Discount on registration if Swiss Robotics Association Member

https://swissroboticsday.ch/

Swiss Robotics Association

swiss-robotics.org

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SWISS ROBOTICS ASSOCIATION

Home About Us Events Job fair Robotics Ecosystem Map News Contact Account **Become a member ↗**

As an individual member, you can use the association to:

Job Board
Search and apply to robotics jobs in Switzerland, tailored to your skills and interests.

Swiss Robotics Day Discounts
Enjoy reduced registration fees for one edition of SRD and connect with Switzerland's robotics community.

Resume Builder
Create and manage your robotics CV directly online for employers to find you.

Workshops & Events
Get invitations to SRA workshops and community e... ne...

https://swiss-robotics.org/

List of Machine Learning Courses at EPFL

https://www.epfl.ch/research/domains/ml/courses/

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Bachelor

- CIVIL-226 – Introduction to machine learning for engineers
- CS-233(a) – Introduction to machine learning (BA3)
- CS-233(b) – Introduction to machine learning (BA4)
- CS-330 – Artificial intelligenceCS-330 – Artificial Intelligence
- BIO-322 – Introduction to machine learning for bioengineers
- MATH-352 – Causal thinking
- ME-390 – Foundations of Artificial Intelligence

Master

- CIVIL-459 – Deep learning for autonomous vehicles
- CS-401 – Applied Data Analysis
- CS-430 – Intelligent Agents
- CS-433 – Machine Learning
- CS-439 – Optimization for Machine Learning

https://www.epfl.ch/research/domains/ml/courses/

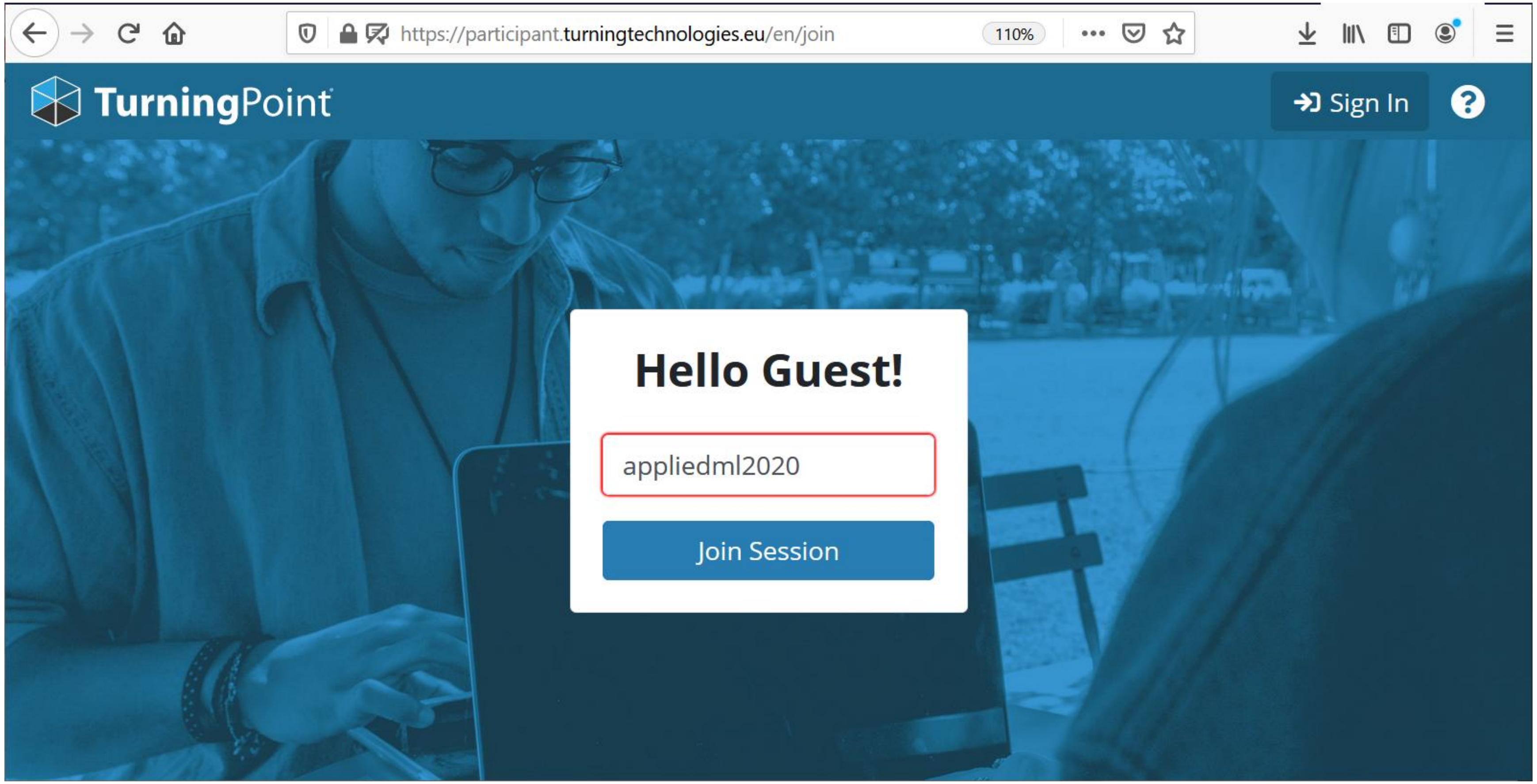
Principal Component Analysis (PCA)

Interactive exercise – lecture session

Launch polling system

https://participant.turningtechnologies.eu/en/join

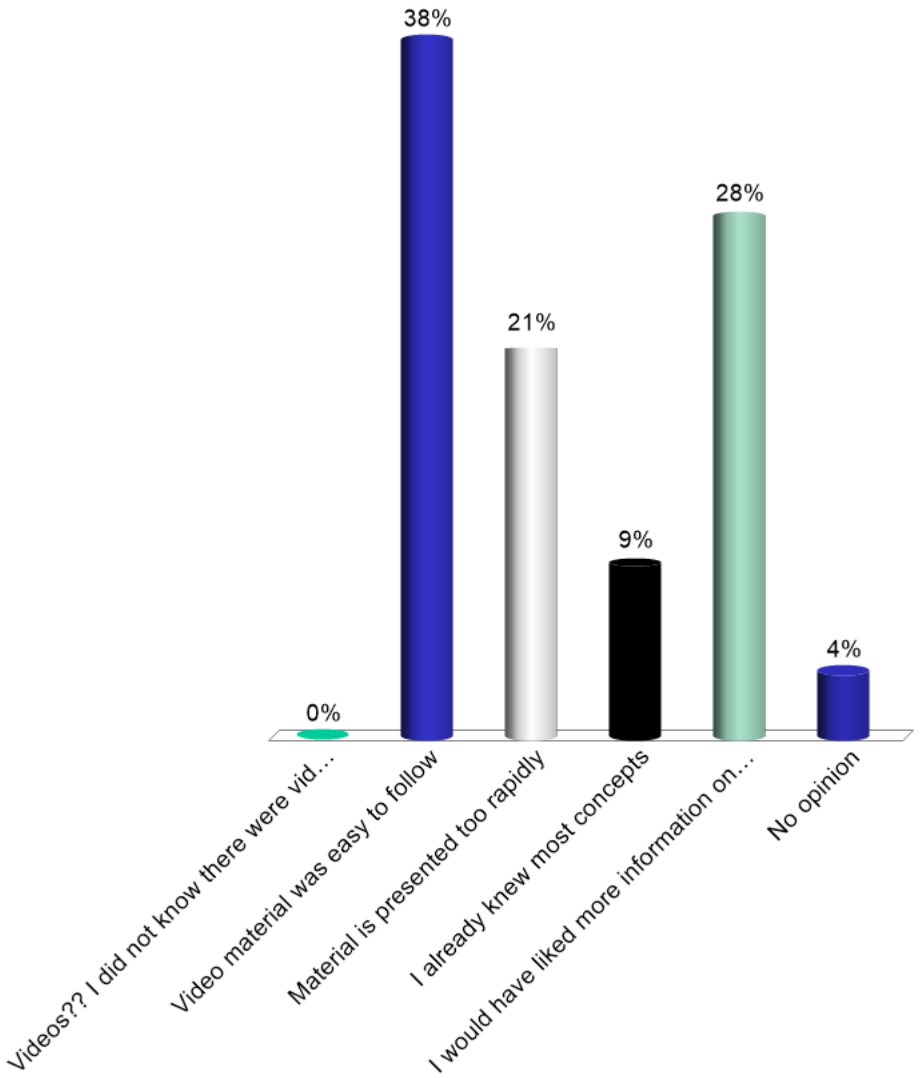
Access as GUEST and enter the session id: *appliedml2020*



Qualify the content of the videos of the theoretical material of the class

Multiple answers possible

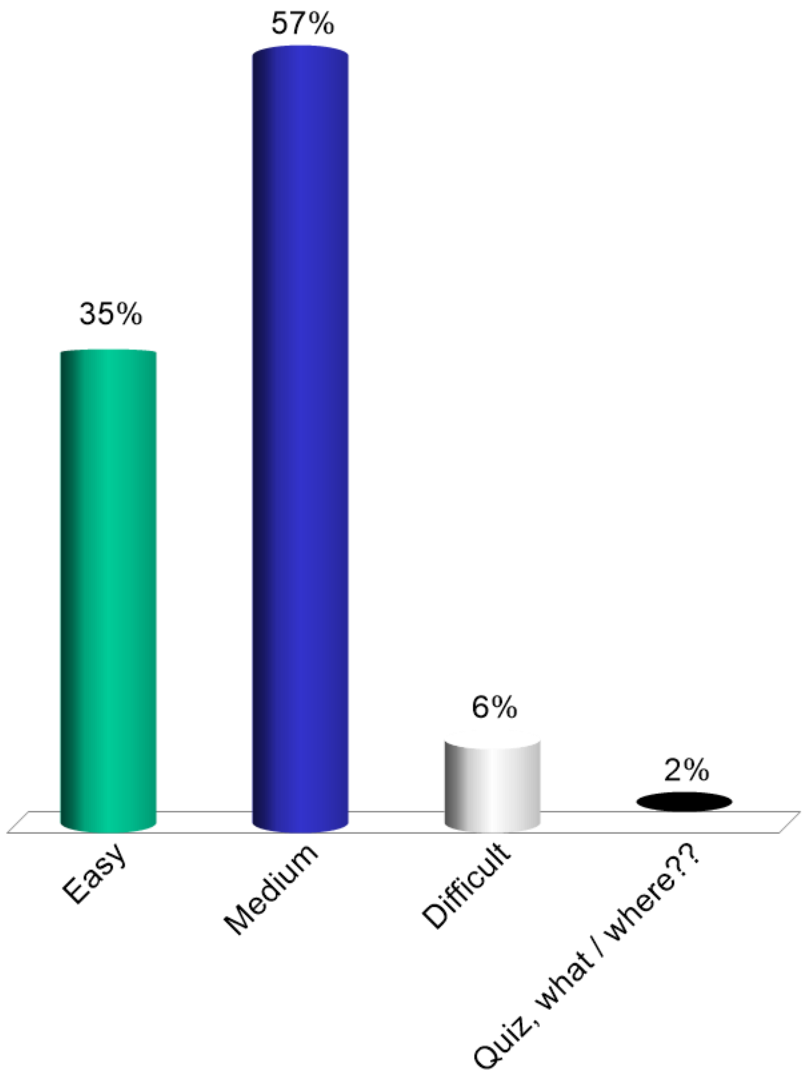
A. Videos?? I did not know there were videos!
B. Video material was easy to follow
C. Material is presented too rapidly
D. I already knew most concepts
E. I would have liked more information on some topics
F. No opinion



Qualify the content of the PCA quiz

Multiple answers possible

A. Easy
B. Medium
C. Difficult
D. Quiz, what / where??



PCA – Key Concepts

PCA has two properties:

1. It reduces the dimensionality of the data.
2. It extracts features in the data.

To achieve 1 & 2, it uses existing correlation across datapoints.

