

## PROJECT 2: *Labelling*

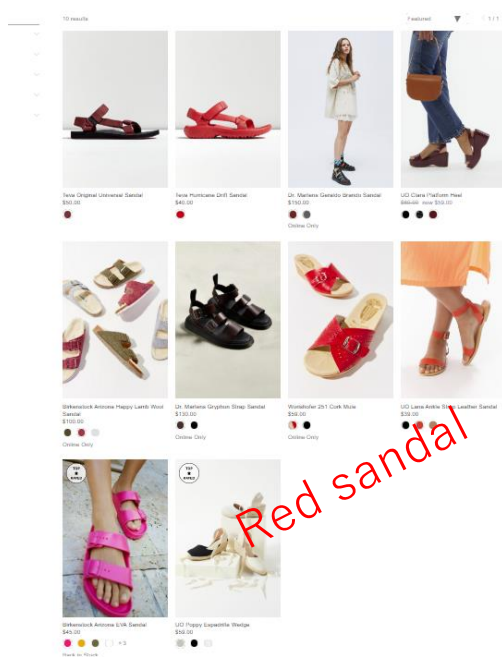
Artificial Intelligence

Universitat Autònoma de Barcelona

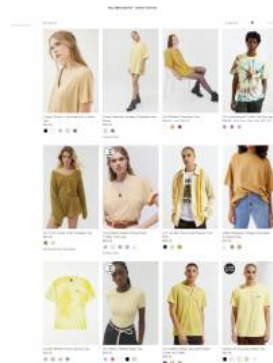
# Project 2

**Goal:** Building an agent able to automatically label images to provide the ability to make smart searches in natural Language for on a online shop that requires a constant update of the catalogue.

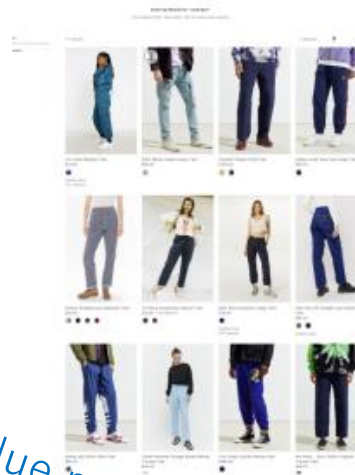
The system should be able to assign two kind of labels to the new products: **Colour and Shape**. Users should be able to search for: *"Red Shirt"* or *"Black Sandals"*



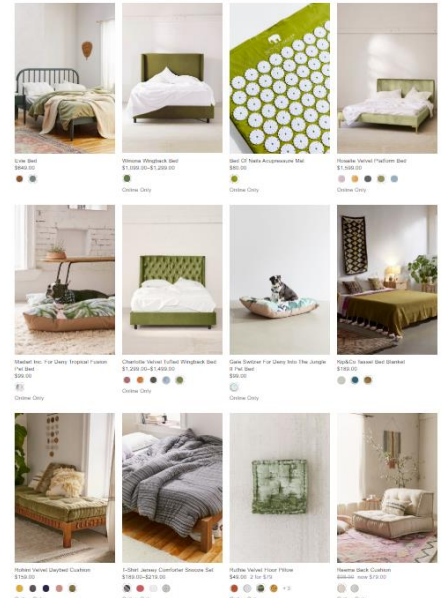
## Yellow t-shirts



Blue pants



## Green beds



# Project 2

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It can be very complex!!! → We will simplify it

## Simplifications:

- Labels are going to be in English
- We will only label 8 cloth classes:

✓ <i>Dresses</i>	✓ <i>Shirts</i>
✓ <i>Flip Flops</i>	✓ <i>Shorts</i>
✓ <i>Jeans</i>	✓ <i>Socks</i>
✓ <i>Sandals</i>	✓ <i>Handbags</i>



- We will label predominant colours for each cloth type, only the 11 universal colour terms:

✓ <i>Red</i>	✓ <i>Green</i>	✓ <i>Black</i>
✓ <i>Orange</i>	✓ <i>Blue</i>	✓ <i>Grey</i>
✓ <i>Brown</i>	✓ <i>Purple</i>	✓ <i>White</i>
✓ <i>Yellow</i>	✓ <i>Pink</i>	



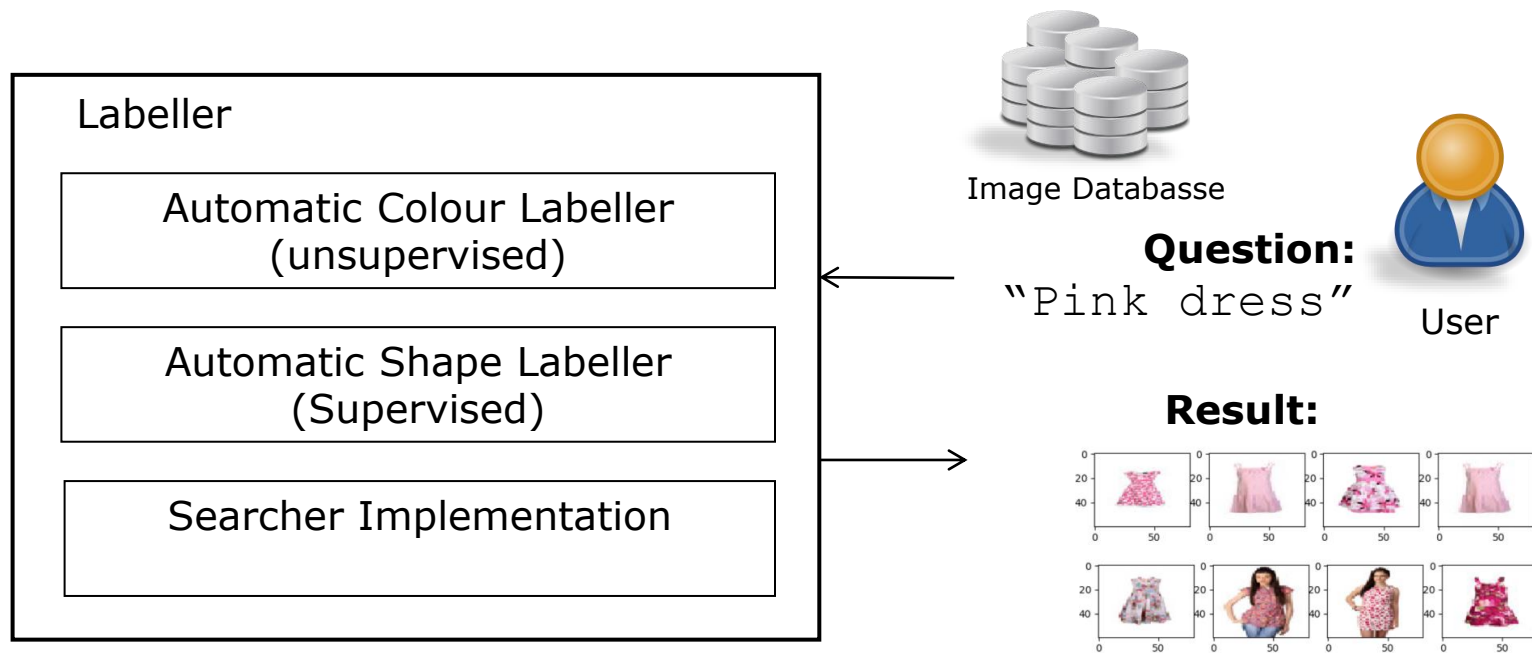
- To reduce running time we will work with low-resolution images (60x80 pixels). We will use the image dataset: Fashion Product Images Dataset del Kaggle

