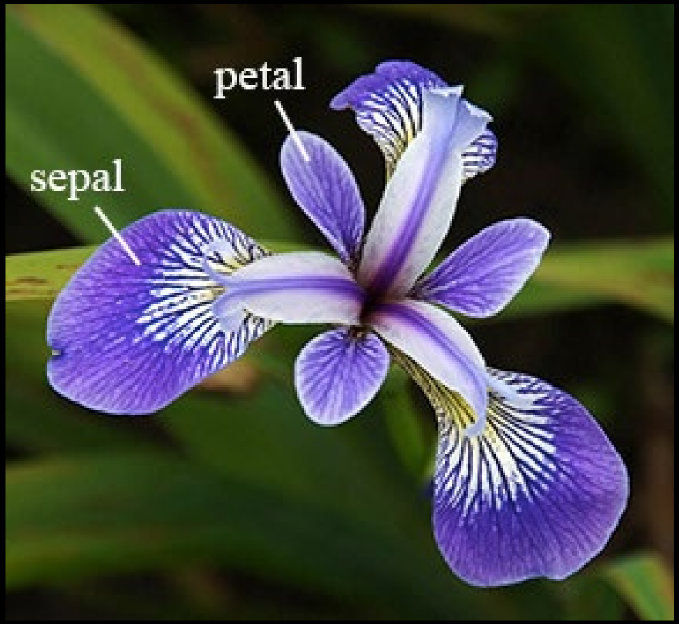

Observation: We can explain quite a lot of the sepal width if we know the sepal lengths