PCA can be used as:

1. Compression method for ease of data storage and retrieval.
2. Pre-processing method before classification to a) reduce computational costs, b) extract features to ease classifier's job.

Reducing the dimensionality by looking for correlations

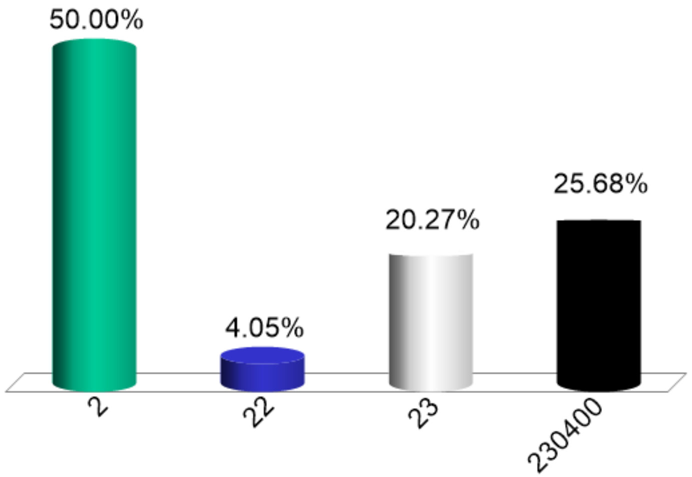
PCA on images

23 images, each of which is of dimension 230400.

$x \in \mathbb{R}^{320 \cdot 240 \cdot 3 = 230400}$

How many eigenvectors do you obtain after PCA?

A. *2*
B. *22*
C. *23*
D. *230400*



PCA on images

M=23 images, each of which is of dimension N=230400.

The covariance matrix is $C = XX^T$.
If X is $N \times M$, then C is $N \times N$.
$N = 230400$.
The eigendecomposition of C generates 230400 eigenvectors.

Only 22 of the 230400 eigenvectors are meaningful. All others have eigenvalue zero.

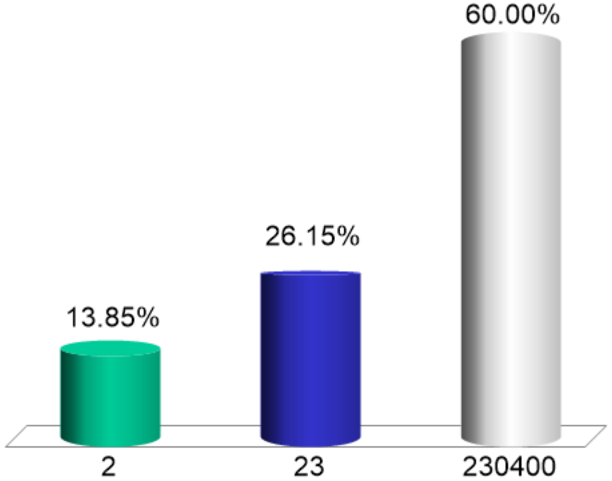
You may then choose to keep only 2 out of these 22 eigenvectors, as they may be sufficient for your task (e.g. classification).

PCA on images

M=23 images, each of which is of dimension N=230400.

What is the dimension of each eigenvector?

A. 2
B. 23
C. 230400



PCA on images

M=23 images, each of which is of dimension N=230400.

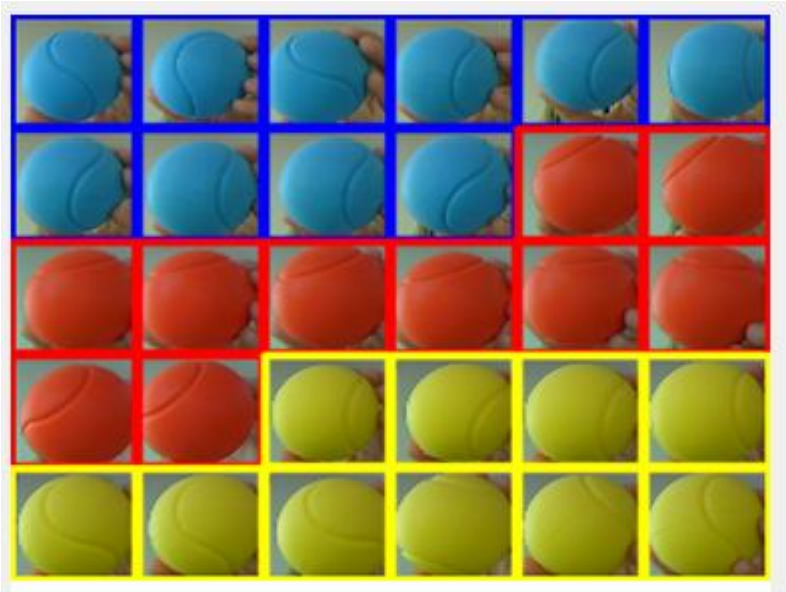
What is the dimension of each eigenvector?

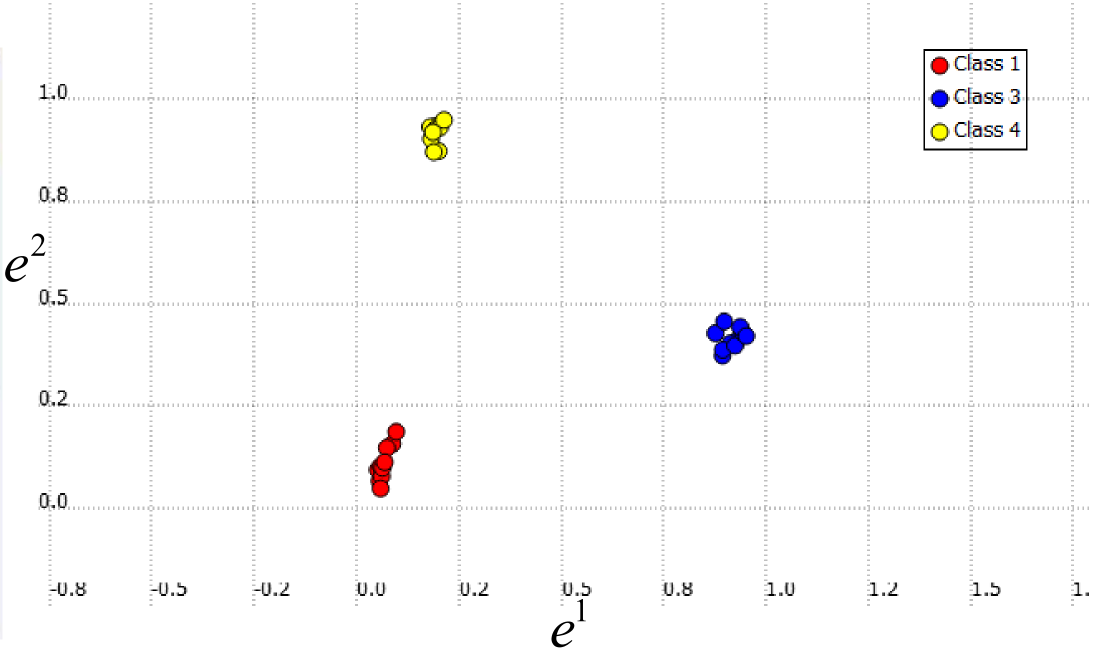
Each eigenvector is of the same dimension as the original images, i.e. N=230400.

An eigenvector of a dataset of images is an image. Such an eigenvector is often referred to as *eigenface.*

Interpreting PCA projections and eigenvectors

Can you explain the “color” of the eigenvectors?