<https://www.kaggle.com/paramaggarwal/fashion-product-images-dataset>

**Kaggle** is a shared folder with datasets for research on Data Science

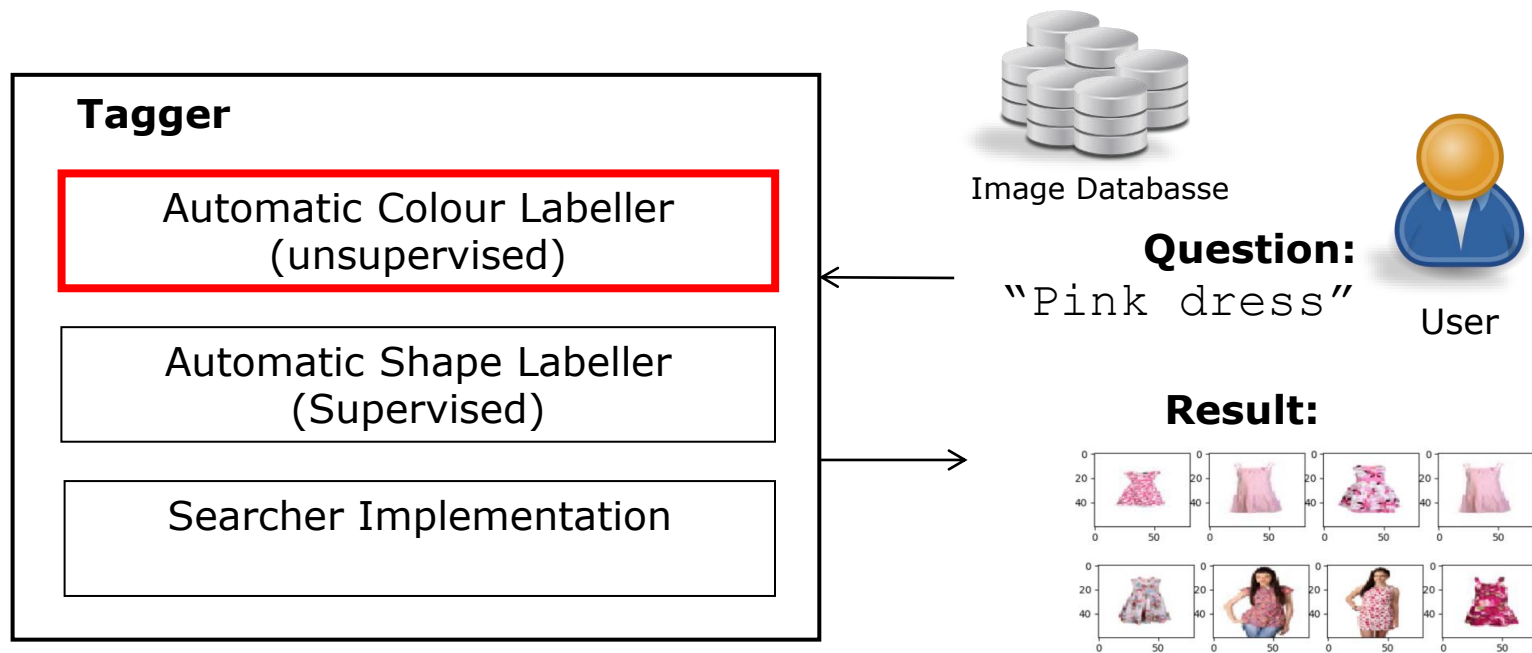
# Project 2

**Problems to solve** to build this tagger:

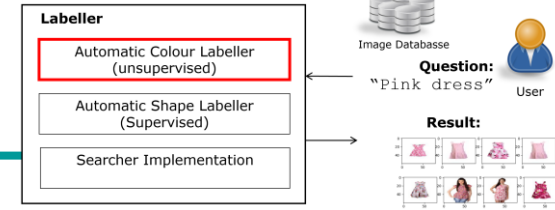


# Project 2

**Problems to solve** to build this tagger:



# Project 2: Colour Labelling




## How can we label the predominant colours?



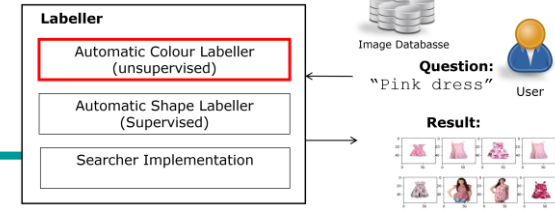
### Predominant colour labels:

*Yellow, Orange, Blue, Black, Green, White*

### 3 Questions:

- How do we represent colour? 
- How can we find the predominant colours of an image?
- How we do assign names to the predominant colours?

# Project 2: Colour Labelling

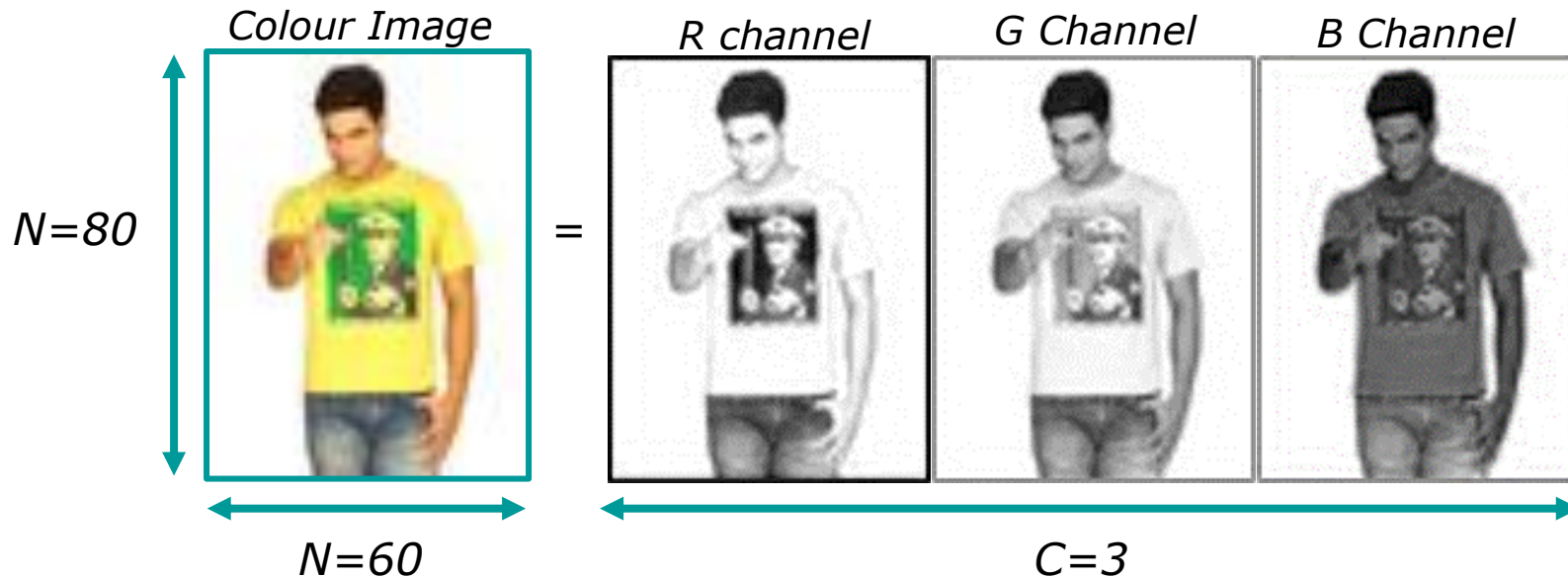


## How do we represent colour?

The answer is related to **how an image is represented?**

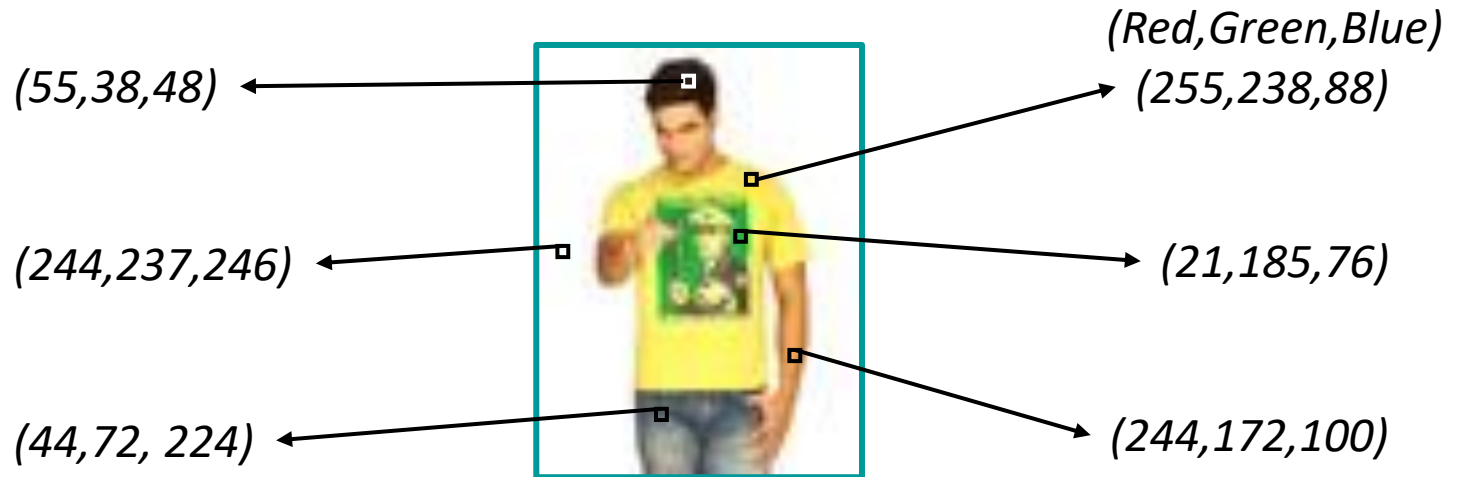
A colour image is a matrix of dimensions:  $N \times M \times C$

**Example:** Colour Image  $80 \times 60 \times 3$  (rows  $\times$  columns  $\times$  channels)  
Grey-level Image  $80 \times 60 \times 1$