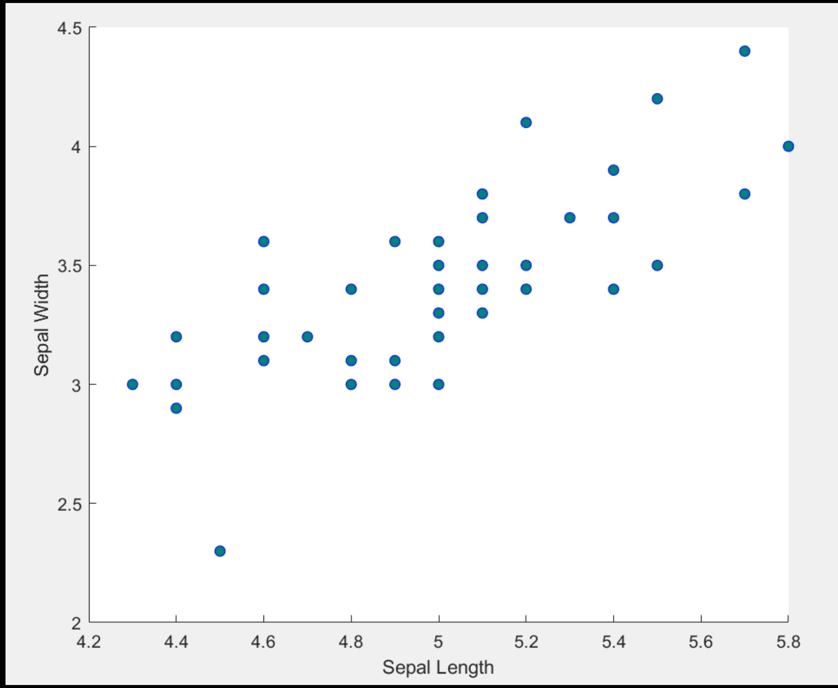
# Low Redundancy

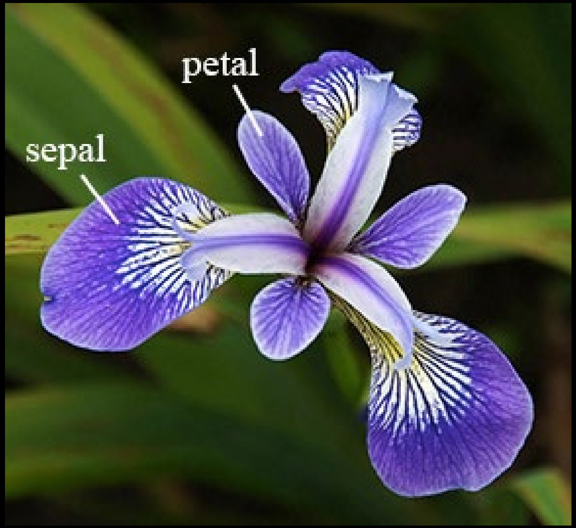


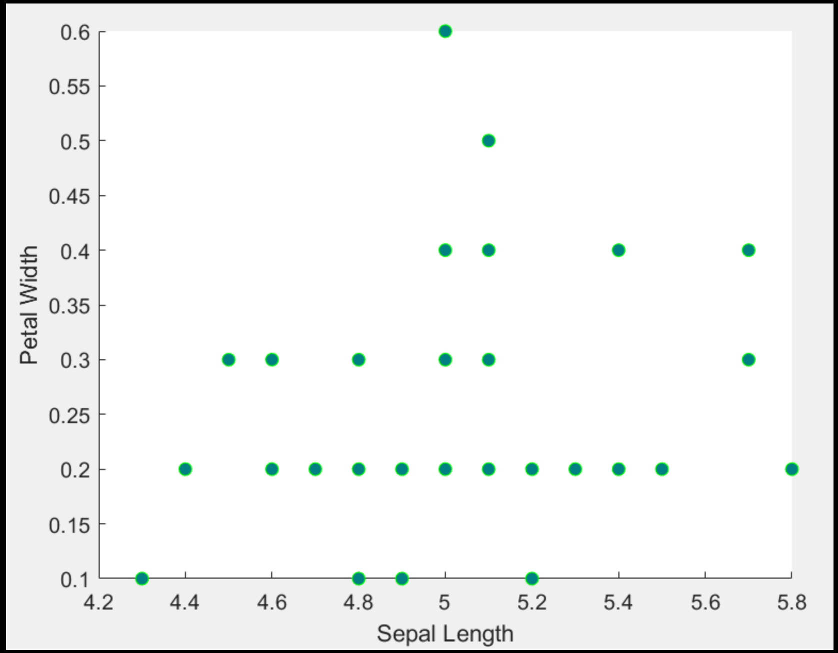

Observation: We can NOT explain the petal length if we know the sepal lengths



# Covariance

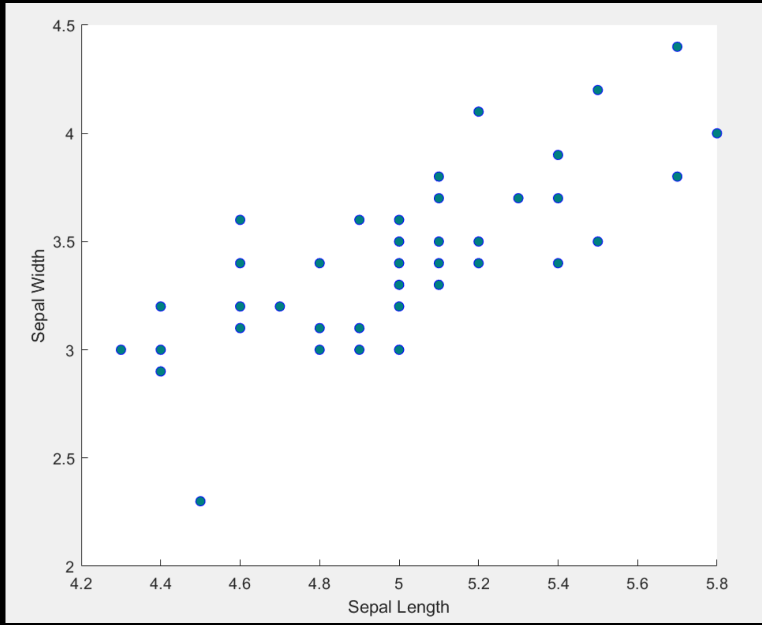


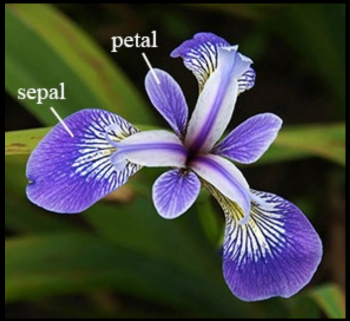




Covariance measures the *relationship* between measurements

# High Covariance




## Sepal length and sepal width

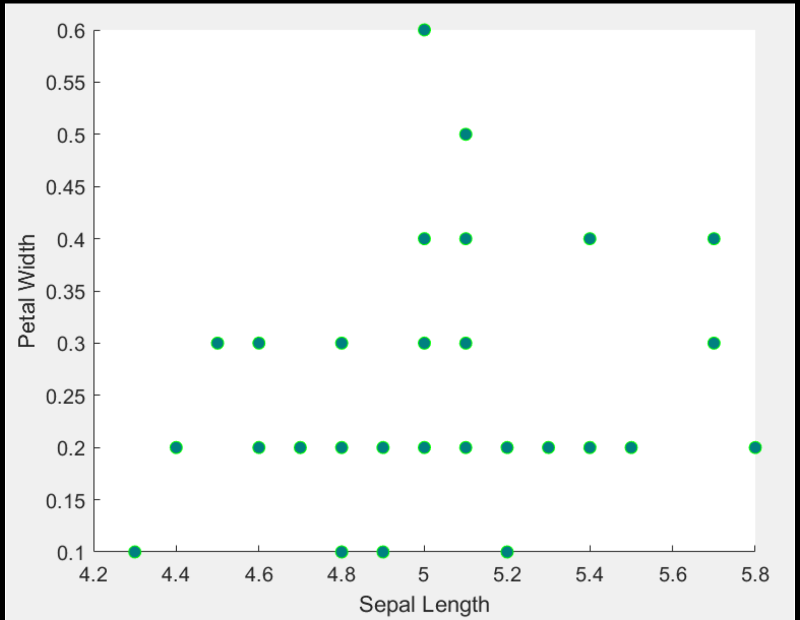
$$a_i = \mathrm{SL} = \{5.1, 4.9 \ldots, 5\}$$

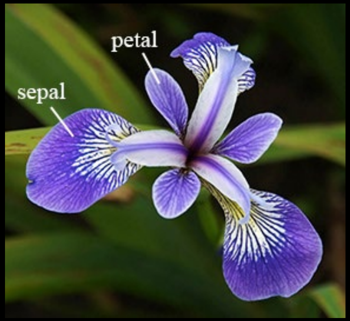
$$\mathrm{b_i} = \mathrm{SW} = \{3.5, 3, \ldots, 3.3\}$$

$$\sigma^2_{\mathrm{SL,SW}} = \frac{1}{n} \sum_i a_i b_i = 17.2578$$

Note that in practice n-1 is used instead of n

# Low covariance

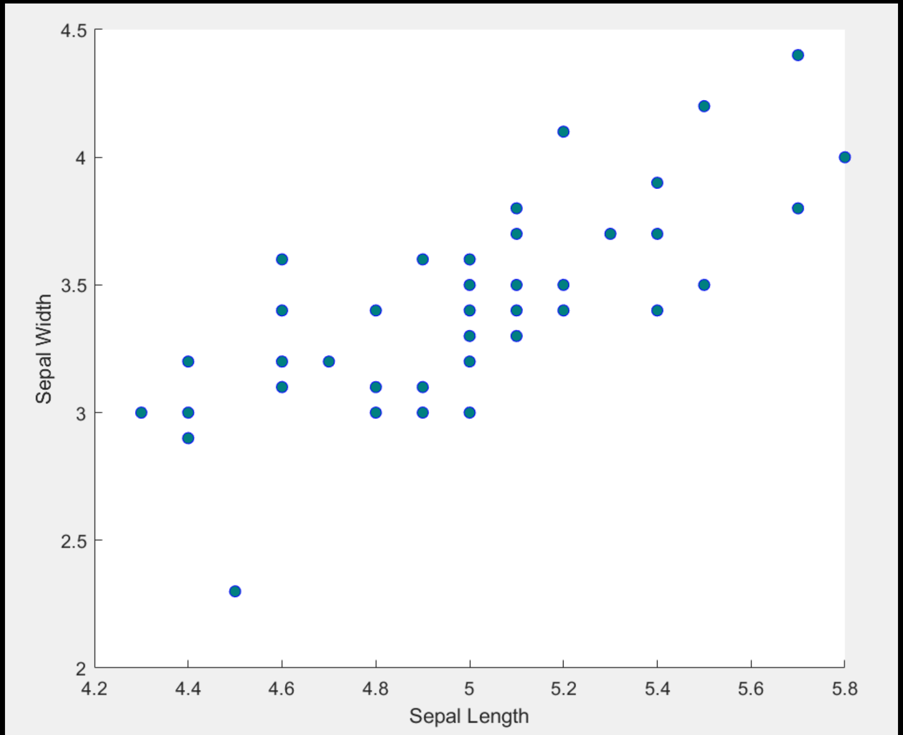



Sepal length and petal width