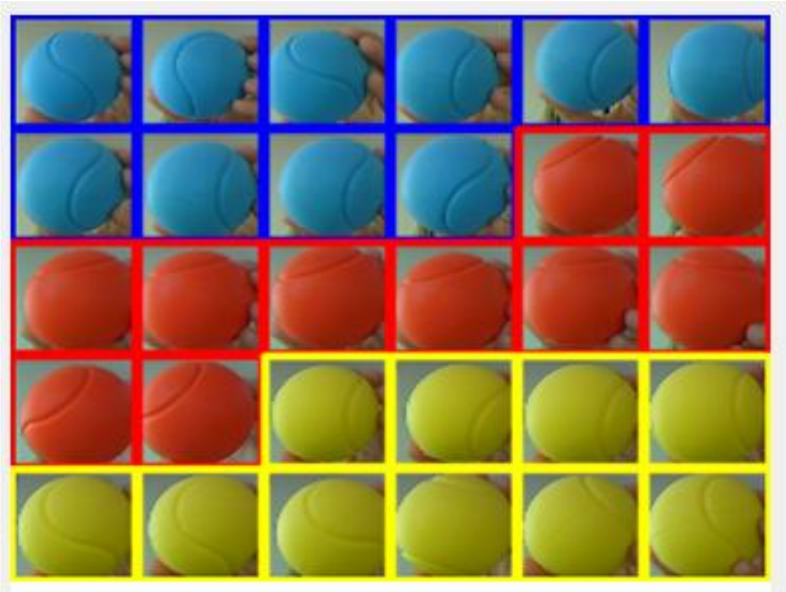


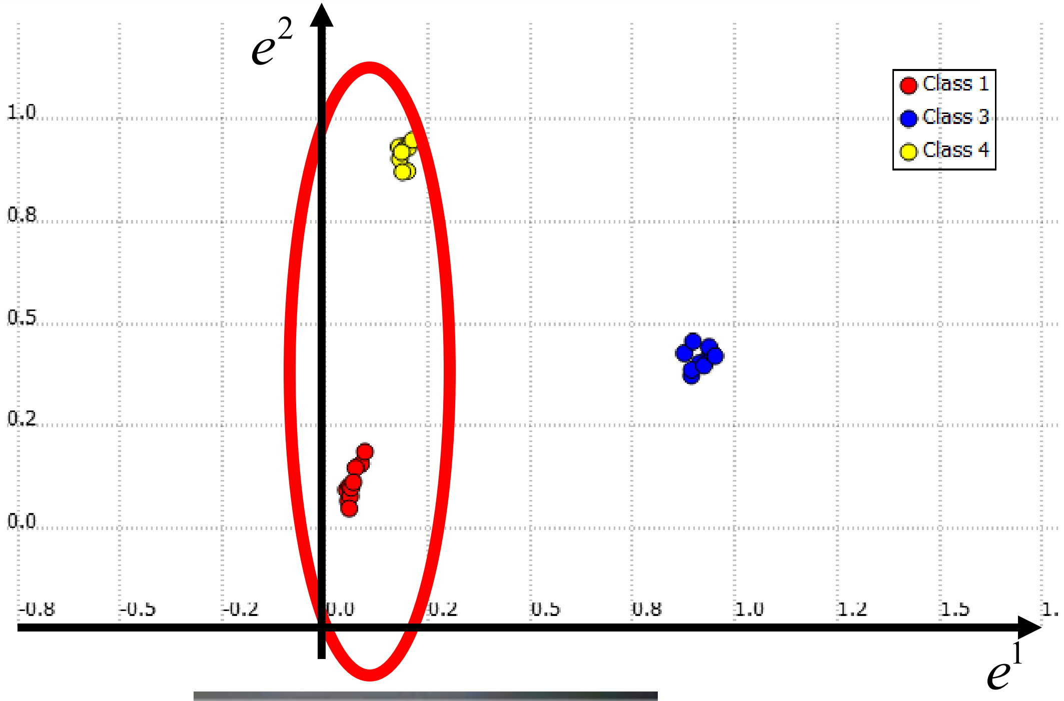


e^1 e^2

Interpreting PCA projections and eigenvectors

The red and yellow images have coordinate ~0 on the 1st eigenvector.

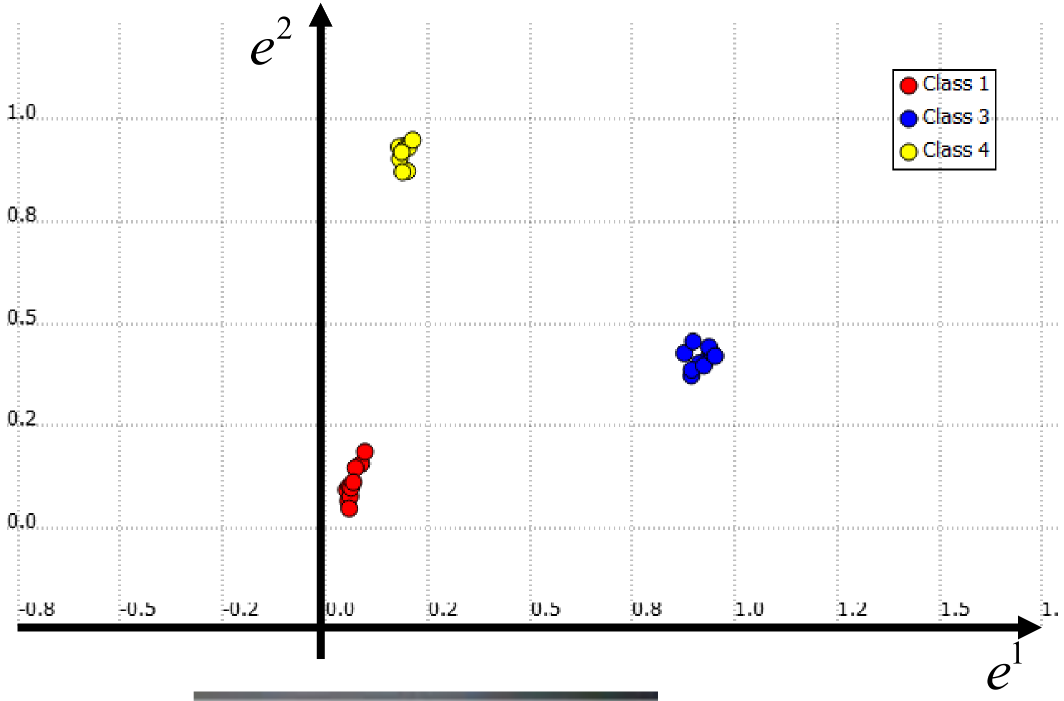




Interpreting PCA projections and eigenvectors

Is there information in the entries of the eigenvectors ?

$$e^1 = \begin{bmatrix} ? \\ ? \\ ? \\ . \\ . \\ . \\ . \\ . \\ . \end{bmatrix} \quad e^2 = \begin{bmatrix} ? \\ ? \\ ? \\ . \\ . \\ . \\ . \\ . \\ . \end{bmatrix}$$



e^1 e^2

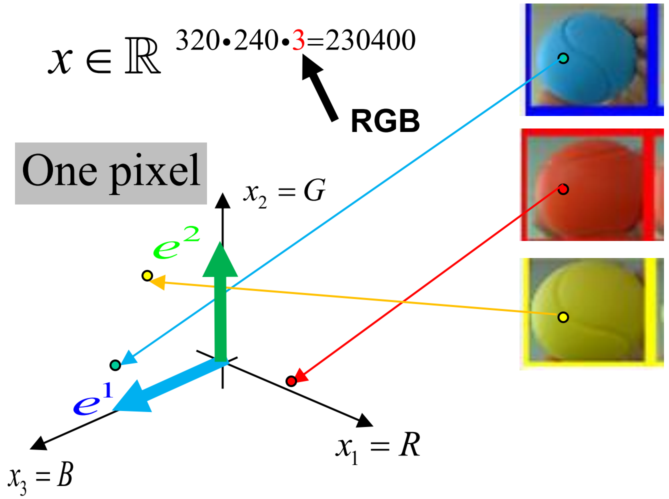
Interpreting PCA projections and eigenvectors

Each image is a high-dimensional vector

$x \in \mathbb{R}^{320 \cdot 240 \cdot 3 = 230400}$

RGB

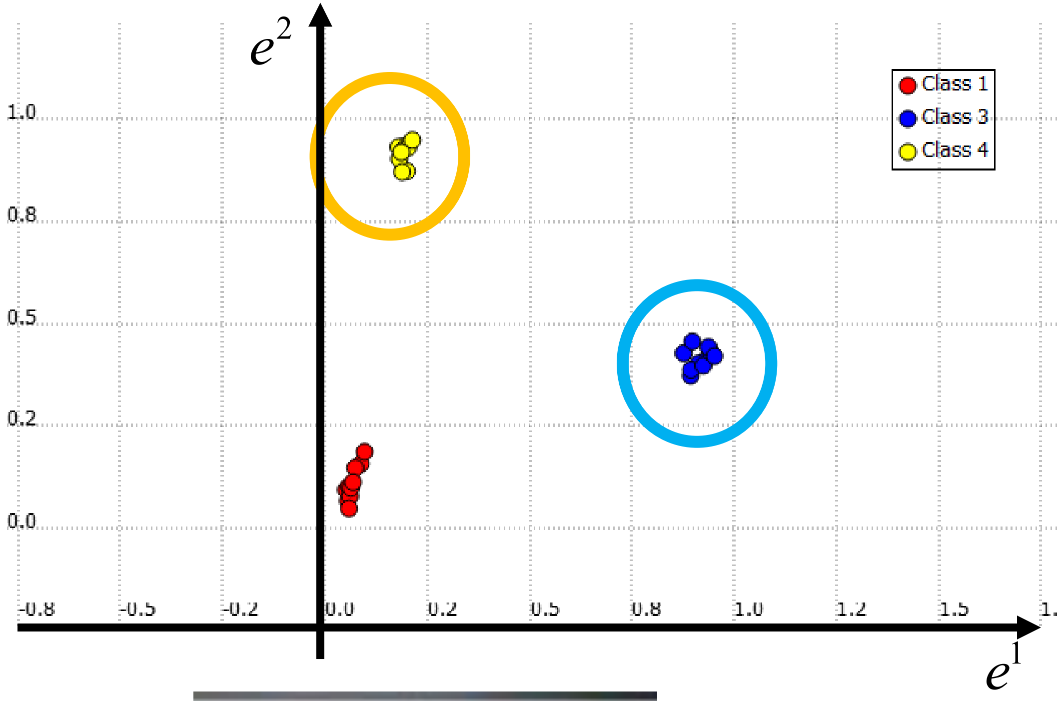
One pixel



$$e^1 = \underbrace{(x_1)^T \cdot e^1}_{\text{coordinate of } e^1 \text{ onto } x_1} x_1 + \underbrace{(x_2)^T \cdot e^1}_{\text{coordinate of } e^1 \text{ onto } x_2} x_2 + \ldots$$

$$e^1 \sim \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \\ 0 \\ 1 \end{bmatrix} \qquad e^2 \sim \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \\ 1 \\ 0 \end{bmatrix}$$

Repeats for each pixel



e^1 e^2

Eigenfaces

PCA applied to a set of 100 faces, coded in a high dimensional pixel space (54 150 dimensions),

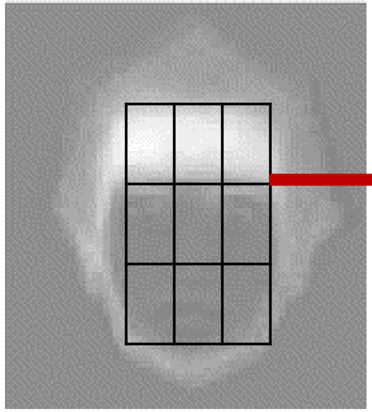
1 2 3 4

First 4 projections (4 principal components with largest eigenvalues)

Hancock, P et al (1996). Face processing: human perception and principal components analysis. *Memory and Cognition* 24 1, pp. 26–40

Interpreting PCA projections and eigenvectors

What would the entries of the first eigenvector look like?