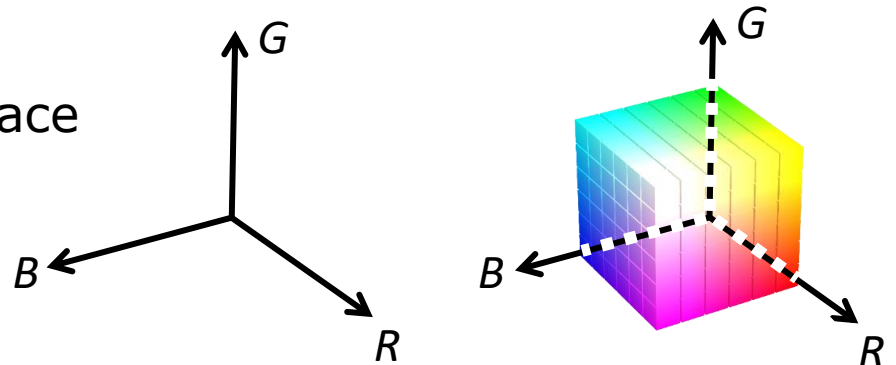
## Project 2: Colour Labelling

Let's look at the pixel level:



Go back to the initial question: **How is color represented?**

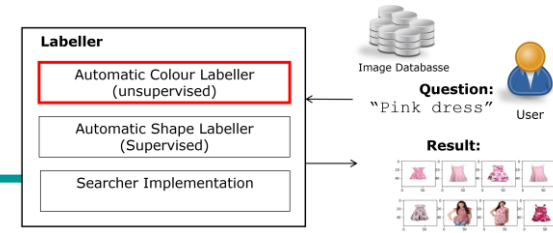
This is a 3-dimensional feature space





# Project 2: Colour Labelling

How can we solve the problem of automatic colour labelling?



**Labels of the predominant colours:**

*Yellow, Orange, Blue, Black, Green, White*

## 3 Questions:

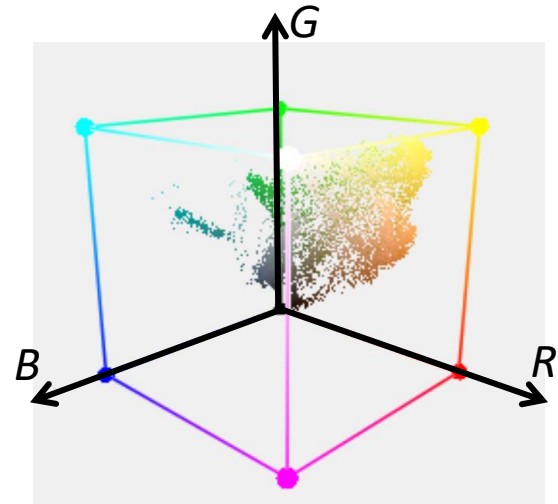
- How is colour represented? ✓
- How can we find the predominant colours of an image? ↖
- How can we assign a name to the predominant colors?

# Project 2: Colour Labelling

How can we find the predominant colours of an image?



Colour image ( $N \times M \times 3$ )  
Nun. of pixels = rows x columns



Dot colours are in the RGB  
colours of each pixel

$$X = \begin{pmatrix} x_R^1 & x_G^1 & x_B^1 \\ \vdots & \ddots & \vdots \\ x_R^n & x_G^n & x_B^n \end{pmatrix} \begin{matrix} \updownarrow \\ N \times M \\ \text{pixels} \end{matrix}$$

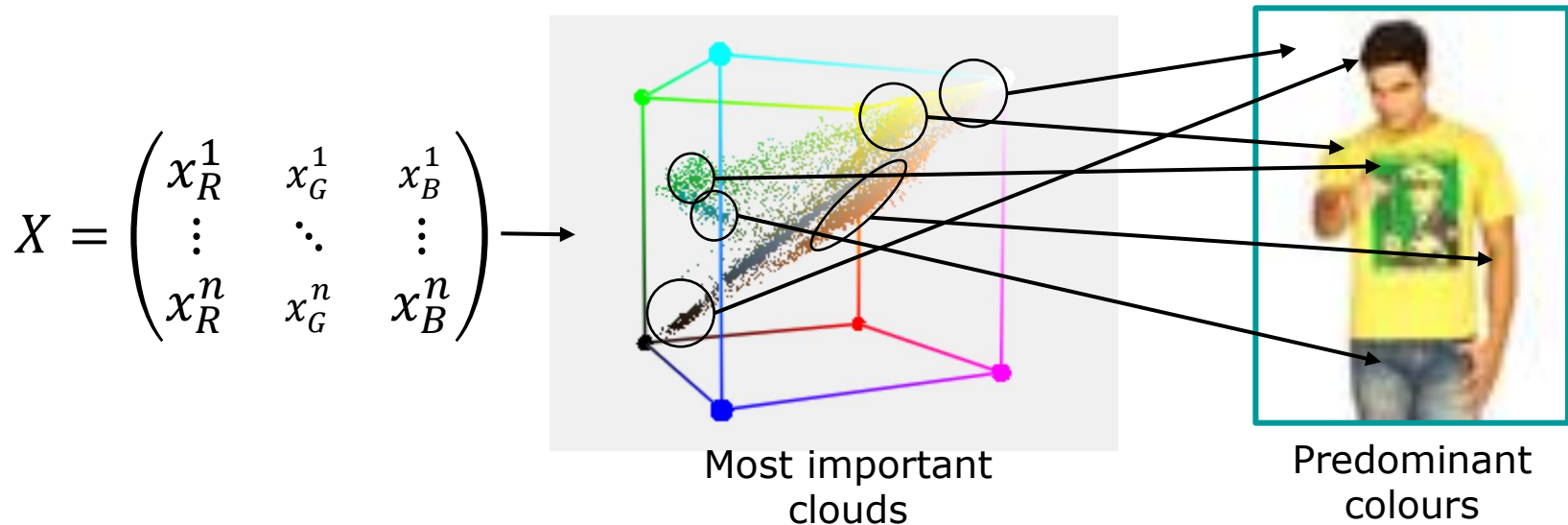
$\longleftrightarrow$  3 channels



**How can we extract  
predominant colours?**

## Project 2: Colour Labelling

**Goal:** We have a set of points in a three-dimensional space and we need to find the most important clouds in this set.



**Solution:** Unsupervised clustering of points

**How do we do it?** **K-means** algorithm

## Project 2: Colour Labelling

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In this project the K-means algorithm will be worked on

File: `Kmeans.py`

Class: `Kmeans`

Class parameters `Kmeans`

- `X`: Image we want to analyse.
- `K`: Number of clusters we will use
- `options`: Additional options (centroid initialization method, maximum number of iterations,...)
- 

First all necessary variables will be initialized when called:

```
Kmeans(X, K=3, options=None)
```

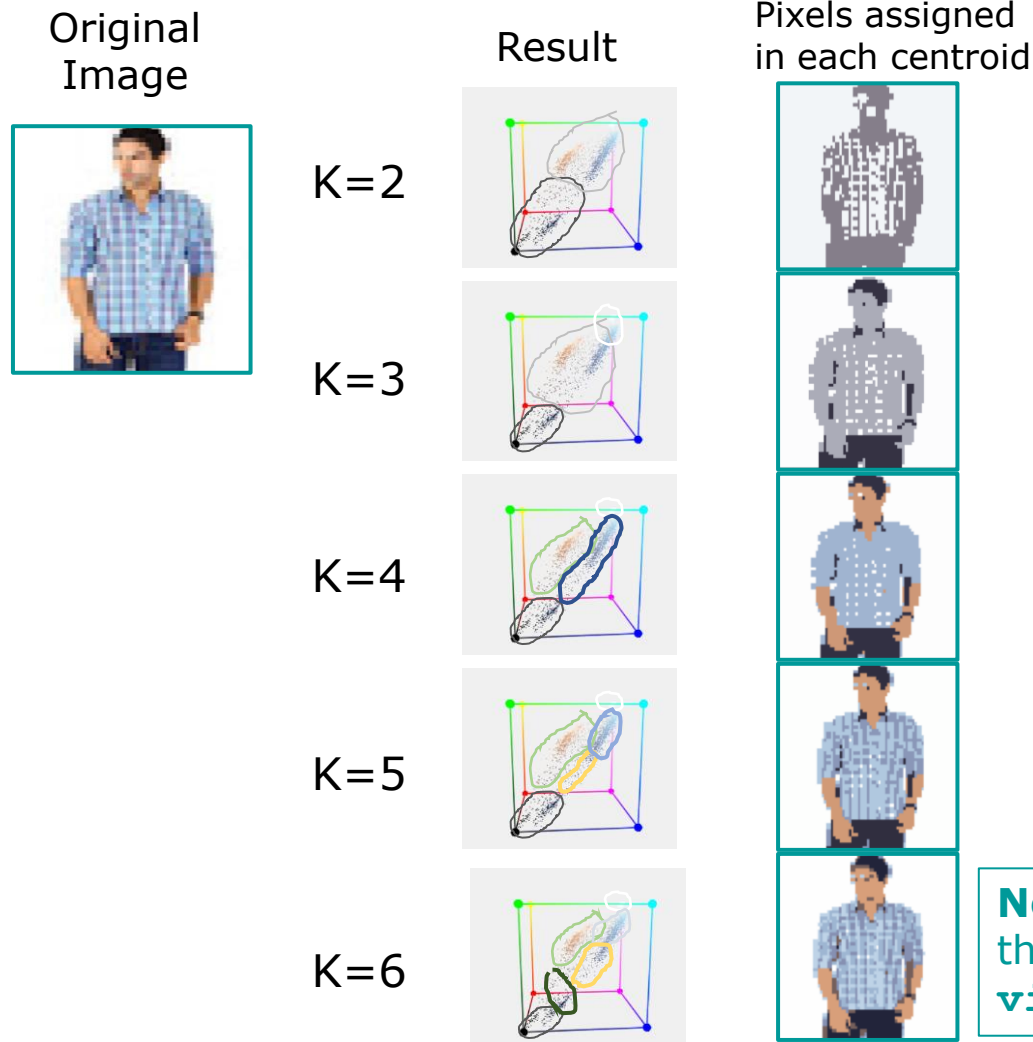
Finally, the algorithm will be applied until it converges:

```
Kmeans.fit()
```