$$\sigma^2_{\mathrm{SL,PW}} = \frac{1}{n}\sum_i a_i b_i = 1.2416$$

# Vector notation for covariance




Sepal length and sepal width

$$\mathbf{a} = \mathrm{SL} = [5.1, 4.9 \ldots, 5]$$

$$\mathbf{b} = \mathrm{SW} = [3.5, 3, \ldots, 3.3]$$

$$\sigma^2_{\mathrm{SL,SW}} = \frac{1}{n}\mathbf{a}\mathbf{b}^T$$

# Matrix notation for covariance

*m x n* matrix (m=4 and n=50)

$$\mathbf{X} = \begin{bmatrix} \text{Sepal length}_1 & \cdots & \text{Sepal length}_{50} \\ \text{Sepal width}_1 & \cdots & \text{Sepal width}_{50} \\ \text{Petal length}_1 & \cdots & \text{Petal length}_{50} \\ \text{Petal width}_1 & \cdots & \text{Petal width}_{50} \end{bmatrix}$$

$$\mathbf{C_X} \equiv \frac{1}{n}\mathbf{X}\mathbf{X}^T$$

*m x m* square matrix (m=4)

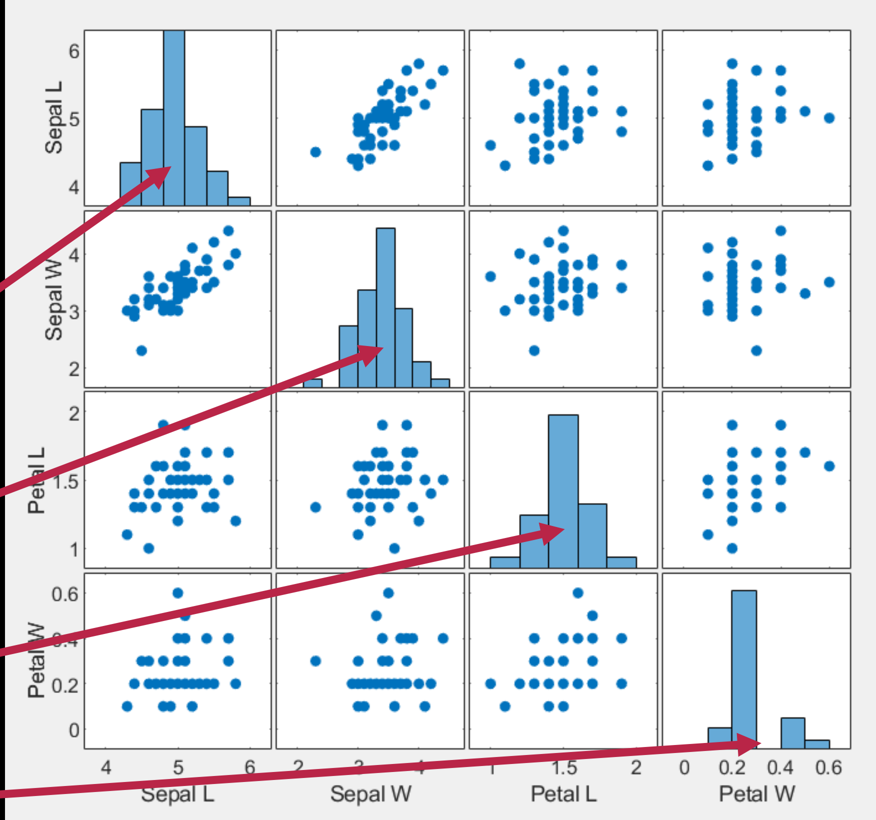
Note that in practice n-1 is used instead of n