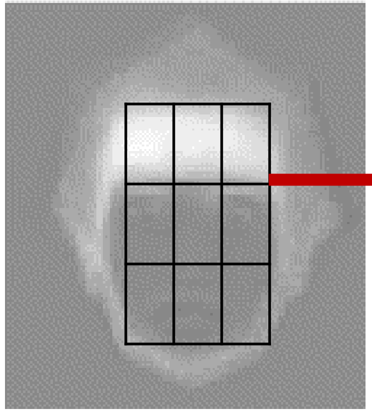


$$e^1 = \begin{bmatrix} ? \\ ? \\ ? \\ ? \\ ? \\ ? \\ ? \\ ? \\ ? \end{bmatrix}$$

Each pixel is coded with a scalar
Grey scale [0 ,1]
0 = Black
1 = White

Interpreting PCA projections and eigenvectors

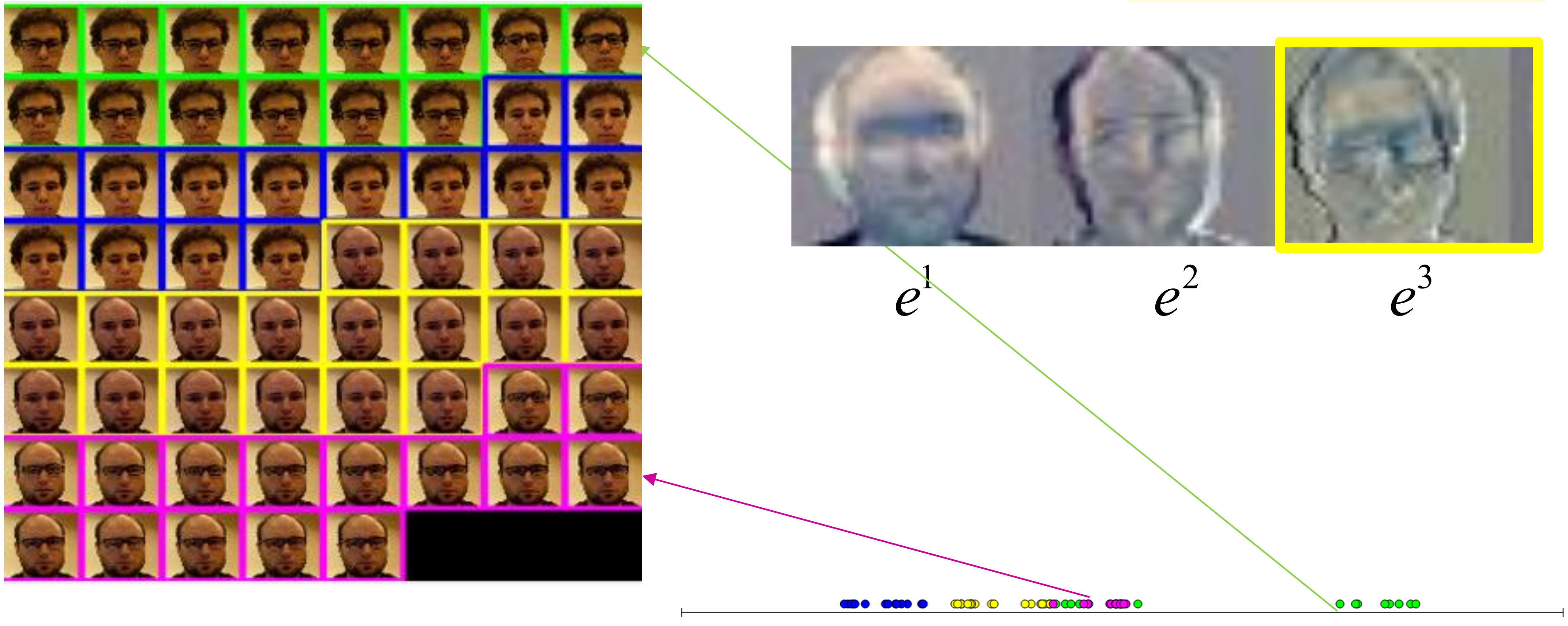
What would the entries of the first eigenvector look like?



$$e^1 \sim \begin{bmatrix} 1 \\ 1 \\ 1 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

Entries not exactly zero

Groups glasses



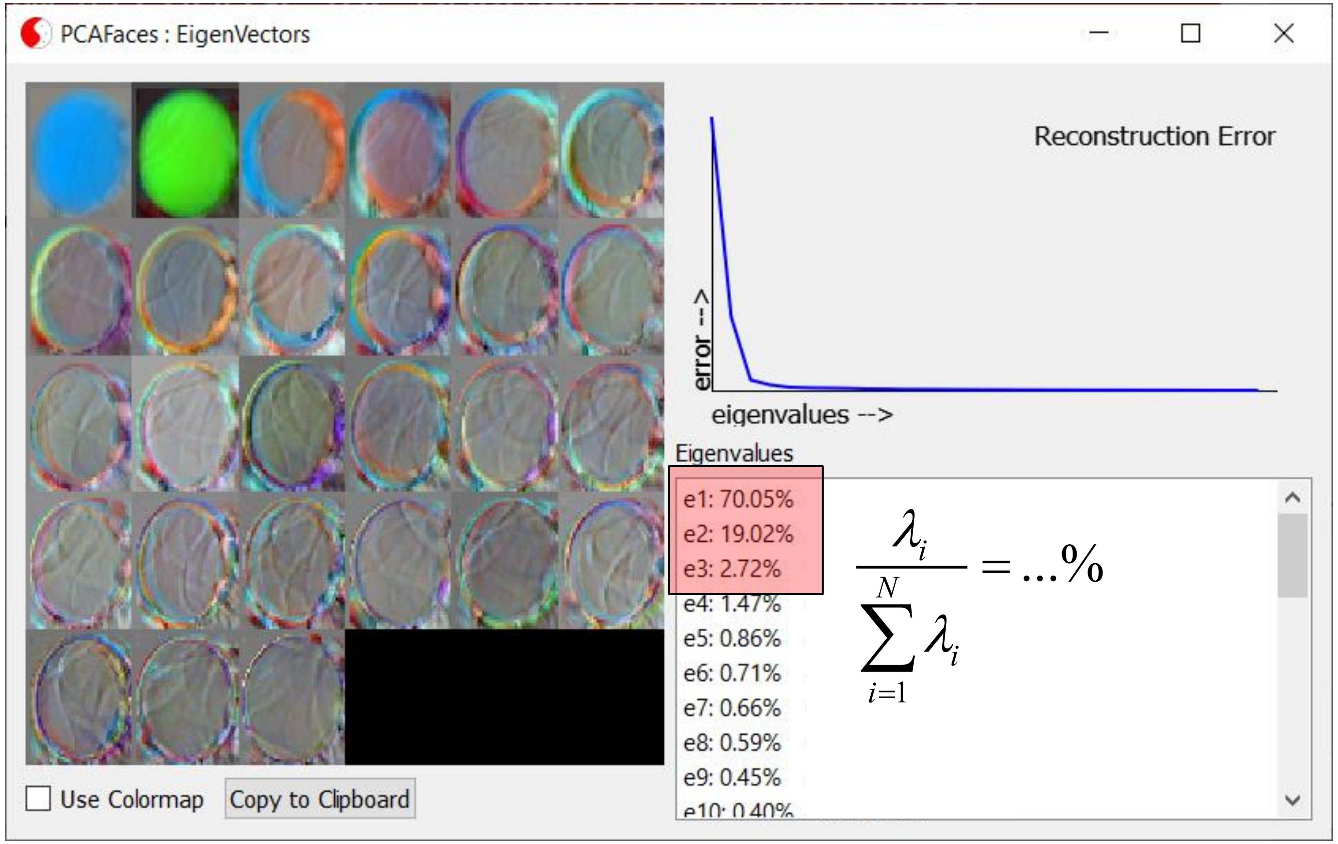
Projection along e^3

How to choose the optimal p eigenvectors?

Choose the smallest number of eigenvectors p but with smallest information loss. In the literature, you will often see that people select a subset of eigenvectors so as to incur no more than 10% information loss.

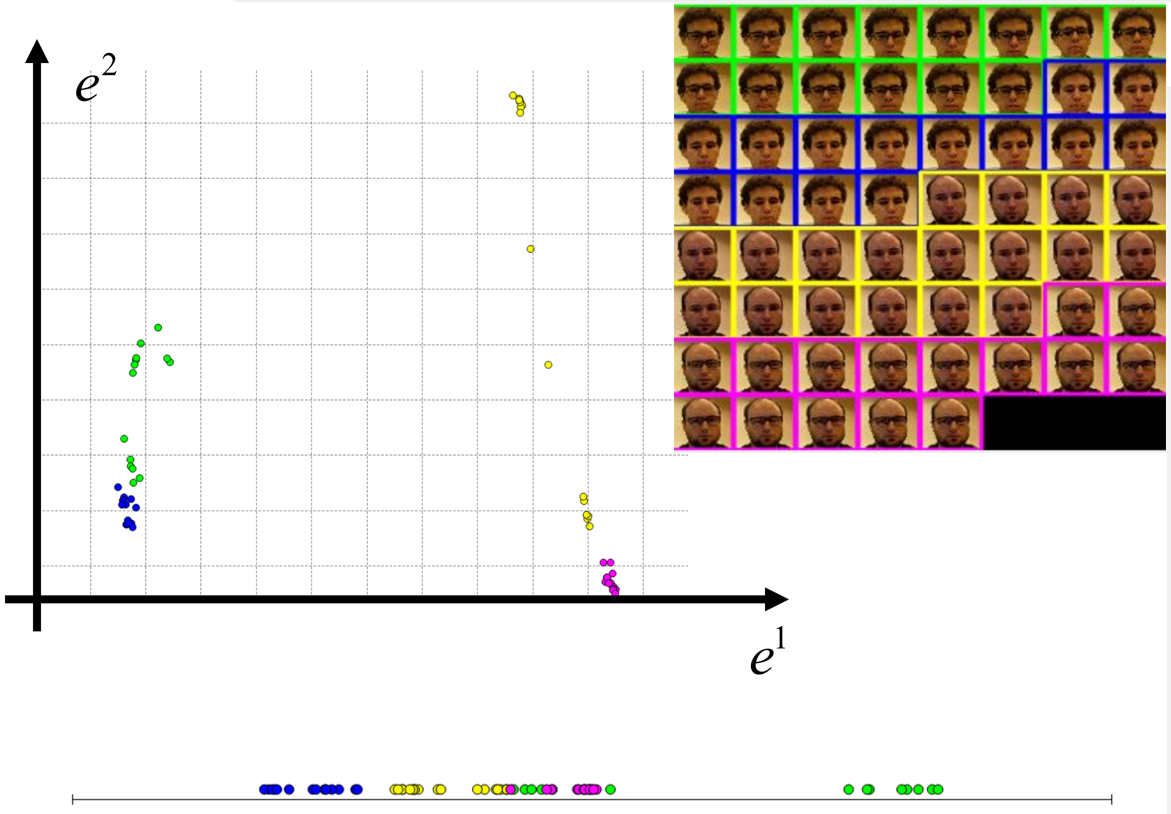
Information loss is measured as fraction of variance of data retained in the projections. Variance is measured by the eigenvalues.