Obtained centroids will be stored at the variable `centroids`

# Project 2: Colour Labelling

**Example:** K-means application for different K values



**Note:** This view is given by the function `visualize_k_means()`

# Project 2: Colour Labelling

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**K-means problem:** Which  $k$  is the best?

In theory lectures, we saw some ideas to choose the best  $k$ :

You can estimate a **Quality measurement of a given classification**, and study how it varies for different numbers of classes ( $k=2, 3, 4, \dots$ )

*(Usually this study is based on an analysis of class variance)*

## Some interesting statistics:

- Intra-class distance
- Inter-class distance
- Fisher's discriminant

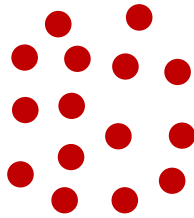
**we will use this one!!**

# Project 2: Colour Labelling

REMINDER from THEORY

## Intra-class distance

Example of 2 classes resulting from k-means:



Compact class  
*Good classification*



Non-compact class  
*Bad classification*



**Estimation:** Sum for all classes, the average distances between all the pairs of points of a class

$$D(C) = \frac{2}{m(m-1)} \sum_{j=1}^m \sum_{i=j+1}^m d(\vec{x}^i, \vec{x}^j) : \vec{x}^i, \vec{x}^j \in C, i, j: 1 \dots m$$

$$\sum_{i=1}^k D(C_i)$$

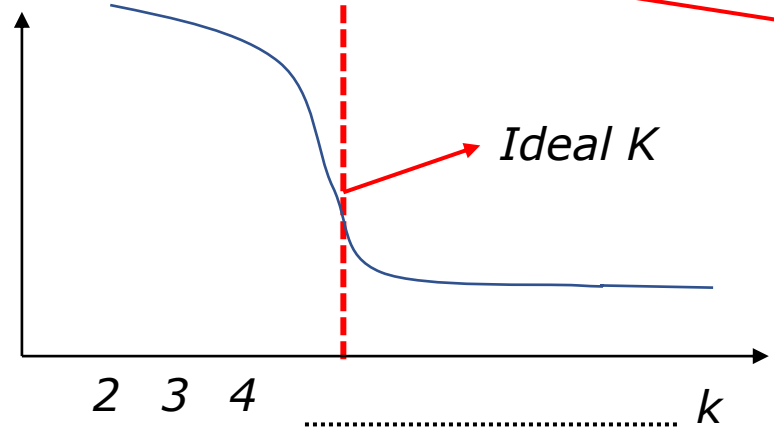


**it's good that it's small !!**

# Project 2: Colour Labelling

## Study of intra-class distance:

*Intra-class distance*

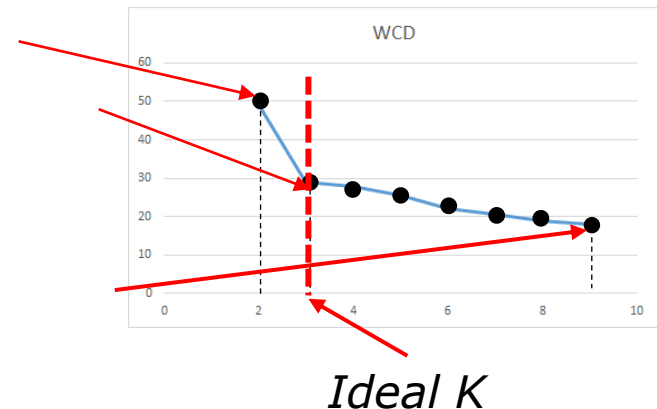


## In our case:

Given an image



`withinClassDistance()` for  $K=2$   
`withinClassDistance()` for  $K=3$   
.....  
`withinClassDistance()` for  $K=9$





# Project 2: Colour Labelling

## Study of intra-class distance:

Given an image

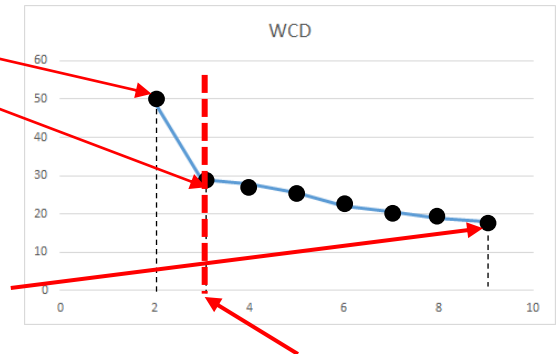


`withinClassDistance()` for K=2

`withinClassDistance()` for K=3

⋮

`withinClassDistance()` for K=9



**How we can find it ?** ← *k ideal*

We can calculate the % of Decrement:

$$\%DEC = 100 \frac{WCD_k}{WCD_{k-1}}$$

A possible threshold is to take the k from which

$$100 - \%DEC < 20\% \text{ (exemple)}$$

K	WCD	%DEC	100-%DEC
2	49.09		
3	29.11	59.29	40.71
4	27.95	96.03	3.97
5	25.68	91.86	8.14
6	22.00	85.70	14.30
7	20.61	93.65	6.35
8	18.82	91.31	8.69
9	18.09	96.15	3.85

*Ideal K*

< 20%

## Project 2: Colour Labelling

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**Problem:** Which  $k$  is the best?

To compute intra-class distance you will program the function:

```
whitinClassDistance()
```

Input: `self`

Output: `valorWCD`

Per a seleccionar la millor  $k$  programareu la funció:

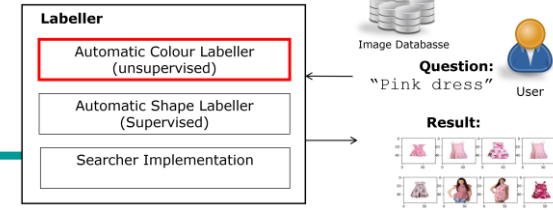
```
find_bestK()
```

Input: `self, max_K`

Output: `K`

# Project 2: Colour Labelling

How can we solve the problem of automatic colour labelling?



**Labels of the predominant colours:**

*Yellow, Orange, Blue, Black, Green, White*

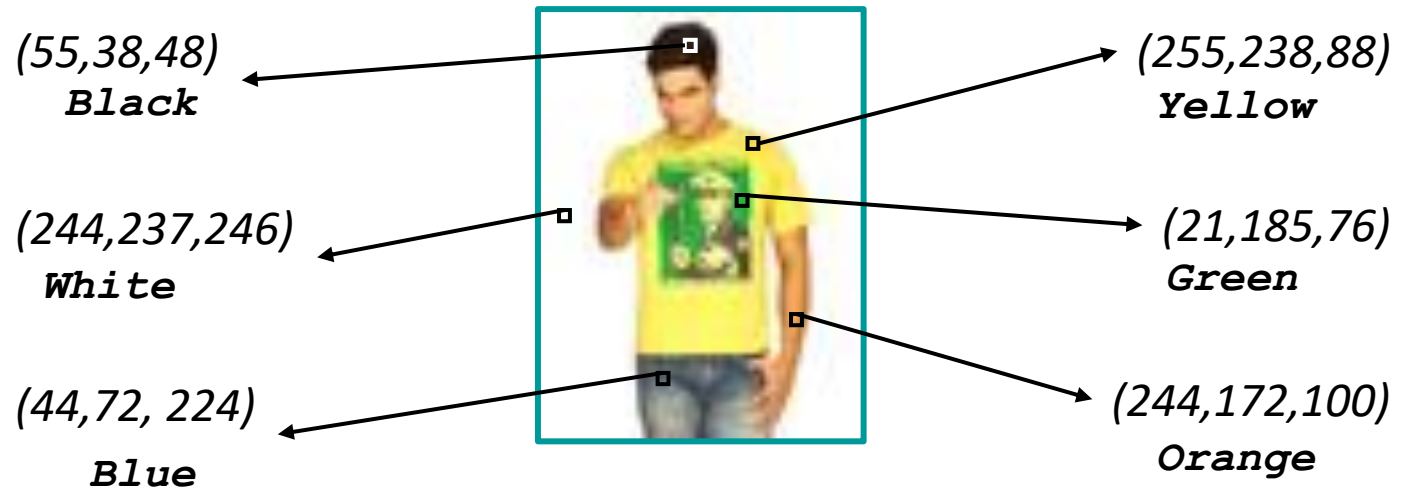
## 3 Questions:

- How is colour represented? ✓
- How can we find the predominant colours of an image? ✓
- How can we assign a name to the predominant colours? ↙

## Project 2: Colour Labelling

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How can we assign a name to the predominant colors?