# Covariance matrix autopsy

$$\mathbf{C_X} \equiv \frac{1}{n}\mathbf{X}\mathbf{X}^T$$

The diagonal elements are the variances

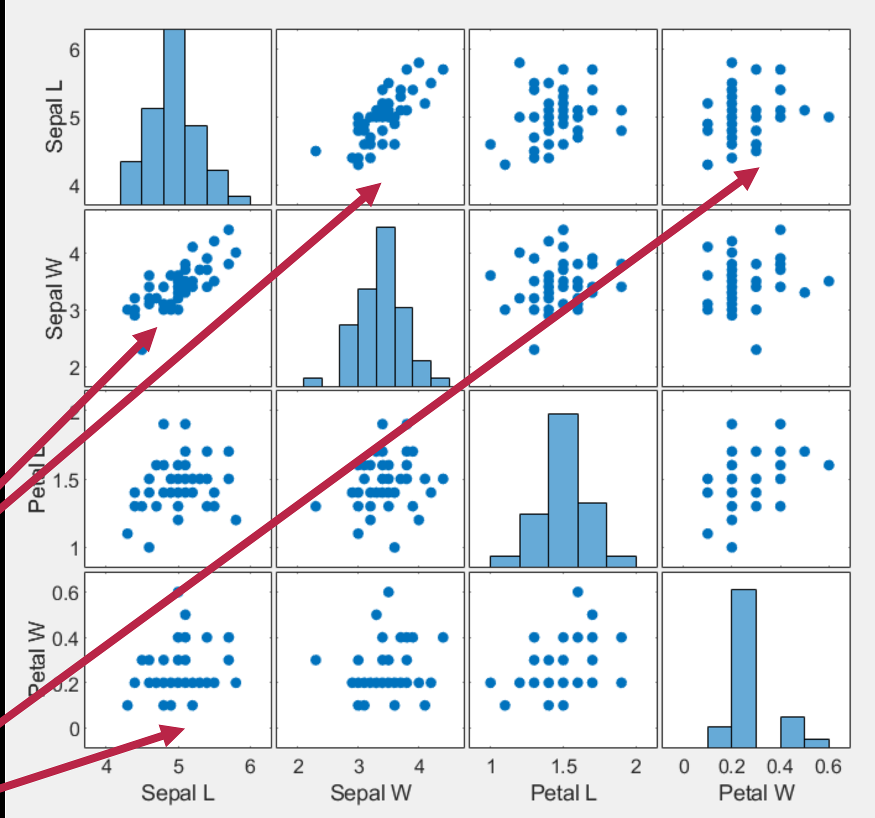
$$\begin{aligned}
\sigma^2_{SL} &= 0.1242 \\
\sigma^2_{SW} &= 0.1437 \\
\sigma^2_{PL} &= 0.0302 \\
\sigma^2_{PW} &= 0.0111
\end{aligned}$$



# Covariance matrix autopsy II

$$\mathbf{C_X} = \frac{1}{n}\mathbf{X}\mathbf{X}^T$$

The off-diagonal elements are the covariance




$$\sigma^2_{\mathrm{SL,SW}} = \frac{1}{n}\sum_i a_i b_i = 17.2578$$

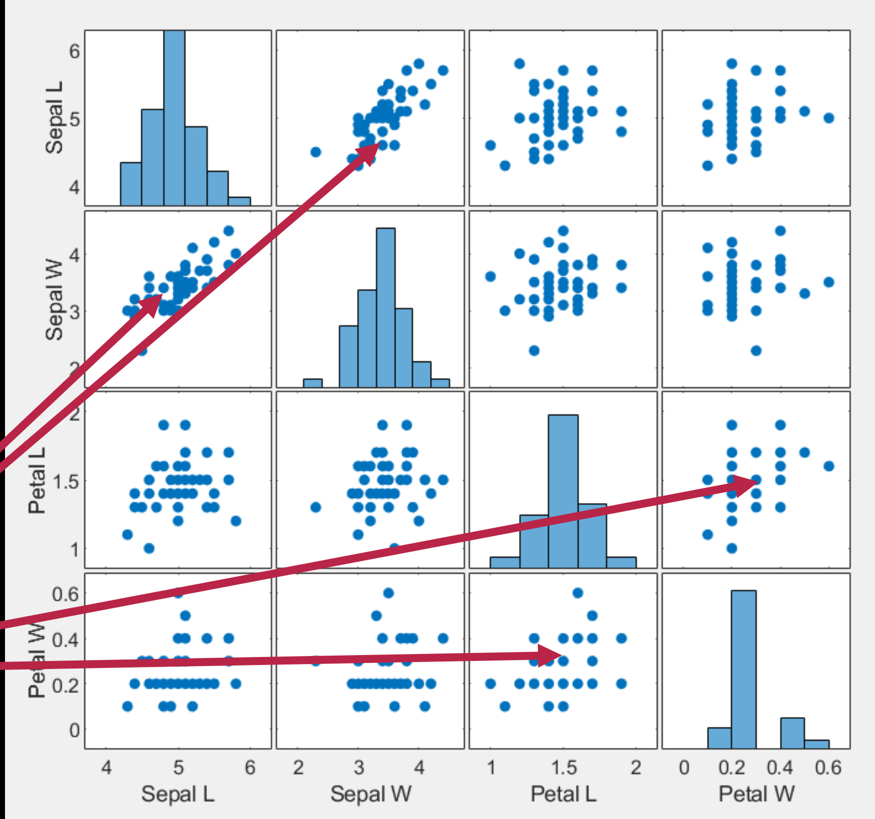
$$\sigma^2_{\mathrm{SL,PW}} = \frac{1}{n}\sum_i a_i b_i = 1.2416$$

Symmetric!

# Covariance matrix autopsy III

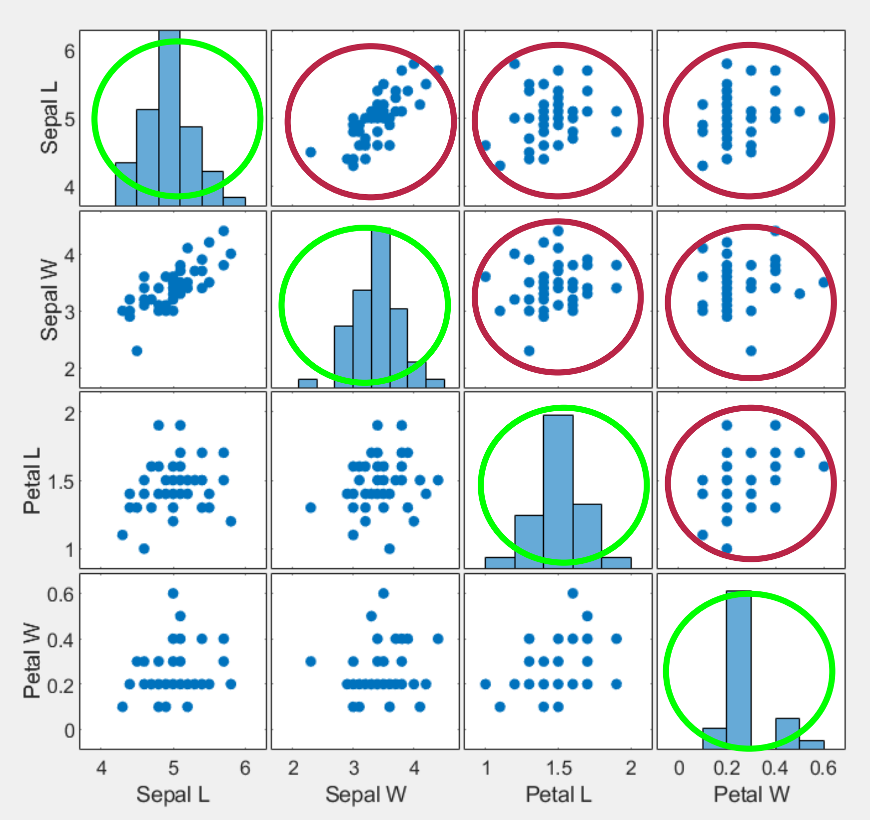
$$\mathbf{C_X} \equiv \frac{1}{n}\mathbf{X}\mathbf{X}^T$$

High redundancy




Symmetric!