$$\frac{\sum_{j=p+1}^{N} \lambda_j}{\sum_{i=1}^{N} \lambda_i} \leq 0.1$$

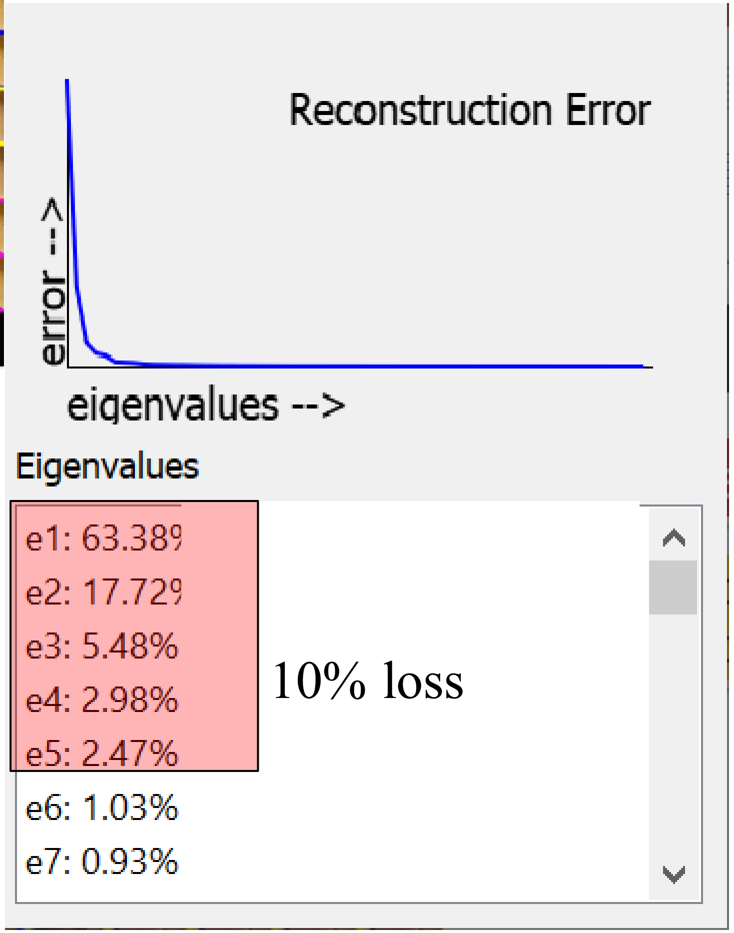


How to choose the optimal p eigenvectors?

But first two eigenvectors are sufficient for separating the two faces and the third eigenvector is sufficient to extract the glasses' class.



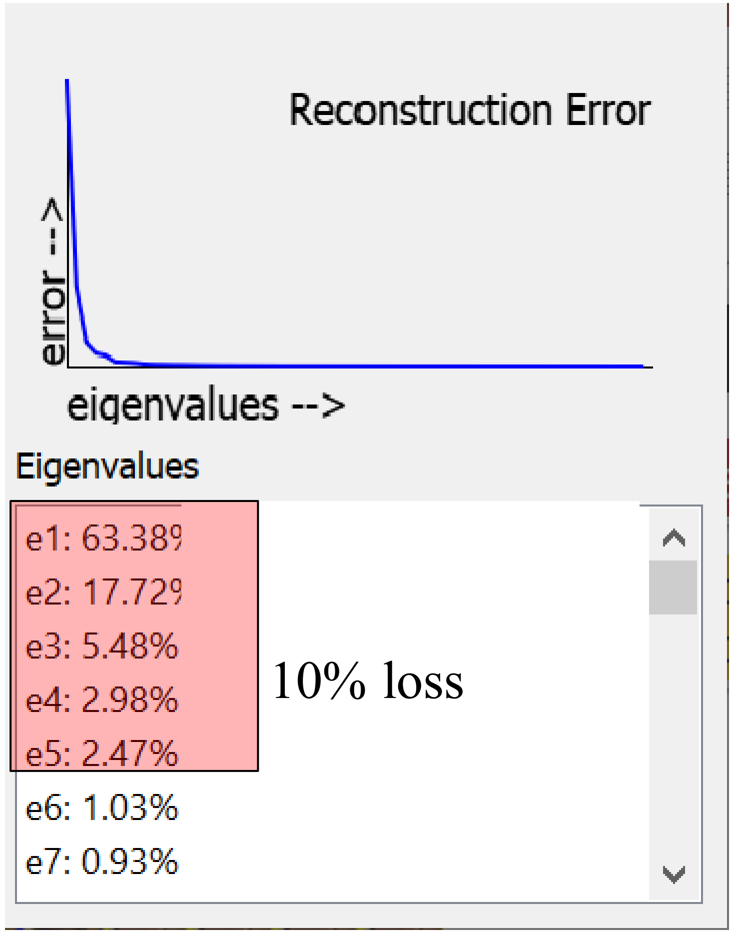
Projection along e^3



10% loss

Take-Home Message

If your goal is to reduce dimensionality of the data with least deformation and information loss, pick the eigenvectors in decreasing order of their eigenvalues, until you reach the % of the variance you wish to retain.



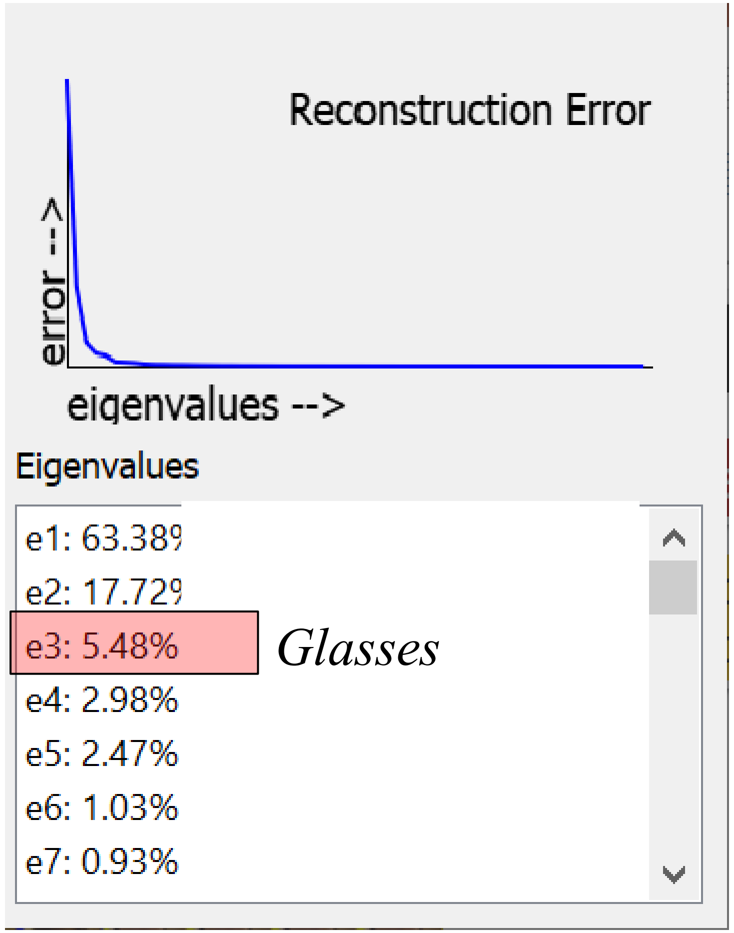
Take-Home Message

If your goal is to **extract some specific information**, pick the eigenvector that conveys this information.

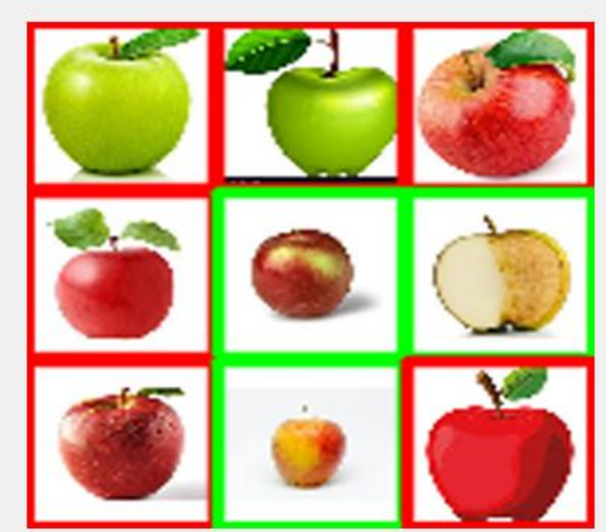
They are not necessarily the first eigenvectors.

Relevant information may be entailed in other eigenvectors, sometimes in eigenvectors with low eigenvalues.

Beware though that if you pick an eigenvector with very low eigenvalue, its statistical power will be low too and you may be picking on noise.