**This problem requires simulating how humans perceive color !!!**

# Project 2: Colour Labelling

This problem has already been solved in a multidisciplinary way:

Experiments in  
Anthropology

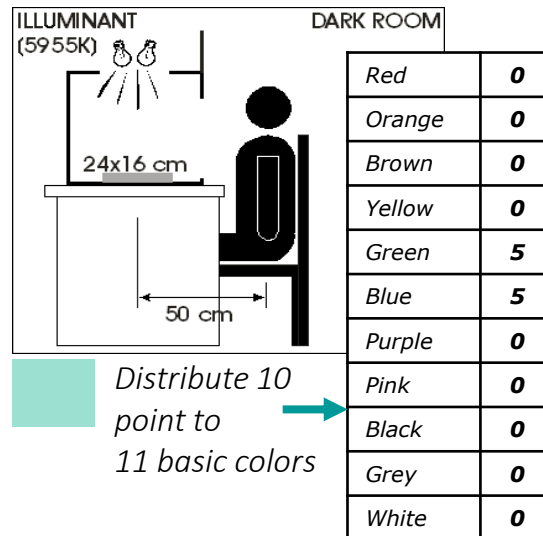
+

Experiments in  
Experimental  
Psychology

+

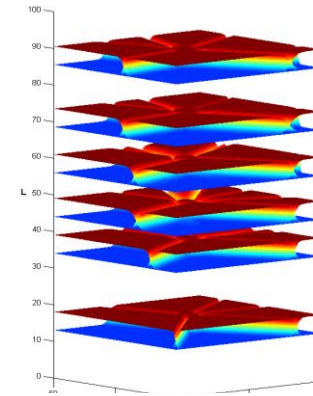
Mathematical  
Models in  
Computer Vision

*Studies on 78 languages have shown that there are 11 universal basic color names shared by the most evolved languages*



Berlin, B., & Kay, P. (1991) *Basic color terms: Their universality and evolution.* Univ of California Press.

R. Benavente, M. Vanrell, R. Baldrich (2006) *A dataset for fuzzy color naming, Color Research and Applications*



$(R, G, B) \rightarrow (P_{Red}, \dots, P_{White})$

Code available at:  
[http://www.cvc.uab.cat/colour\\_naming](http://www.cvc.uab.cat/colour_naming)

R. Benavente, M. Vanrell, R. Baldrich (2008) *Parametric fuzzy sets for automatic color naming, Journal of the OSA.*

**We will use this code!!!**

## Project 2: Colour Labelling

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### How we can assign a name to the predominant colors?

Using the results of the previous works, we will move from the RGB space to the space of the 11 color names:

$$(R, G, B) \rightarrow (P_{Red}, P_{Orange}, P_{Brown}, P_{Yellow}, P_{Green}, P_{Blue}, P_{Purple}, P_{Pink}, P_{Black}, P_{Grey}, P_{White})$$

for each RGB returns a vector of **11 probabilities of a human assigning each of the color names.**

The code of this conversion is given to you:

Function: `get_color_prob()`

File: `utils.py`

To assign labels to all the predominant colors, you will program:

Function: `get_color()`

File: `kmeans.py`

# Project 2: Colour Labelling

## Example:



centroid



[241, 184, 94]

( R , G , B )

Get\_color\_prob([241, 184, 94])

[ 0 , 0.0562 , 0 , 0.943 , 0 , 0 , 0 , 0 , 0 , 0 , 0 ]


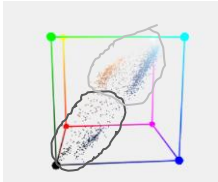

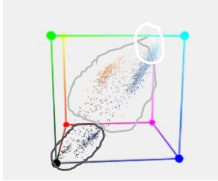

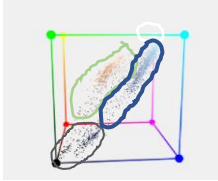

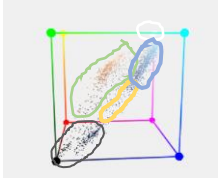

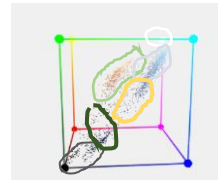

(Red, Orange, Brown, Yellow, Green, Blue, Purple, Pink, Black, Grey, White)

Probability( (241, 184, 94)=Yellow ) = 0.943

**Maximum**

# Project 2: Colour Labelling

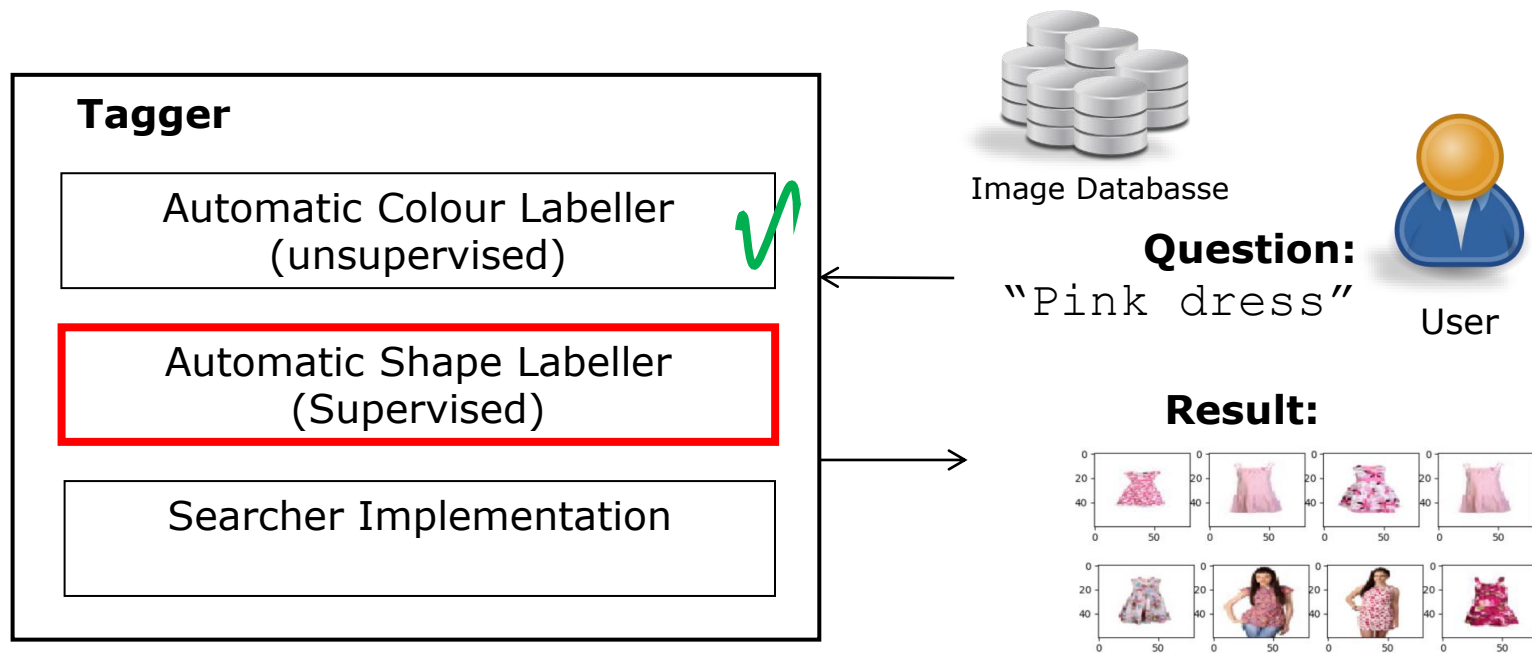
**Example:** application of labels for different results

Input image		Result	Assigned Pixels to centroids	Centroid labels
	K=2			<i>[Grey, Grey]</i>
	K=3			<i>[White, Grey, Black]</i>
	K=4			<i>[White, Blue, Orange, Black]</i>
	K=5			<i>[White, Blue, Purple Orange, Black]</i>
	K=6			<i>[White, Blue, Purple, Brown, Orange, Black]</i>



## Project 2

**Problems to solve** to build this tagger:



# Project 2: Shape Labelling

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How can we solve the problem of automatically labelling clothes?