# Goals

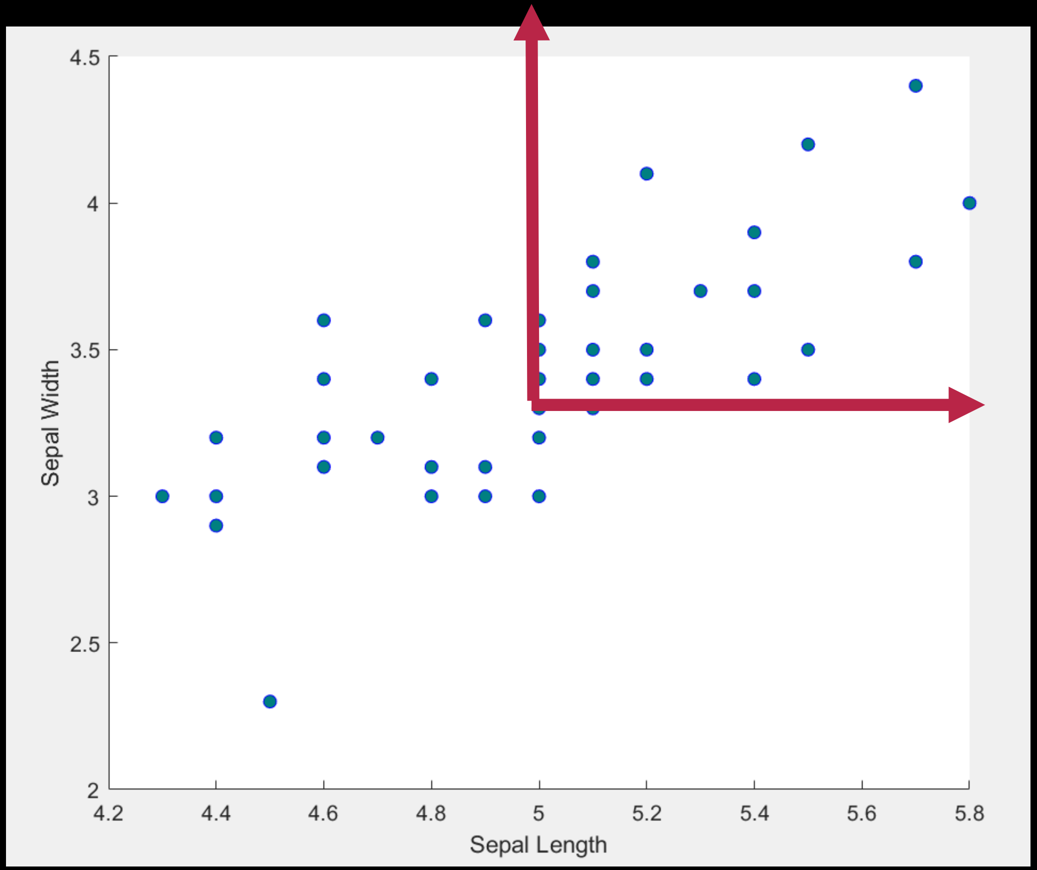



- Minimize redundancy
  - Covariance should be small
- Maximize signal
  - Variance should be large

Signal to noise ratio:

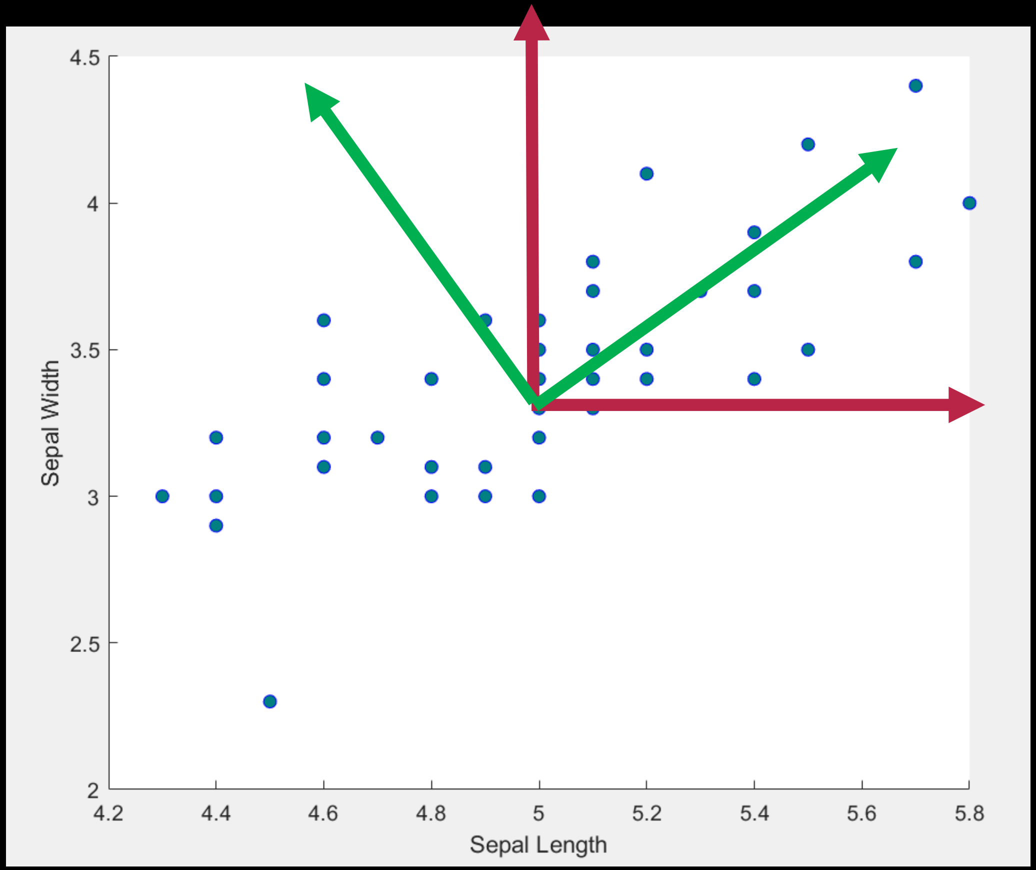
$$\mathrm{SNR} = \frac{\sigma^2_{\mathrm{signal}}}{\sigma^2_{\mathrm{noise}}}$$

# Changing basis

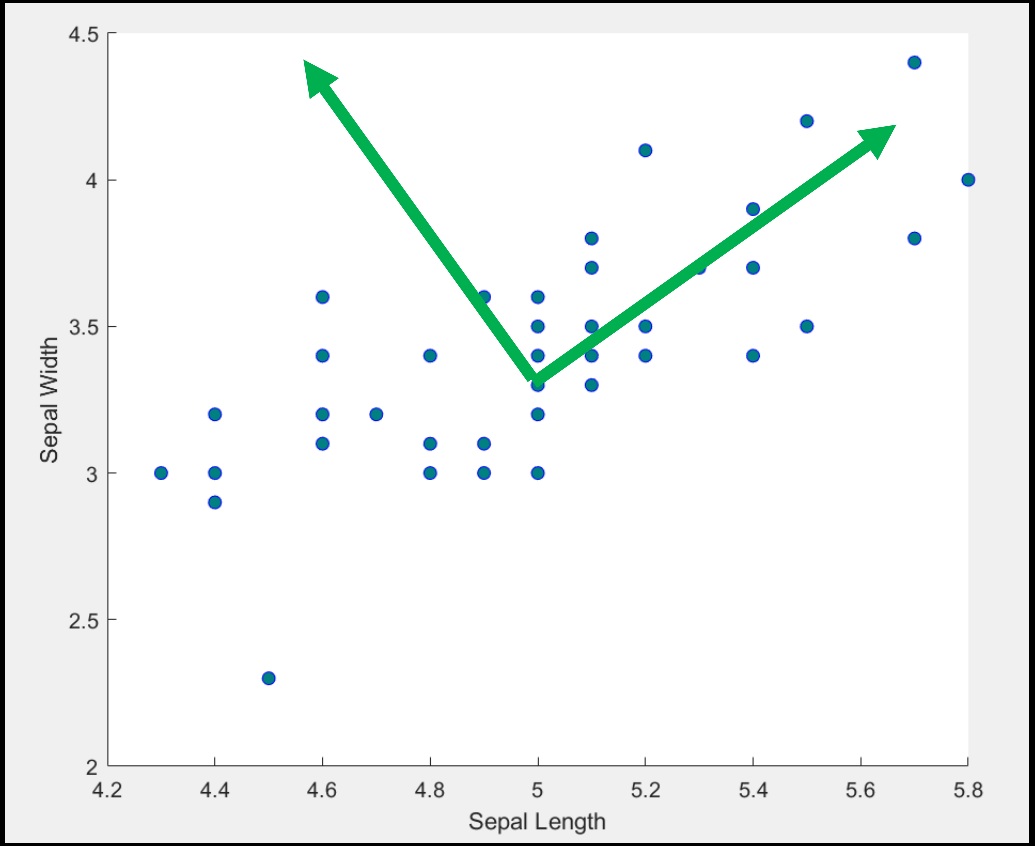



- We start by subtracting the mean
  - Centering data
- Red lines are the default basis