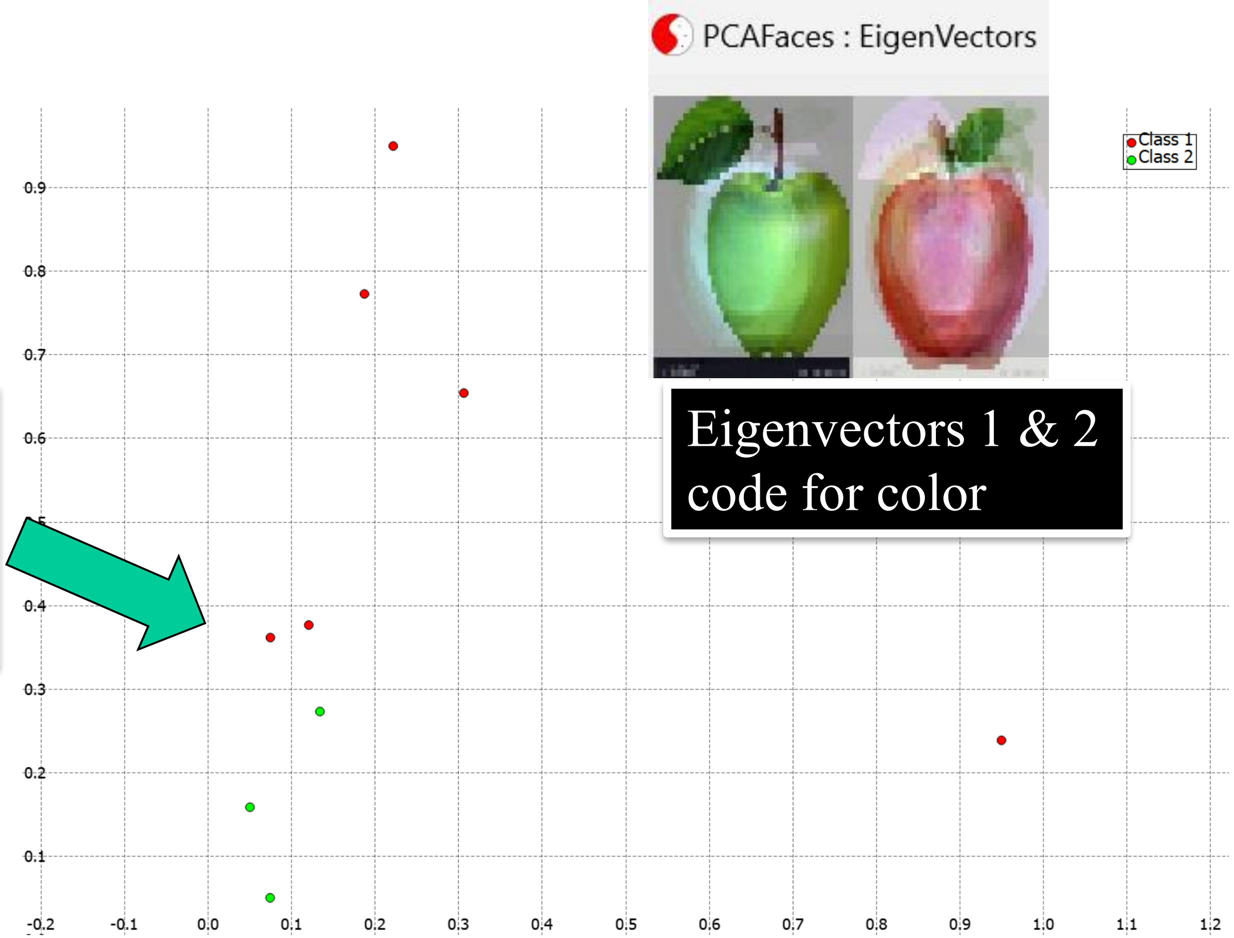
2nd Example – Fruit Dataset



Classes: Apple with a leaf vs. Apple without a leaf

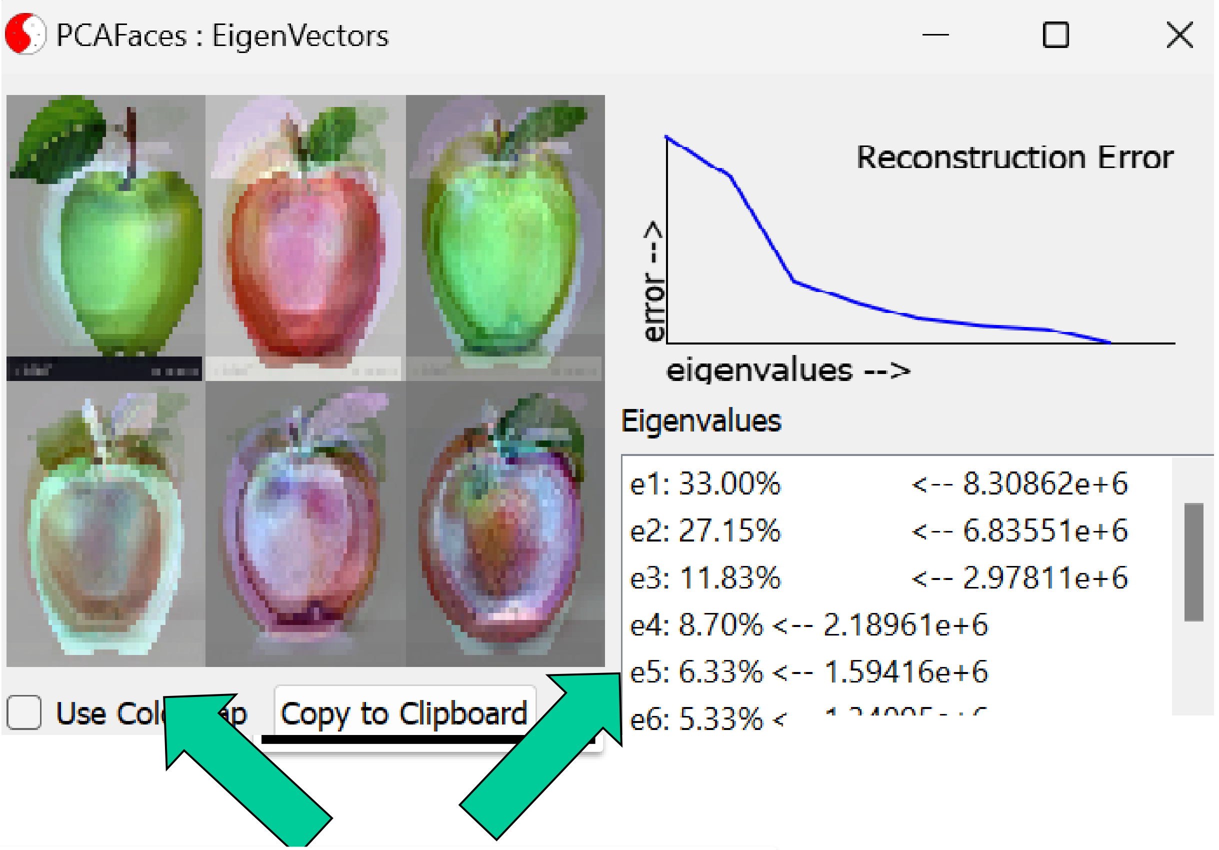
Eigenvectors 1 & 2 code for color

Difficult to separate the two classes. You may need more eigenvectors (see next week's practice session)

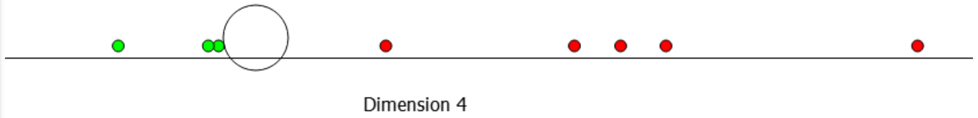


Projection along e^1 and e^2

2nd Example – Fruit Dataset



Eigenvector 4 entails information about the leafs, but it has very low statistical significance due to the fact that the leaf is encapsulated in few pixels.



Projection along e^4

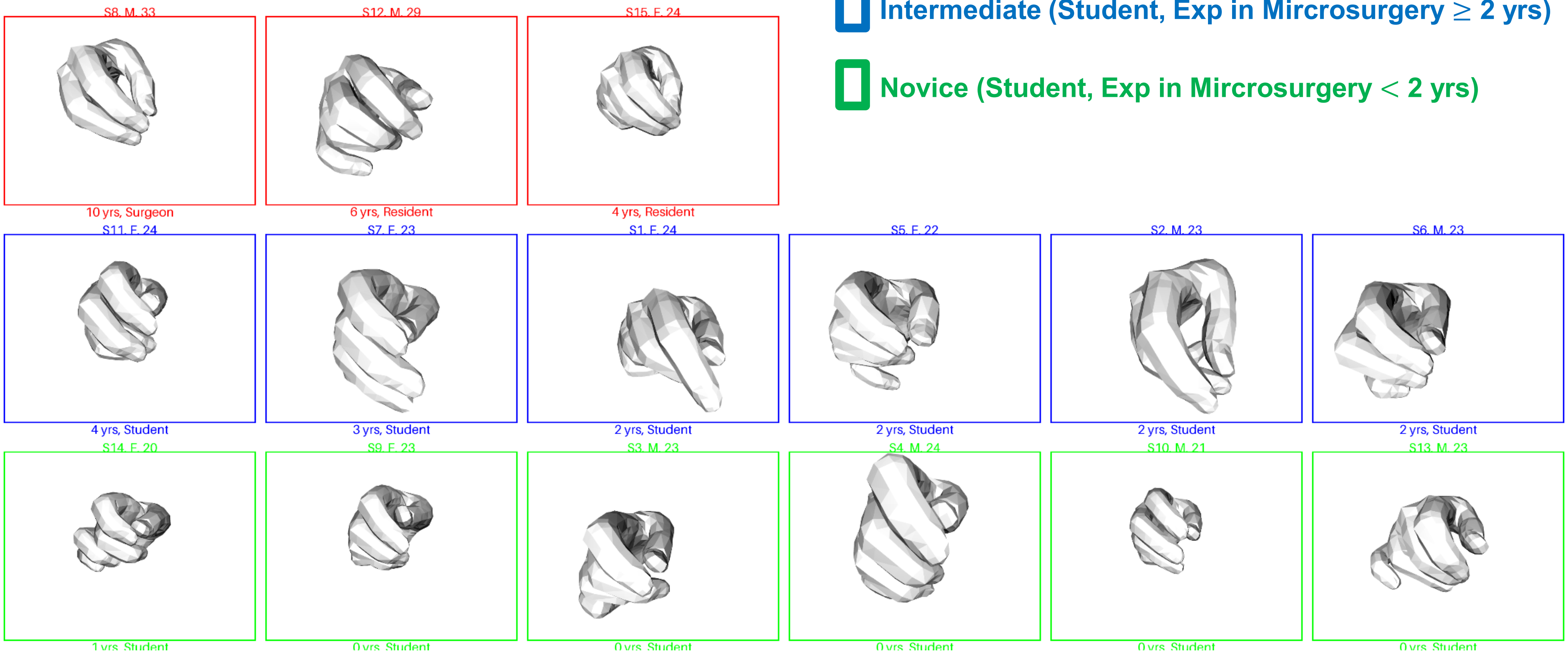
Example Application of PCA to Analyse Diversity of Handposes


S8, M, 33
10 yrs, Surgeon
S12, M, 29
6 yrs, Resident
S15, F, 24
4 yrs, Resident
Expert (Surgeon, Resident)
Intermediate (Student, Exp in Mircrosurgery ≥ 2 yrs)
Novice (Student, Exp in Mircrosurgery < 2 yrs)
S11, F, 24
4 yrs, Student
S7, F, 23
3 yrs, Student
S1, F, 24
2 yrs, Student
S5, F, 22
2 yrs, Student
S2, M, 23
2 yrs, Student
S6, M, 23
2 yrs, Student
S14, F, 20
S9, F, 23
S3, M, 23
S4, M, 24
S10, M, 21
S13, M, 23

Expert (Surgeon, Resident)