**Shape Label:**

*Shirt*



## 3 Questions:

- How can we represent the shape of clothes? 
- How can we learn to classify clothes?
- How we assign the clothing type label to a new image?

# Project 2: Shape Labelling

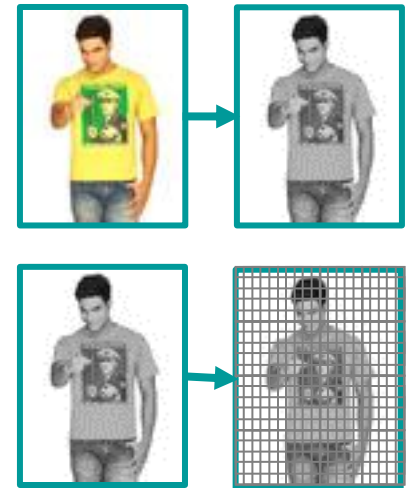
---

## How can we represent the shape of clothes?

What **feature space** we could use to represent the shape of clothes?

This is a **computer vision problem** that since we do not know enough, we will solve it in a very simple way as follows:

- 1) We will remove color, since we do not need it to represent the shape
- 2) We will take the pixels of the image directly as the feature of each position of the image.



# Project 2: Shape Labelling

## How can we represent the shape of clothes?

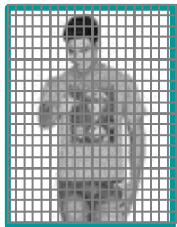
Extracting **image shape features**:

- 1) Removing colour, since we do not need it to represent the shape

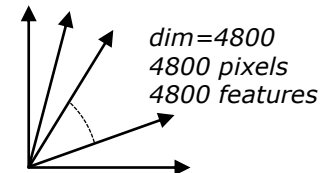
$$(R, G, B) \rightarrow \left( \frac{R + G + B}{3}, \frac{R + G + B}{3}, \frac{R + G + B}{3} \right)$$



- 2) We will take the pixels of the image directly as the feature of each position of the image.



$(1, 0, 0.5, \dots, 1) \rightarrow 80 \times 60$  pixel vector  
dimension=4800



# Project 2: Shape Labelling

---

How can we solve the problem of automatically labelling clothes?



**Shape Label:**

*Shirt*



## 3 Questions:

- How can we represent the shape of clothes? ✓
- How can we learn to classify clothes? ↖
- How we assign the clothing type label to a new image?

# Project 2: Shape Labelling

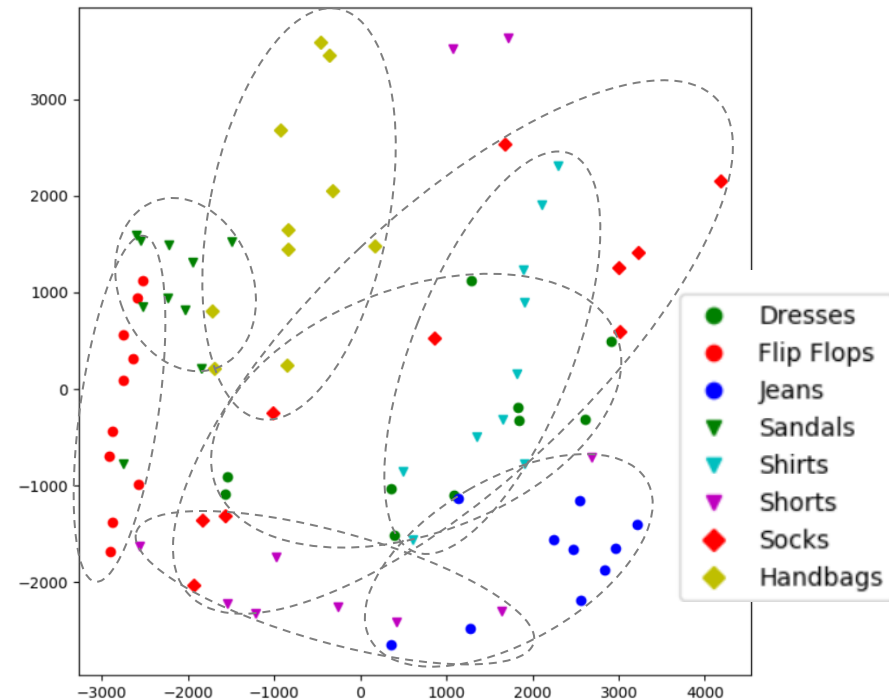
## How can we learn how to classify clothes?

Given the sample that we will use as a learning set, we can visualize this space of 4800 dimensions to an observable space of 2 dimensions:

$$X = \begin{pmatrix} x_1^1 & \dots & x_{4800}^1 & C_1 \\ \vdots & \ddots & \vdots & \vdots \\ x_1^{n_1} & \dots & x_{4800}^{n_1} & C_1 \\ x_1^1 & \dots & x_{4800}^1 & C_2 \\ \vdots & \ddots & \vdots & \vdots \\ x_1^{n_2} & \dots & x_{4800}^{n_2} & C_2 \\ \vdots & \ddots & \vdots & \vdots \\ x_1^1 & \dots & x_{4800}^1 & C_k \\ \vdots & \ddots & \vdots & \vdots \\ x_1^{n_k} & \dots & x_{4800}^{n_k} & C_k \end{pmatrix}$$

Principal Component  
Analysis (PCA)

*Change to the basis of the  
eigen vectors and take the  
first 2 dimensions*



**Observation of clusters despite the  
high loss of information (4800 to 2)**

# Project 2: Shape Labelling

## How can we learn to classify clothes?

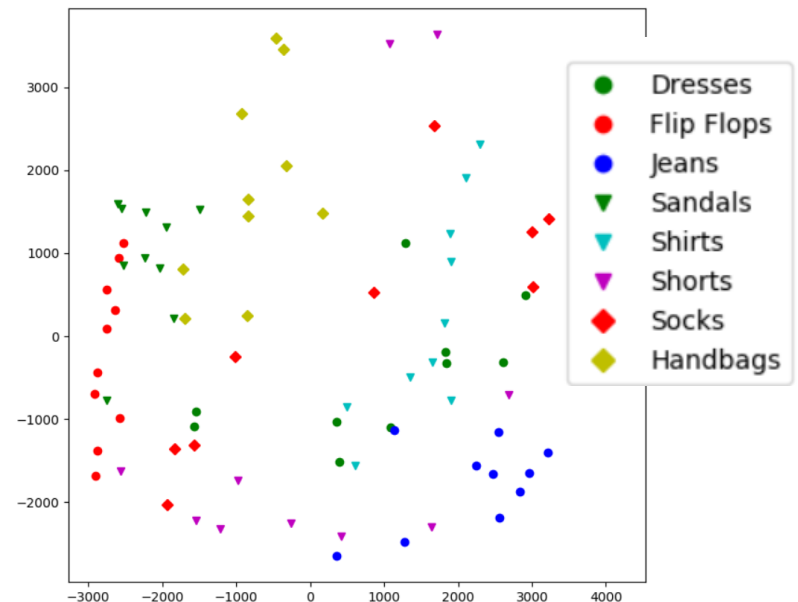
In theory lectures we have seen different families of classifiers:

- Linear classifier
- Nonlinear classifier
- Probabilistic classifier

**When the data present a clear model (linear, non-linear, probabilistic, ...)**

- Nearest k-neighbor classifier (KNN)

**When there is no clear model**



# Project 2: Shape Labelling

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How can we solve the problem of automatically labelling clothes?