# Changing basis

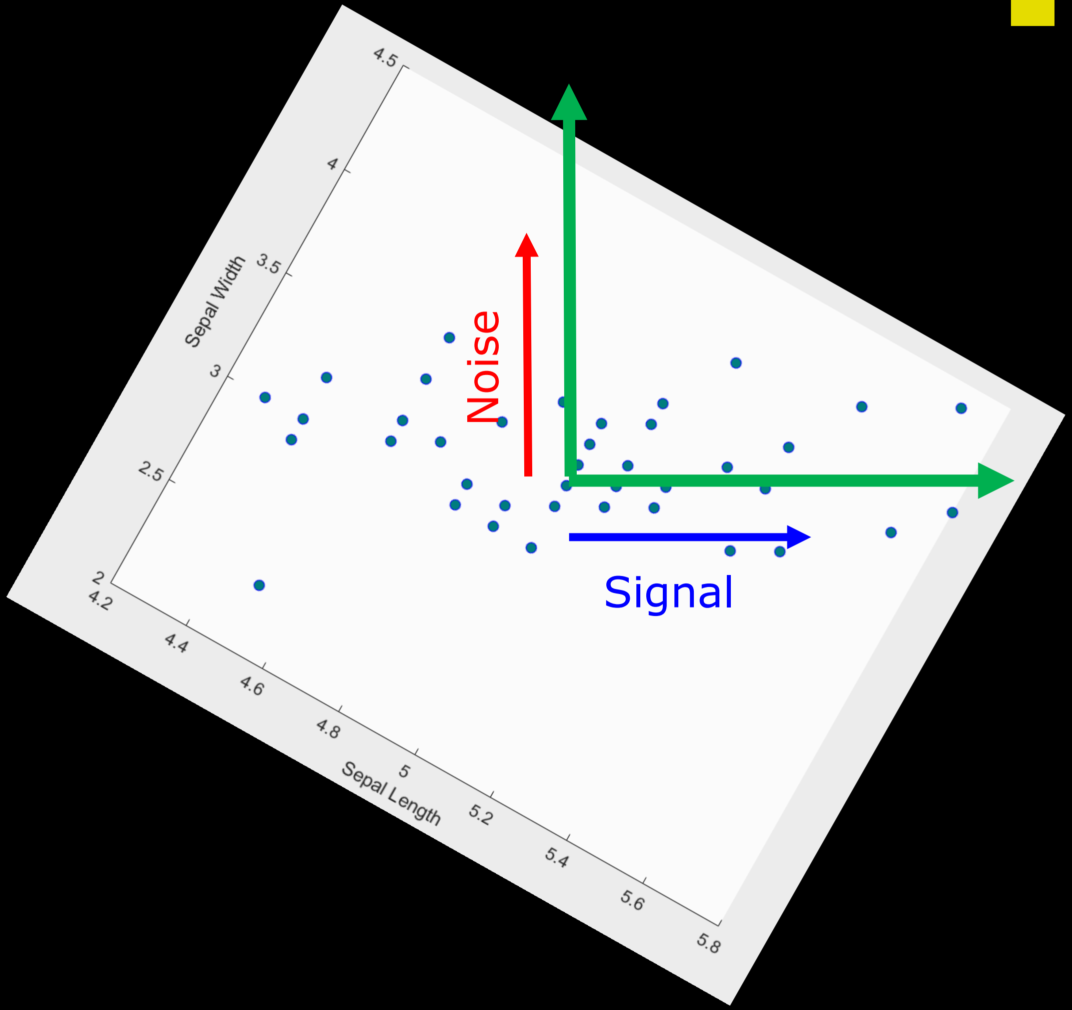


# Changing basis



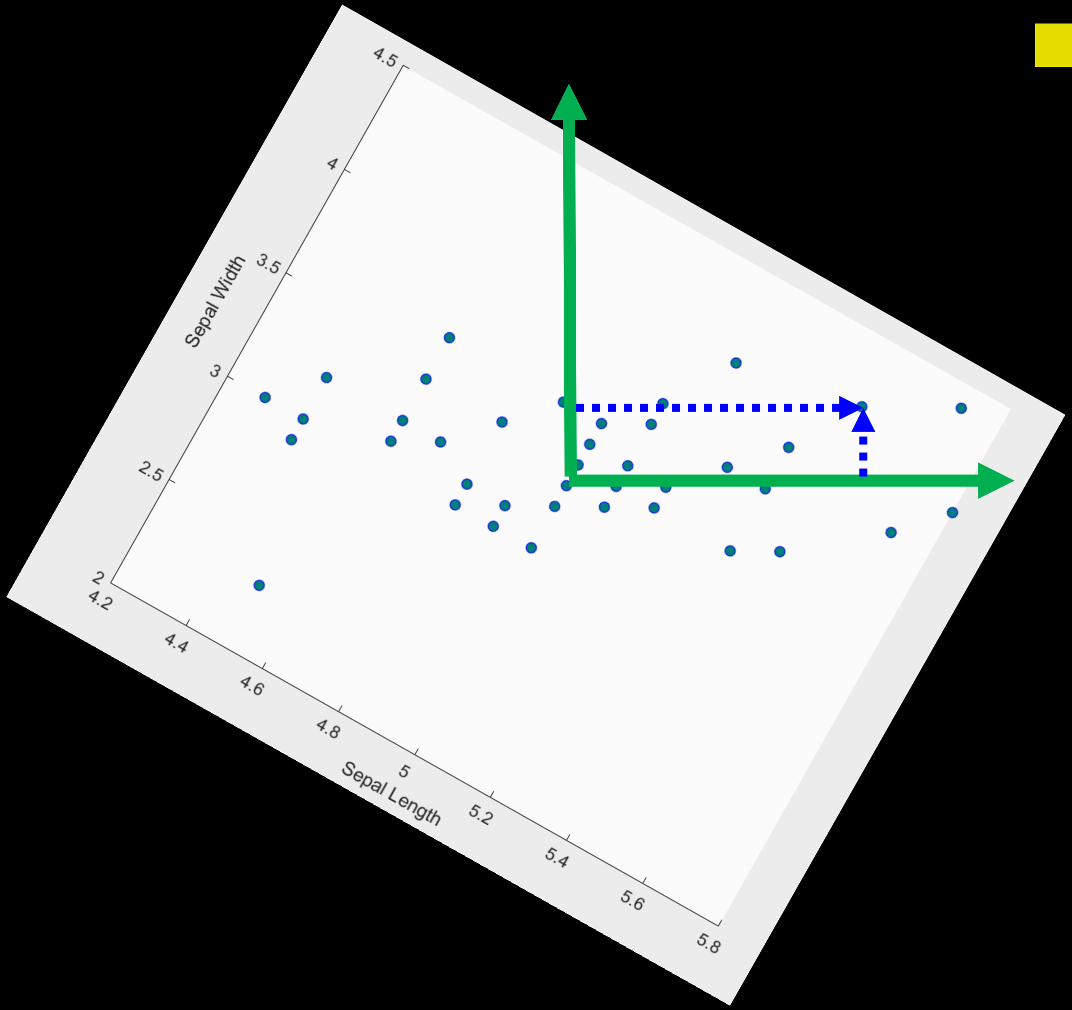

- A new basis that follows the *covariance* in the data

# Changing basis



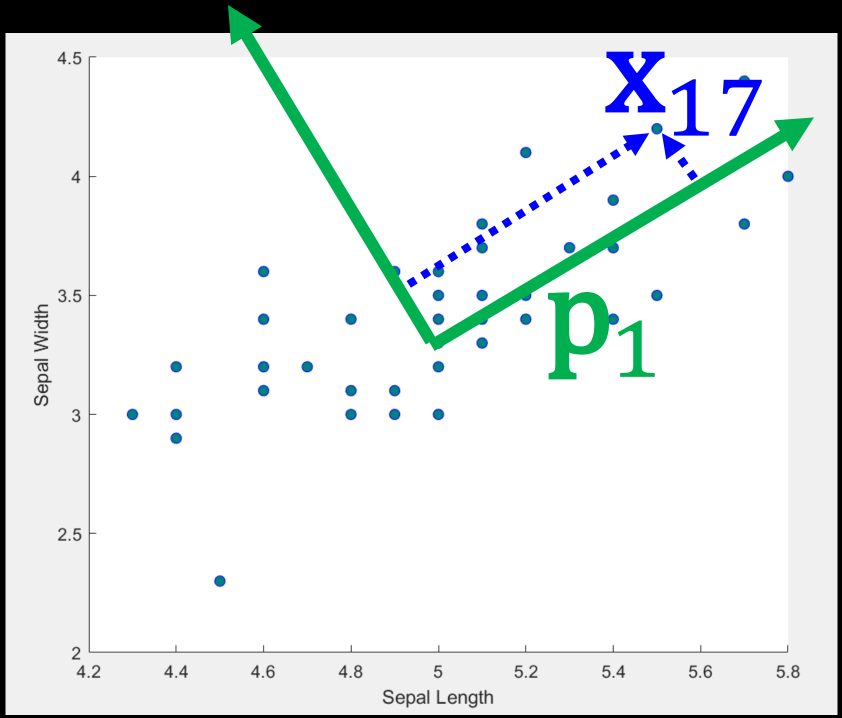

- Lets try to rotate the data – for visualisation

# Changing basis




- Finding the measurement values in the new basis

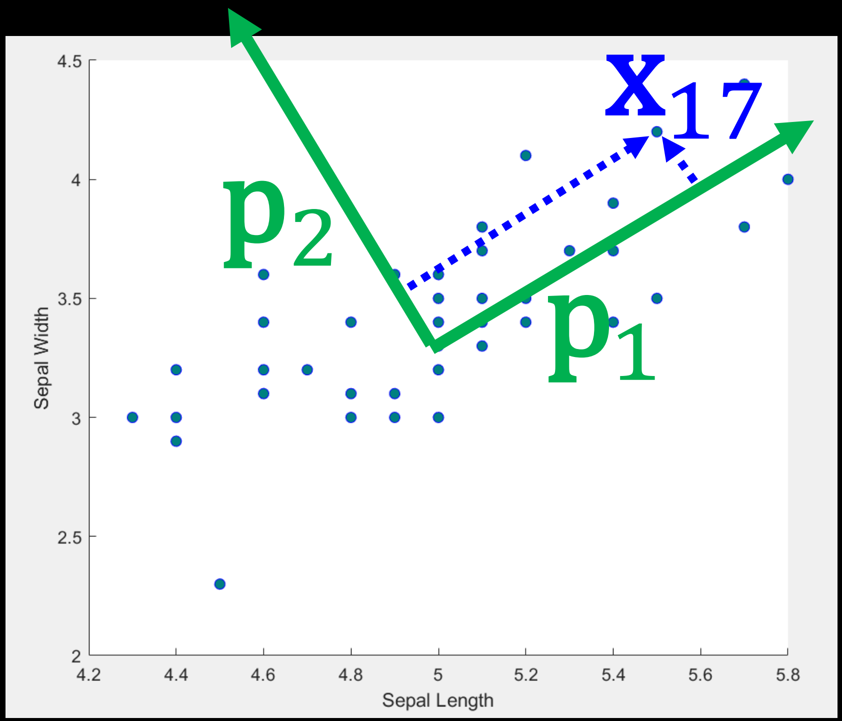
# Changing basis




- The dot product projects a point down to a new axis

$$\mathbf{x}_{17,\text{new}} = x_{17} \cdot p_1$$

# Changing basis



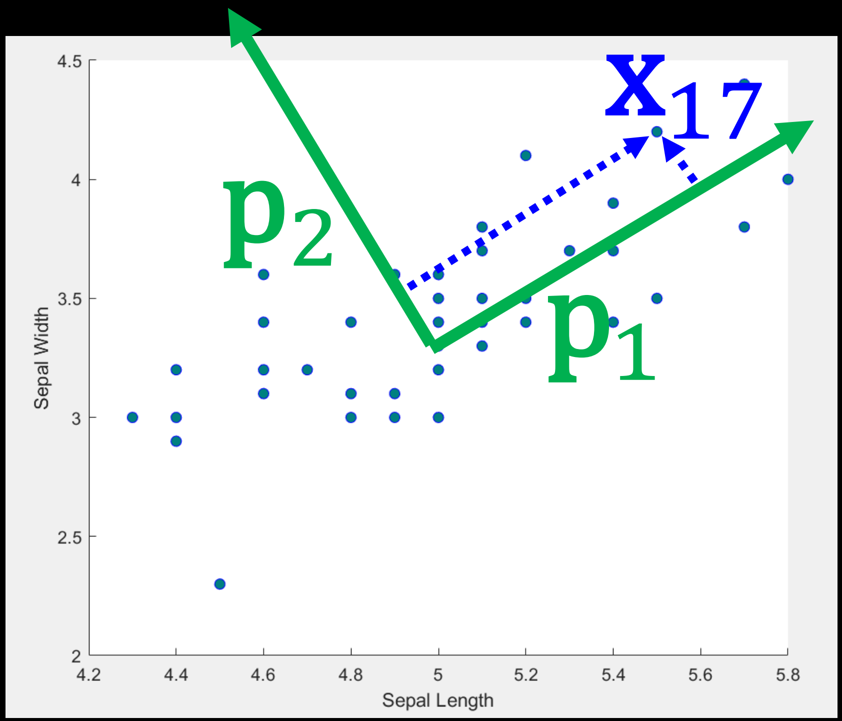

- The dot product projects a point down to a new axis

$$\mathbf{P}\mathbf{X} = \mathbf{Y}$$

- $\mathbf{p}_1$ and $\mathbf{p}_2$ are the rows of $\mathbf{P}$

$$\mathbf{X} = \begin{bmatrix} \text{Sepal length}_1 & \cdots & \text{Sepal length}_{50} \\ \text{Sepal width}_1 & \cdots & \text{Sepal width}_{50} \\ \text{Petal length}_1 & \cdots & \text{Petal length}_{50} \\ \text{Petal width}_1 & \cdots & \text{Petal width}_{50} \end{bmatrix}$$