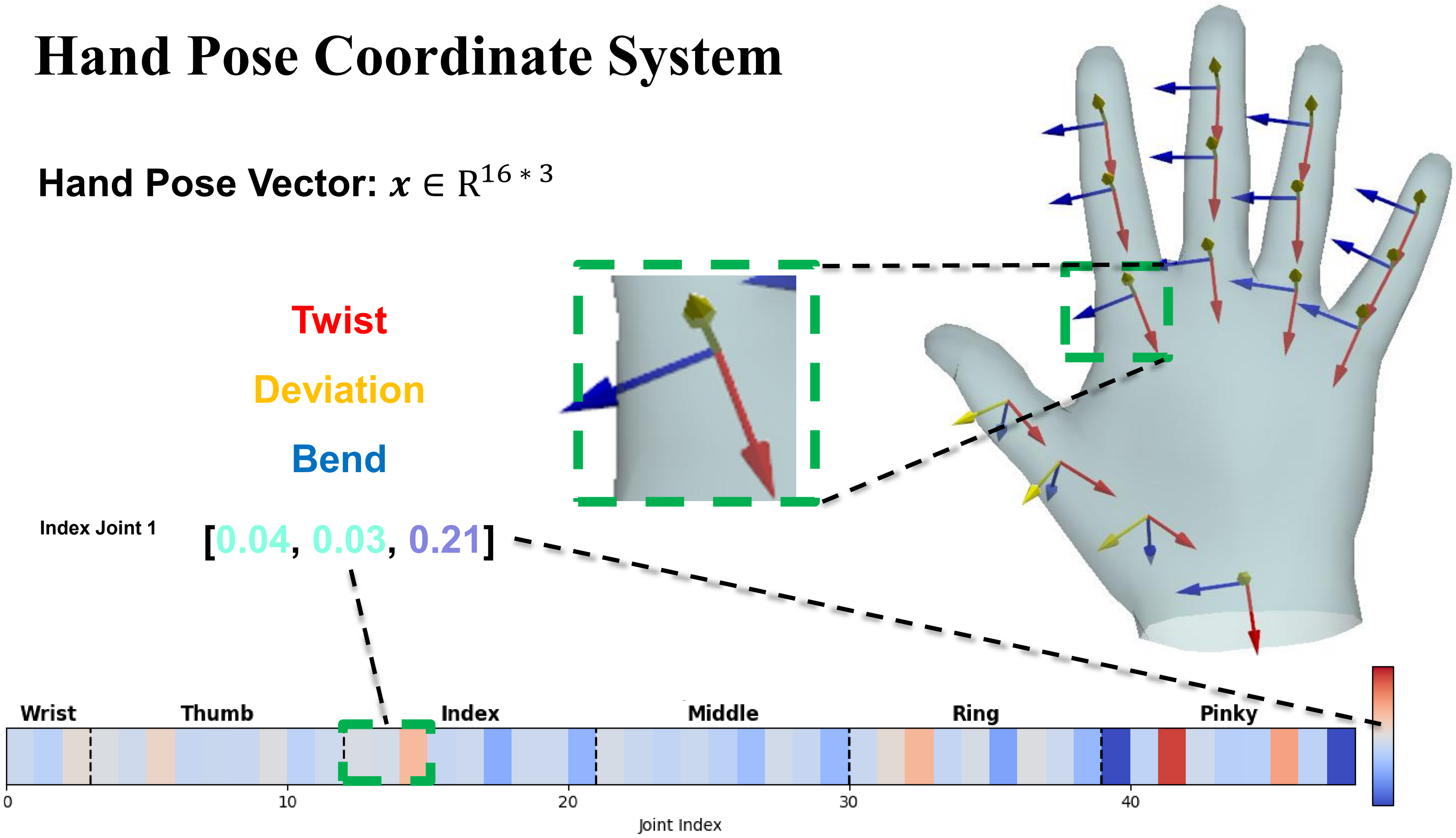
Intermediate (Student, Exp in Mircrosurgery $\geq$ 2 yrs)

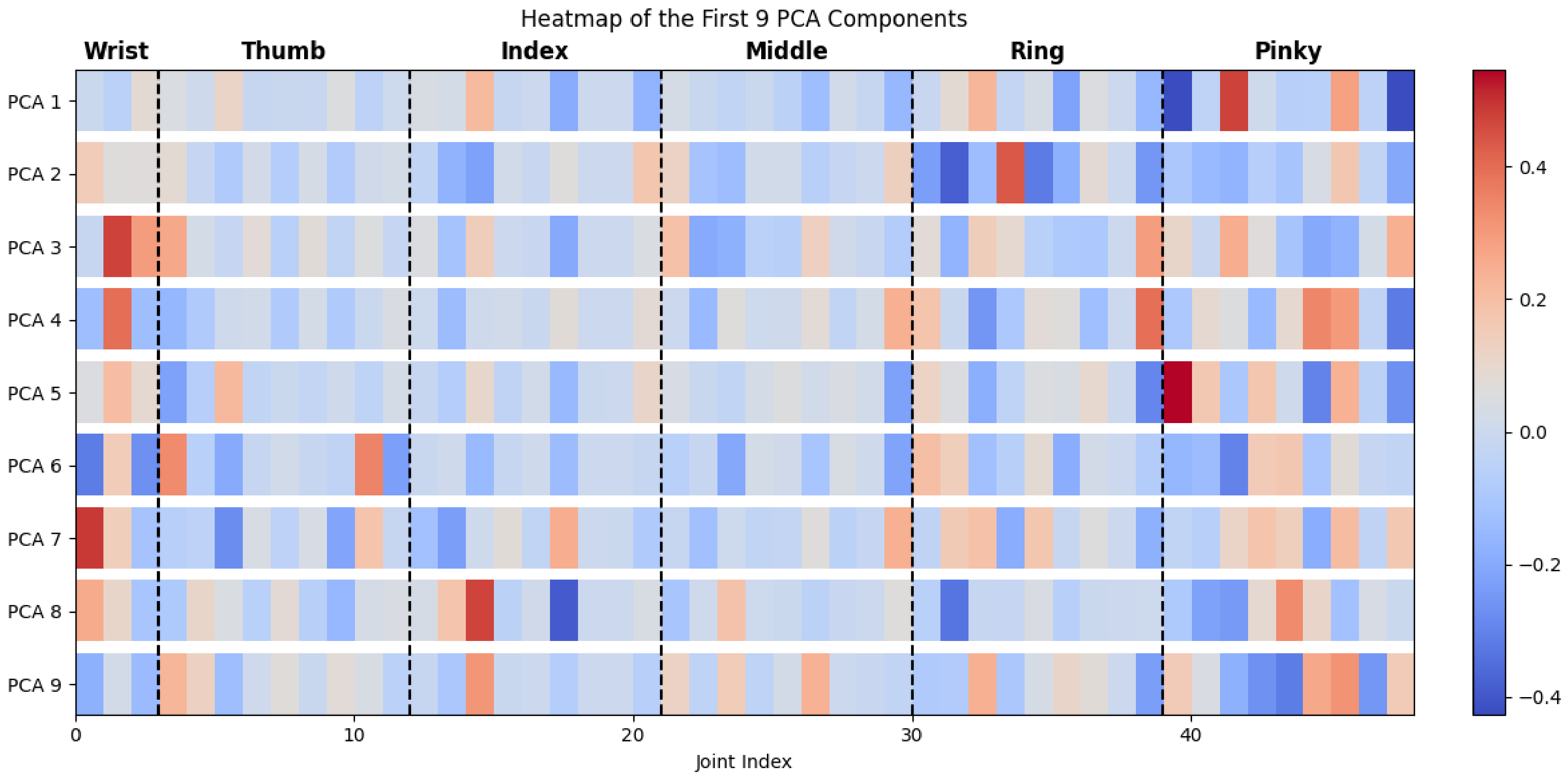
Novice (Student, Exp in Mircrosurgery $<$ 2 yrs)

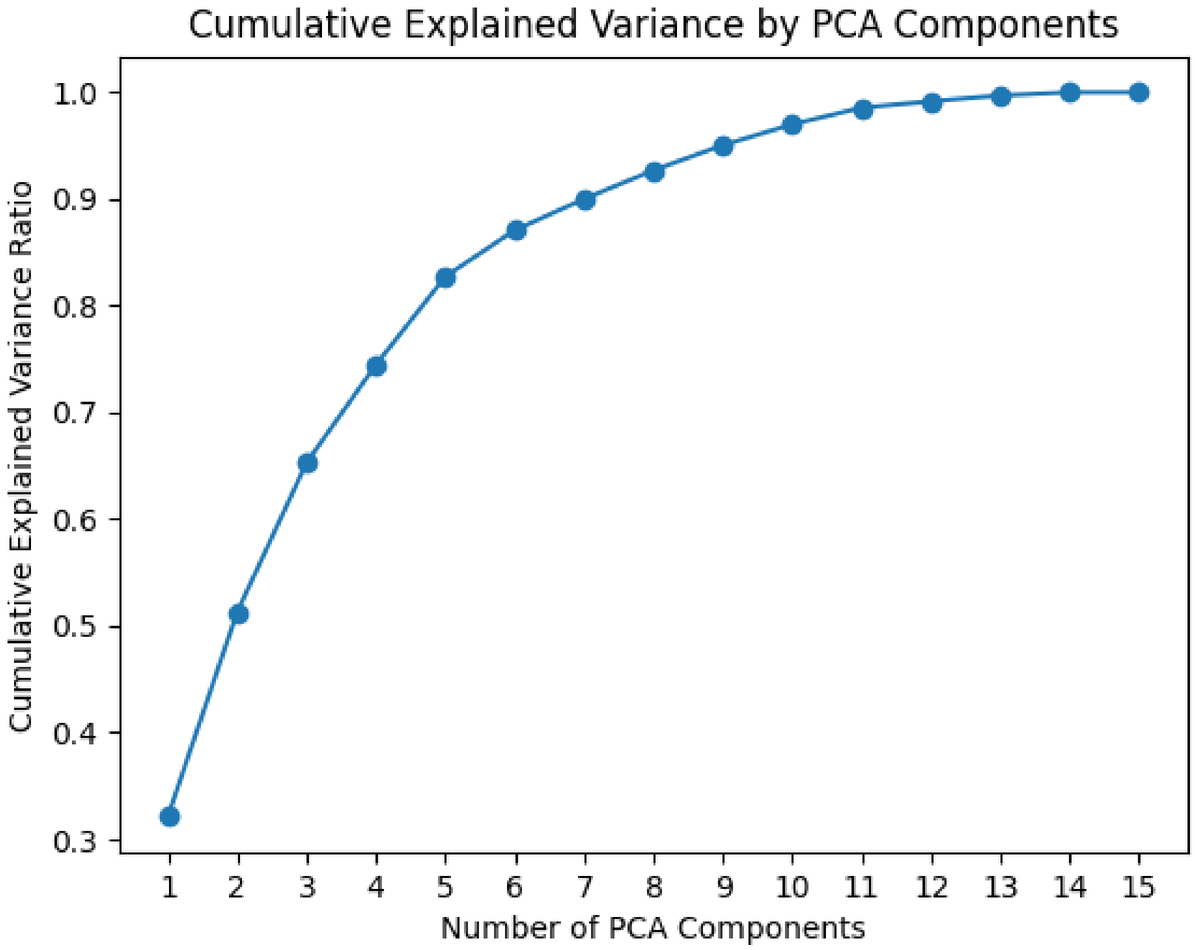


Hand Pose Coordinate System

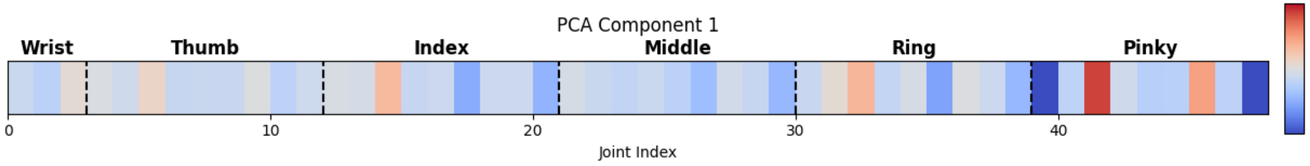
Hand Pose Vector: $x \in \mathrm{R}^{16*3}$