**Shape Label:**

*Shirt*



## 3 Questions:

- How can we represent the shape of clothes? ✓
- How can we learn to classify clothes? ✓
- How we assign the clothing type label to a new image? ↗

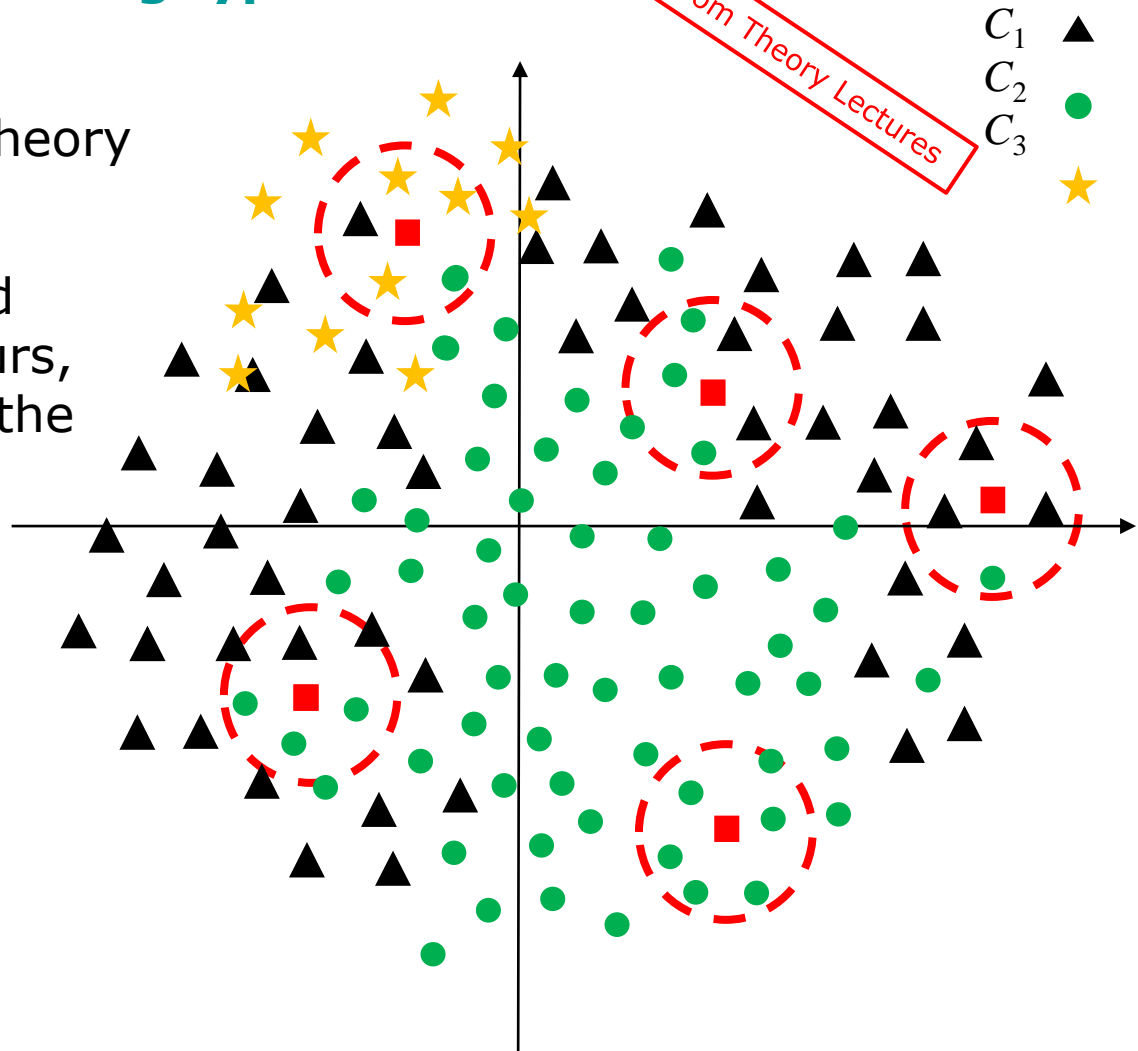


# Project 2: Shape Labelling

How do we assign the clothing type label to a new image?

**K-NN Algorithm** seen in theory lectures,

**Idea:** The decision is based on the closest neighbours, considering what class the closest N-neighbours belongs to.

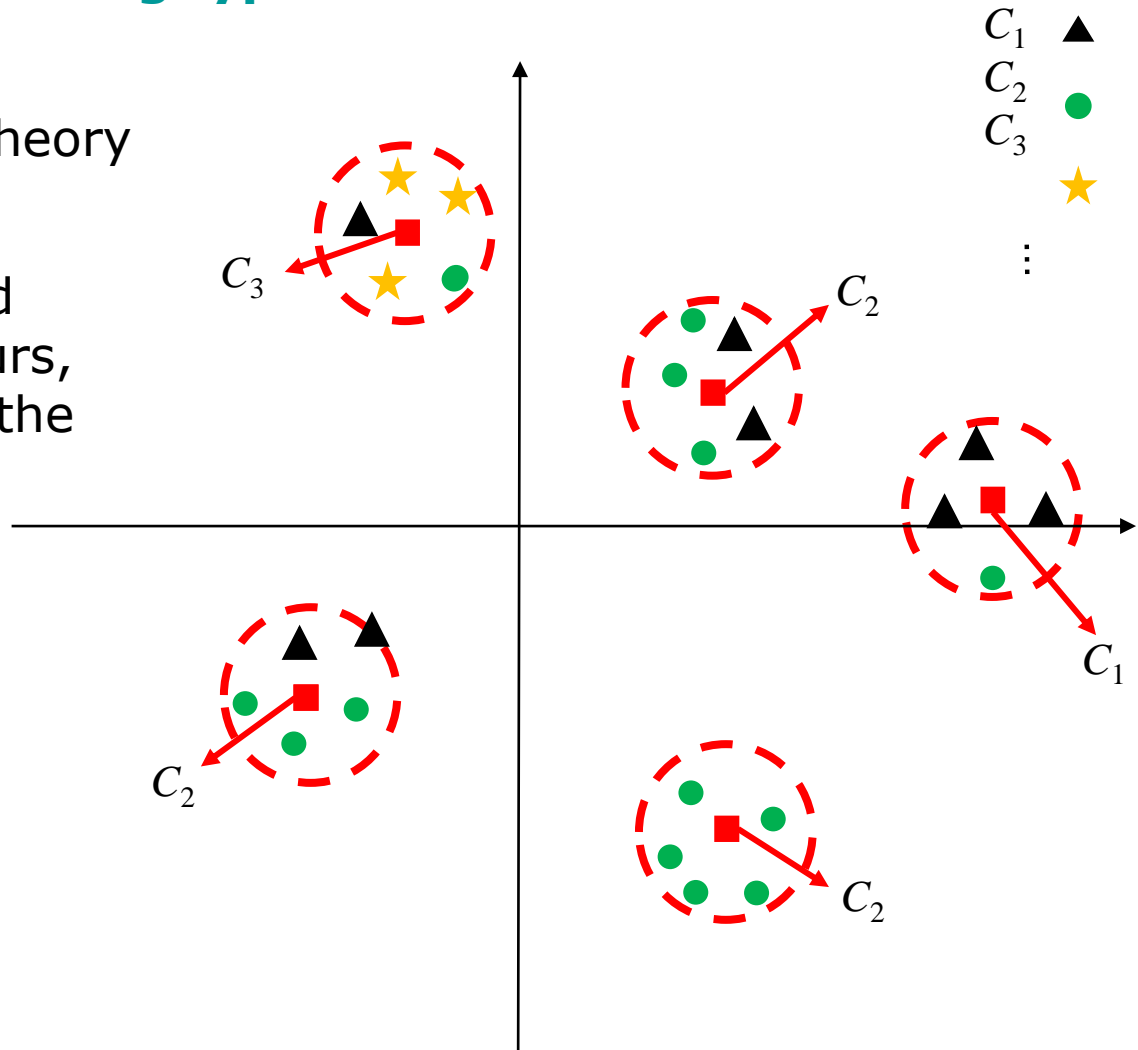


# Project 2: Shape Labelling

How do we assign the clothing type label to a new image?

**K-NN Algorithm** seen in theory lectures,

**Idea:** The decision is based on the closest neighbours, considering what class the closest N-neighbours belongs to.



# Project 2: Shape Labelling

How do we assign the clothing type label to a new image?

## K-NN Algorithm

Function decision  
(to classify  $\vec{y}$ )

```
For ( $\vec{x}^j \in X$ ) do
    List = insert( $[d(\vec{y}, \vec{x}^j), C_j]$ , List)
fFor
    Neighbours = First_k(sorted_d(List))
If ( $\#(\text{Neighbours}, C_1) > \#(\text{Neighbours}, C_2)$ )
     $\vec{y} \in C_1$ 
Sinó
     $\vec{y} \in C_2$ 
fSi
```

$$d(\vec{y}, \vec{x}^i) \rightarrow \begin{pmatrix} x_1^1 & \dots & x_{4800}^1 C_1 \\ \vdots & \ddots & \vdots \\ x_1^{n_1} & \dots & x_{4800}^{n_1} C_1 \\ x_1^1 & \dots & x_{4800}^1 C_2 \\ \vdots & \ddots & \vdots \\ x_1^{n_2} & \dots & x_{4800}^{n_2} C_2 \\ \vdots & \ddots & \vdots \\ x_1^1 & \dots & x_{4800}^1 C_k \\ \vdots & \ddots & \vdots \\ x_1^{n_k} & \dots & x_{4800}^{n_k} C_k \end{pmatrix}$$

## Example:

$$\vec{y} = [1, 1, 1, 0.2, 0.5, 0, 0, 1, \dots, 1]$$



$d=23$

$$[1, 1, 1, 0.1, 0.4, 0.2, 1, 1, \dots, 1]$$



$d=59$

$$[0, 0, 0, 0.7, 0.5, 1, 0, 1, \dots, 1]$$



$d=103$

$$[0, 0, 0, 0.2, 1, 1, 0, 0.4, \dots, 0]$$



# Project 2: Shape Labelling

---

How can we solve the problem of automatically labelling clothes?