# Changing basis

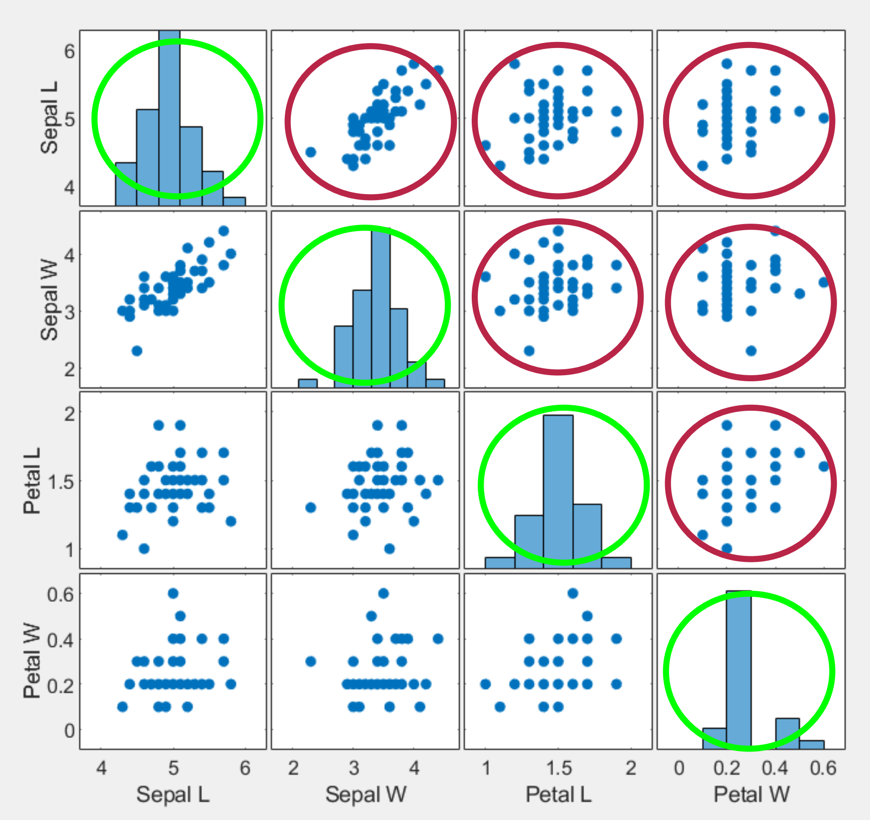



- The dot product projects a point down to a new axis

$$\mathbf{PX} = \mathbf{Y}$$

- Here **Y** contains the new coordinates/measurements per sample

# Goals



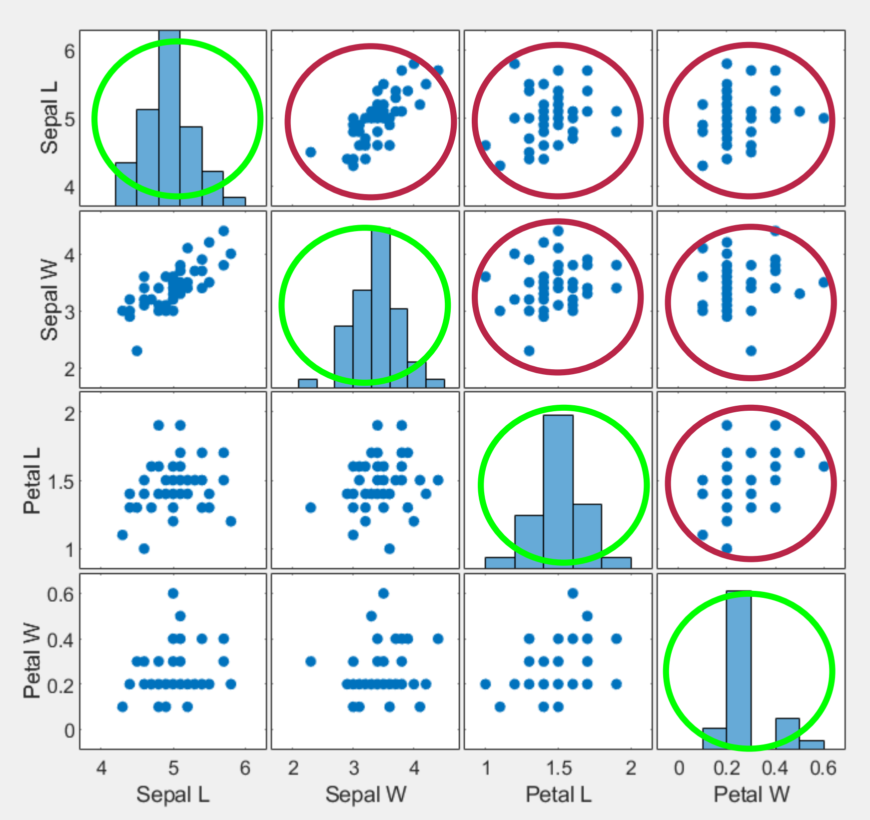

- Minimize redundancy
  - Covariance should be small
- Maximize signal
  - Variance should be large
- Transform our data
  - Rotating and scaling the basis

$$\mathbf{Y} = \mathbf{PX}$$

- So it will have

$$\mathbf{C_Y} \equiv \frac{1}{n}\mathbf{YY}^T$$

# Goals




- The covariance matrix

$$\mathbf{C_Y} \equiv \frac{1}{n}\mathbf{Y}\mathbf{Y}^T$$

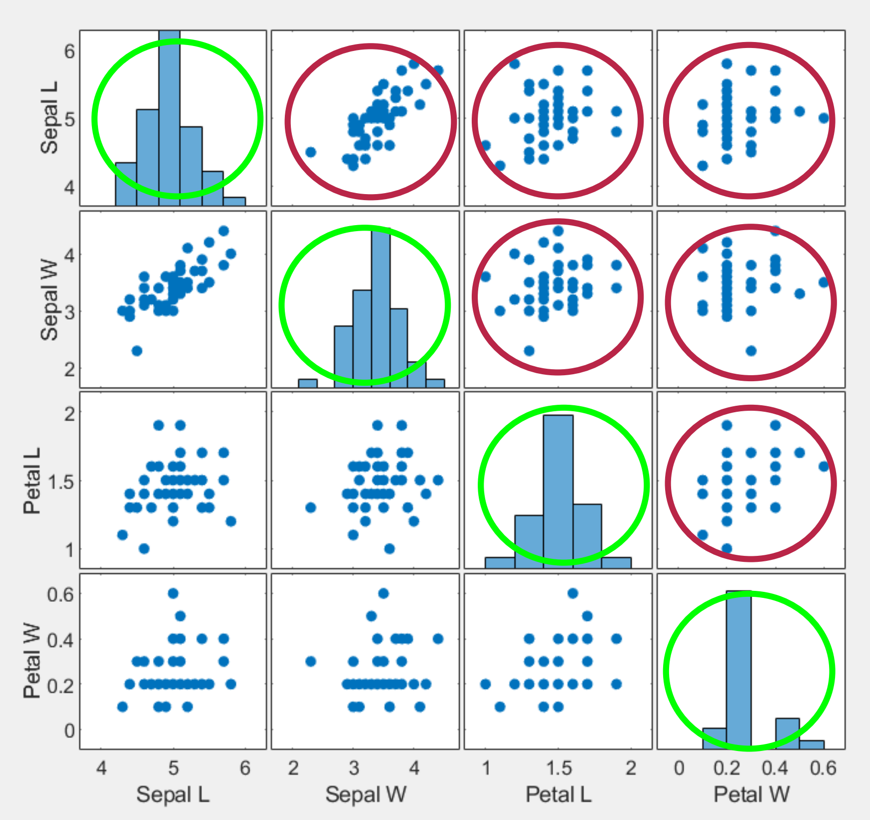
- Should be *as diagonal as possible*

- We do this by

$$\mathbf{Y} = \mathbf{P}\mathbf{X}$$

  – Where **P** are the principal components

# Computing the principal components

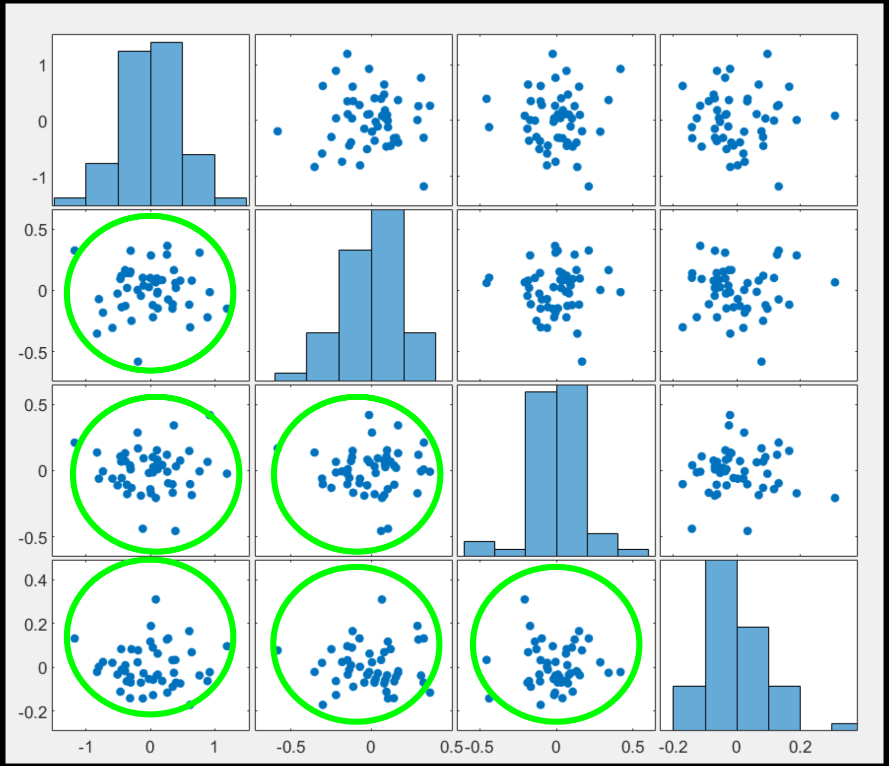



- The Principal Components of $\mathbf{X}$ are the eigenvectors of

$$\mathbf{C_X} = \frac{1}{n}\mathbf{X}\mathbf{X}^T$$

- The i'th diagonal value of $\mathbf{C_Y}$ is the variance along principal component number i