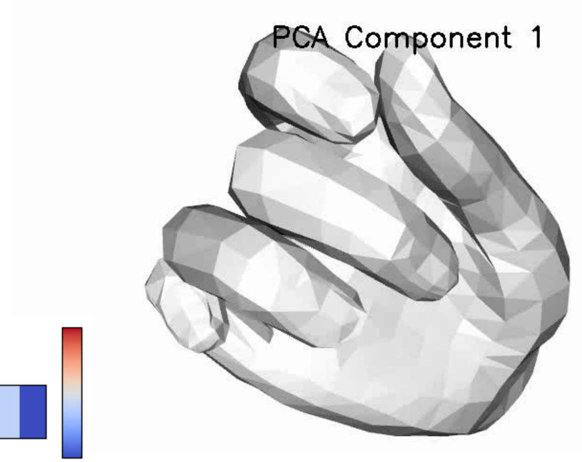



Heatmap of the First 9 PCA Components
Wrist
Thumb
Index
Middle
Ring
Pinky
PCA 1
PCA 2
PCA 3
PCA 4
PCA 5
PCA 6
PCA 7
PCA 8
PCA 9
0
10
20
30
40
Joint Index
0.4
0.2
0.0
−0.2
−0.4

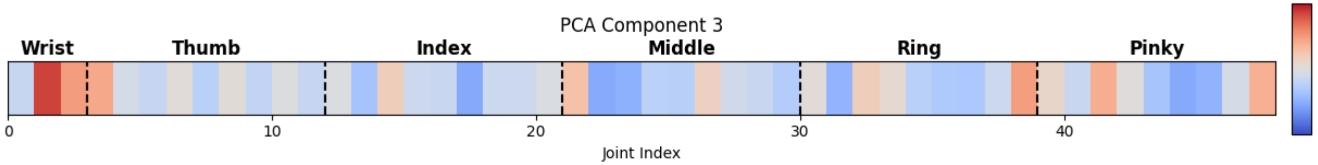

Cumulative Explained Variance by PCA Components
Cumulative Explained Variance Ratio
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15
Number of PCA Components

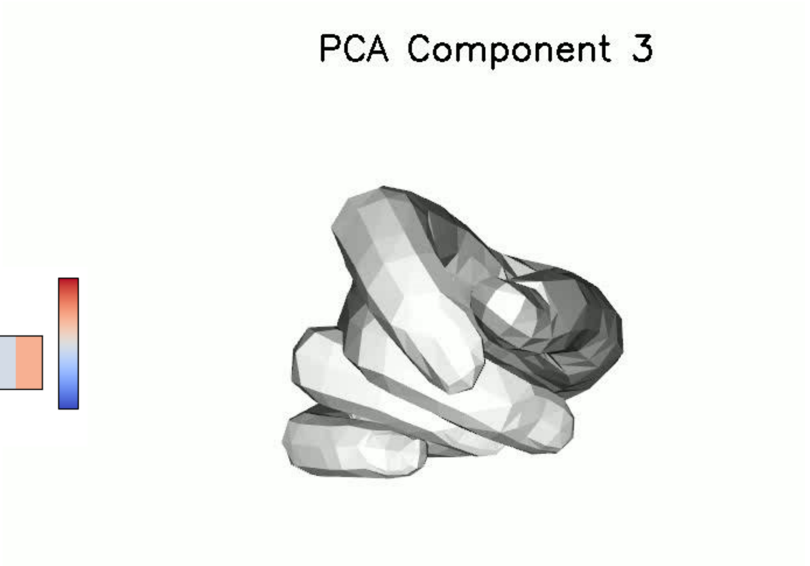
$$\mathbf{x} = [\boldsymbol{\mu} - 3\sigma_1 \boldsymbol{c}_1, \dots, \boldsymbol{\mu} + 3\sigma_1 \boldsymbol{c}_1]$$

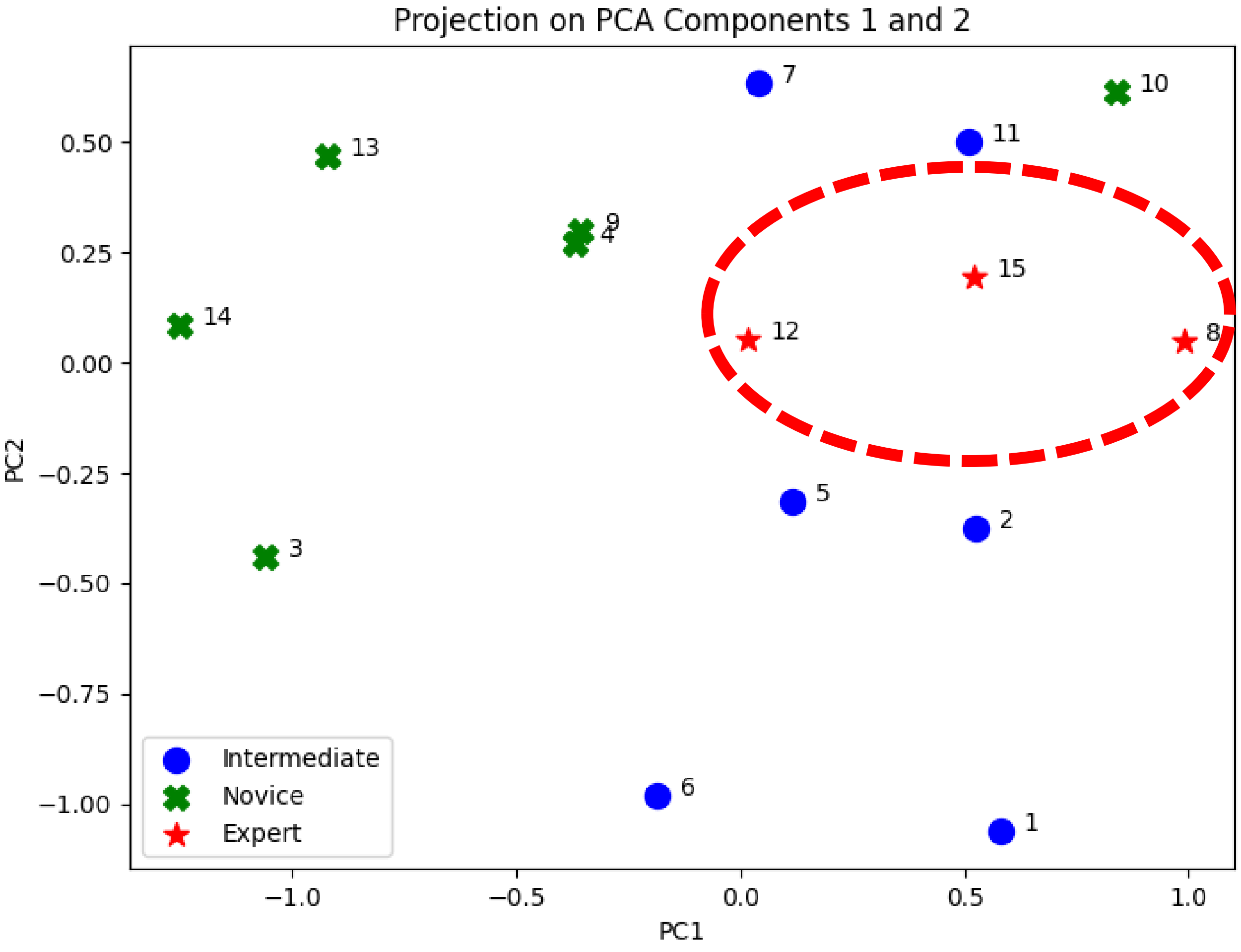


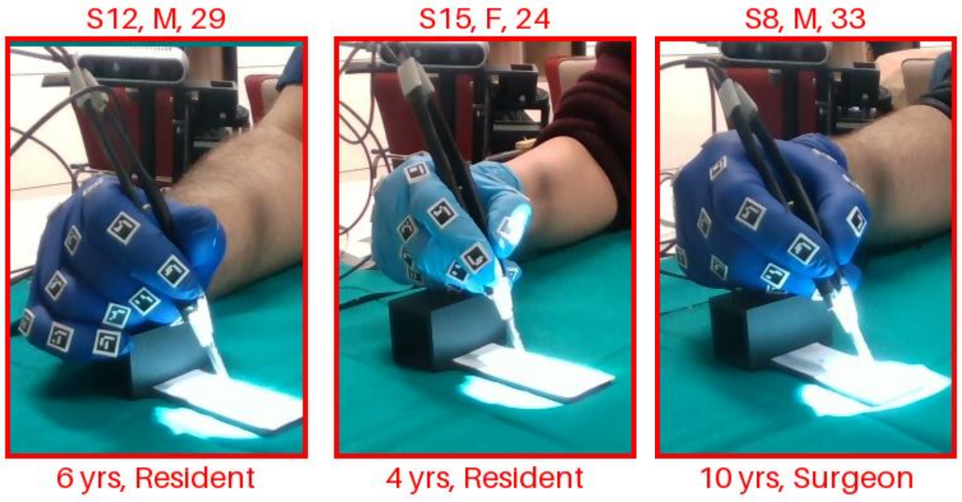


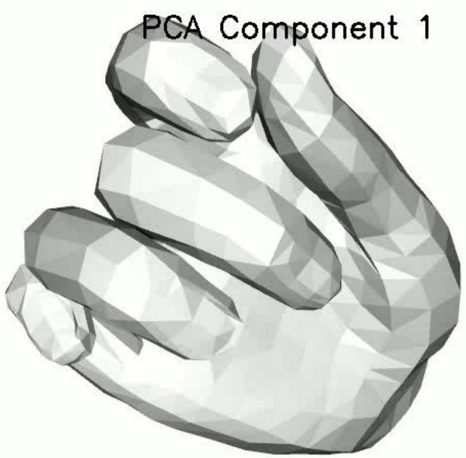
$$\mathbf{x} = [\boldsymbol{\mu} - 3\sigma_3 \boldsymbol{c}_3, \dots, \boldsymbol{\mu} + 3\sigma_3 \boldsymbol{c}_3]$$






Projection on PCA Components 1 and 2
PC2
PC1
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
−1.0
−0.5
0.0
0.5
1.0
7
10
11
13
9
4
15
14
12
8
5
2
3
6
1
Intermediate
Novice
Expert


S12, M, 29
S15, F, 24
S8, M, 33
6 yrs, Resident
4 yrs, Resident
10 yrs, Surgeon


PCA Component 1

Qualify the content of the interactive class

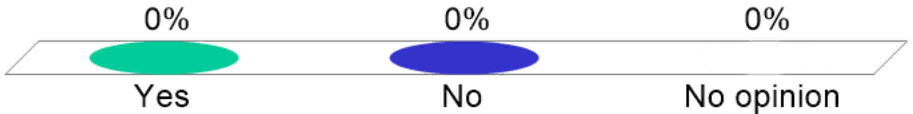
Multiple answers possible

A. Too easy
B. Right level
C. Too fast / too difficult

For those of you following class on-line:

Did you find it easy to interact with TA on and zoom during the interactive exercise sessions?

A. Yes
B. No
C. No opinion



NEXT WEEK!

Class starts at 10h15am → 13h00

Computer-based practice session on PCA

On site

In classrooms

BC 07 – 08, CM 1103

On-line

But only introduction

zoom