**Shape Label:**

*Shirt*



## 3 Questions:

- How can we represent the shape of clothes? ✓
- How can we learn to classify clothes? ✓
- How we assign the clothing type label to a new image? ✓

## Project 2: Shape Labelling

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### The answer to the 3 questions in the code:

- How can we represent the shape of clothes?

Function: `read_dataset()`

Folder: `images/train`

File: `utils_data.py`

- How can we learn to classify clothes?

Function: `KNN.__init__()`

File: `KNN.py`

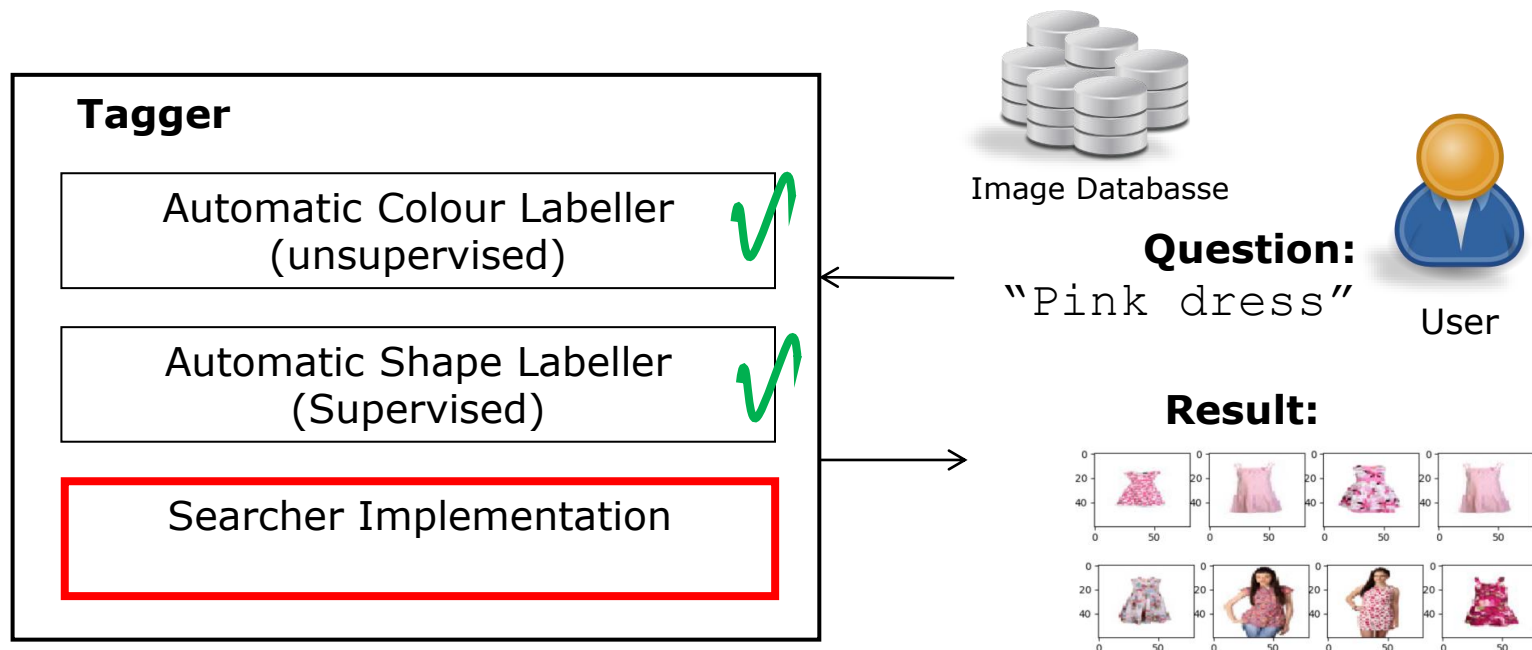
- How do we assign the clothing type label to a new image?

Function: `KNN.predict()`

File: `KNN.py`

# Project 2

**Problems to solve** to build this tagger:



# Project 2: Image Searcher

---

## How do we implement a search engine based on color and shape labels?

We already have images labeled COLOR and SHAPE,

To search with labels, you need to code the functions:

```
Retrieve_img_by_color()
```

```
Retrieve_img_by_class()
```

```
Retrieve_combine()
```

```
File: my_labeling.py
```

# Project 2

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## Planning

**Part 1: CODING** Kmeans and colour

**Online Sessions:** Week of **March 27th**

**Delivery:** What? Exercises indicated in Part 1 Guidelines (GuiaP2\_Part1.pdf)  
When? Before **Monday, April 10th** at 23:55h.

**Part 2: CODING** kNN and shape

**Online Sessions:** Week of **April 17th**

**Delivery:** What? Exercises indicated in Part 2 Guidelines (GuiaP2\_Part2.pdf)  
When? Before **Tuesday, May 2nd** at 23:55h.

**Part 3: Performance Evaluation and Analysis**

**Online Sessions:** Week of **May 8th**

**Delivery:** What? Report indicated in Part 3 Guidelines (GuiaP2\_Part3.pdf)  
and whole code with the experiments  
When? Before **Thursday, May 18th** at 23:55h.

**ORAL Presentation**, explanation of your whole Project

**Online Sessions:** Week of **May 22nd**

**Delivery:** Slides of the presentation before **Thursday, June 1st** at 23:55h



# Project 2

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## Practical tips for the 1st Delivery:

- Exercises are in file `<Practica2_1.pdf>` you will find it at `cv.uab.cat` in Practicum Section > Project 2. This document will guide you in all the coding.
- Save all the functions in the file `<Kmeans.py>`
- Code the functions exactly how they are specified. Pay attention on the input parameters and output results.
- Delivery will be at `cv.uab.cat`, you will deliver the file `Kmeans.py` with all the functions you worked on this Part 1.
- We highly recommend you to **attend the online session with the exercises practically coded** in order you can use the session to solve the final details with your lecturer, and in the way to achieve the deadline.

# Project 2

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## Practical tips for the 2nd Delivery:

- Exercises are in file `<Practica2_2.pdf>` you will find it at `cv.uab.cat` in Practicum Section > Project 2. This document will guide you in all the coding.
- Save all the functions in the file `<KNN.py>`
- Delivery will be at `cv.uab.cat`, you will deliver the file `KNN.py` with all the functions you worked on this Part 2
- We highly recommend you to **attend the online session with the exercises practically coded**. In this way, you can use the session to solve the final details with the help of your lecturer to achieve the delivery deadline.

# Project 2

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## Practical tips for the 3rd Delivery:

- Exercises are in file `<Practica2_3.pdf>` you will find it at `cv.uab.cat` in Practicum Section > Project 2. This document will guide you in all the coding.
- Save all the functions in the file `<my_labeling.py>`
- Delivery will be at `cv.uab.cat`, you will deliver the files `Kmeans.py`, `KNN.py`, and `my_labeling.py` with all the functions you work on this project, and the **report** where you describe all the obtained results and analysis done.
- We highly recommend to **attend the online session with the exercises practically coded**. In this way, you can use the session to solve the final details with the help of your lecturer to achieve the delivery deadline.

# Project 2

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## Tips to prepare Report and Oral Presentation:

Both should be organized as follows:

- **Introduction** (list of contents and summary about what you did different from the rest)
- **At least 3 analysis** from those we mentioned in the guideline 3. An analysis should contain the following:
  - **Brief Introduction about which parameter/method** are you analysing
  - **Comparison between the original result and the new results.**
  - **Explanation of the results** (*Why it works better?, or worse?, if it is more efficient?, Could you find cases where one method works better than the other?*)
- **Conclusion**  
*Main problems you found out, what have you learnt?, what would you improve now?*

## Different parameters or methods to be analysed

- Centroid initialization method
- Using a colour space different from RGB
- Using different K values
- Using different methods to find the best K Interclass variance, Fisher,...)
- Using different methods to label color (multiple labels, new color terms, ...)
- Using different features for KNN → Different image sizes
- Using different features for KNN → Features computed separately (*average value of all pixels, pixels on the right side versus left side, pixels at top versus bottom, ...*)
- ...

# Project 2

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## Evaluation:

***Mark Project 2 = 0.75 \* Group Mark + 0.25 \* Individual Mark***

❖ ***Group Mark = 0.6 \* Code Mark + 0.3 \* Report + 0.1 \* Group Presentation***

❖ ***Individual Mark = 0.5 \* Individual Presentation + 0.5 \* Group Participation***