# New covariance matrix for Iris data




Covariance: 0

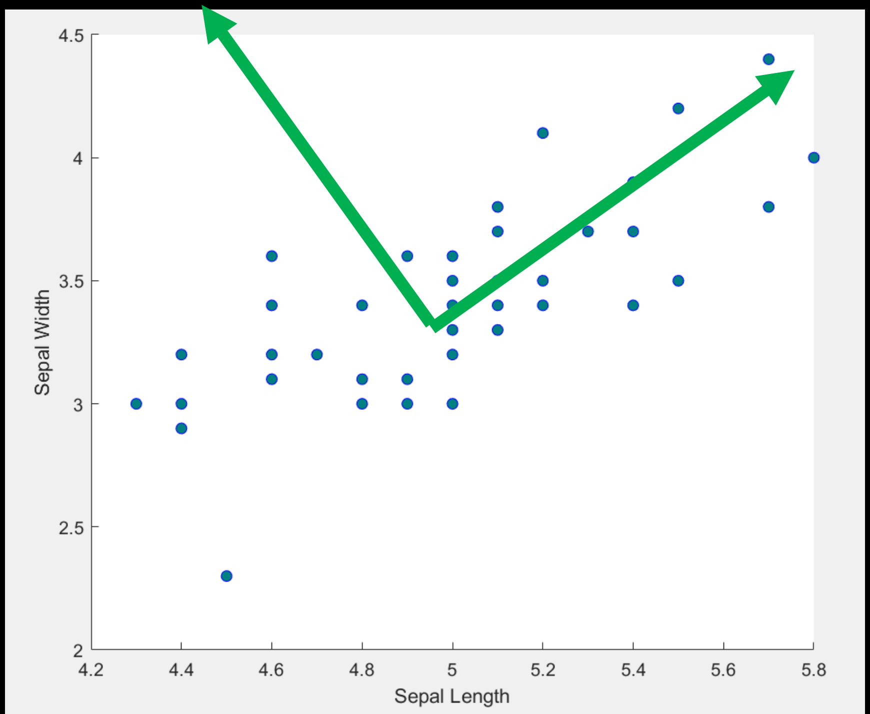
- The principal component are found and

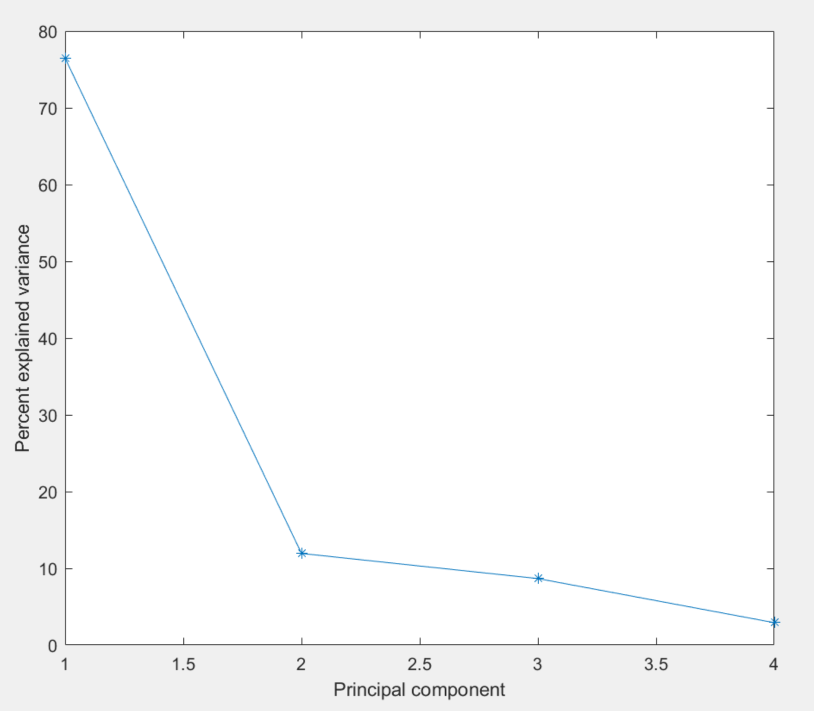
$$\mathbf{Y} = \mathbf{PX}$$

- With the covariance matrix

$$\mathbf{C_Y} \equiv \frac{1}{n}\mathbf{YY}^T$$

# Explained variance




One component explains 75% of the total variation – so for each flower we can have one number that explains 75% percent of the 4 measurements!

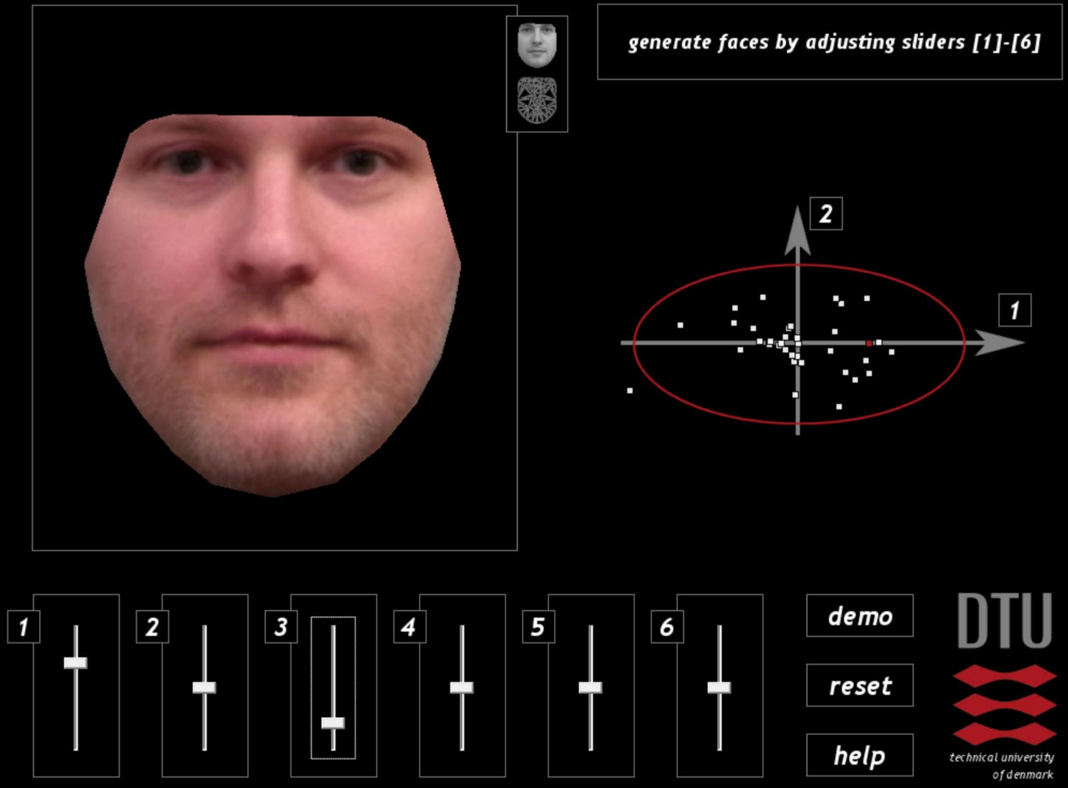
# What can we use it for?

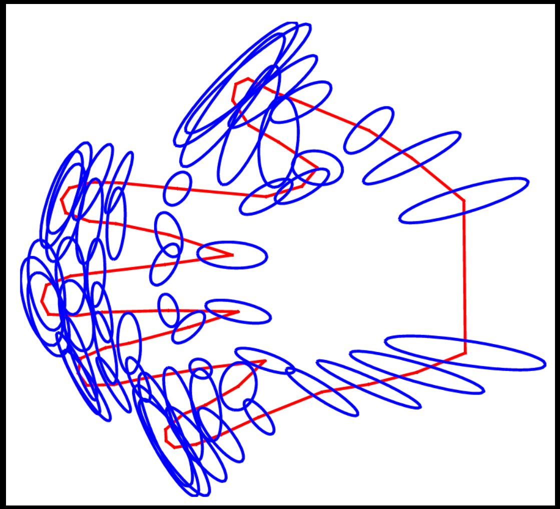
- Classification

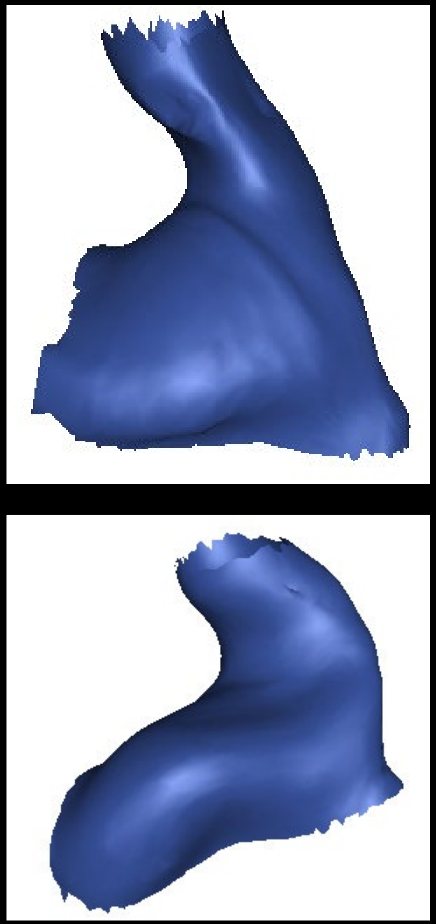
Based on one value instead of 4

# What can we use it for?

- Many more examples in the course





# Final note – practical estimation of covariance matrix

$$\mathbf{C_x} \equiv \frac{1}{n}\mathbf{X}\mathbf{X}^T$$

In practice n-1 is used instead of n for exercises and in the exam.

$$\mathbf{C_x} \equiv \frac{1}{n-1}\mathbf{X}\mathbf{X}^T$$