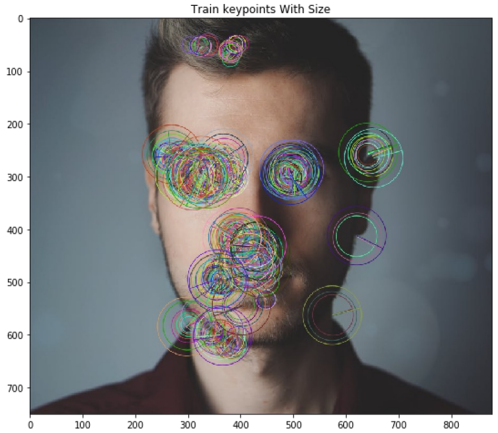
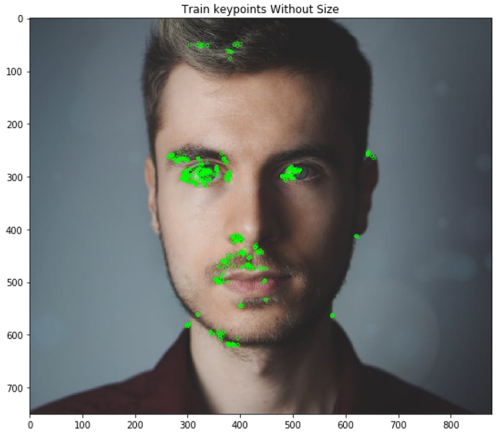
Computer Vision

Exploration & feature engineering

Plan





- **Data quality**
  - **Visualize**
  - **Aspect ratio and size**
  - **Label composition**
  - **Datasets comparison**
  - **Normalization & transformation**
- **Feature engineering**
  - **SIFT**
  - **ORB**
- **Dimensionality reduction**
  - **PCA**
  - **t-SNE**

Data quality

- Can I do my job with it ?
- Can I get around with it ?

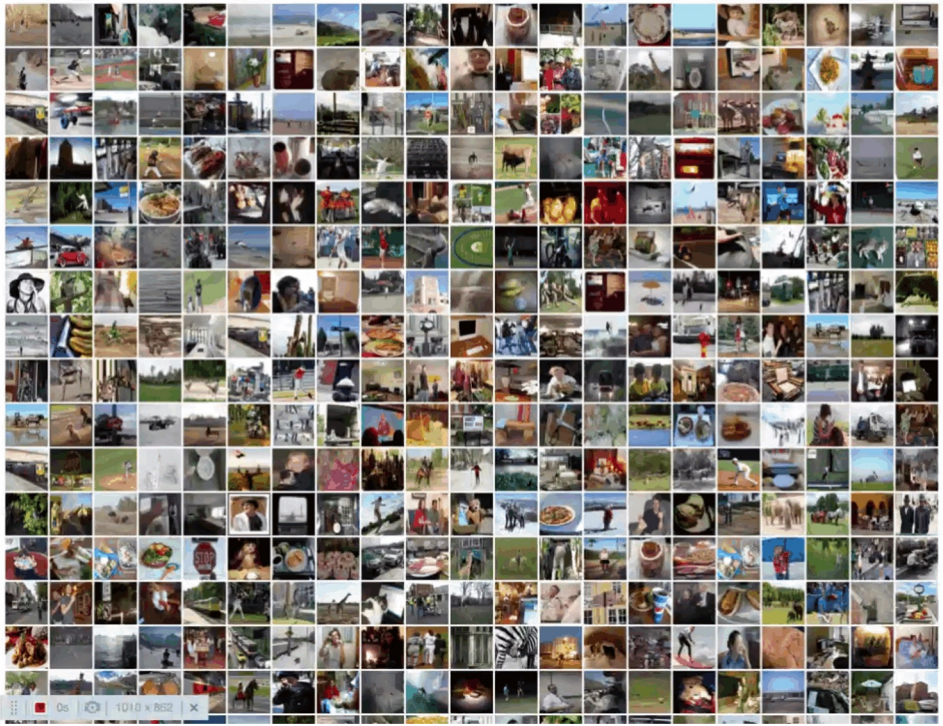
Visualize

- Visual inspection
  - easyimages (py module)
  - HTML renderer
- Test each image path
- Images / label

- Missing labels (mixed datasets)
- Wrong labeling

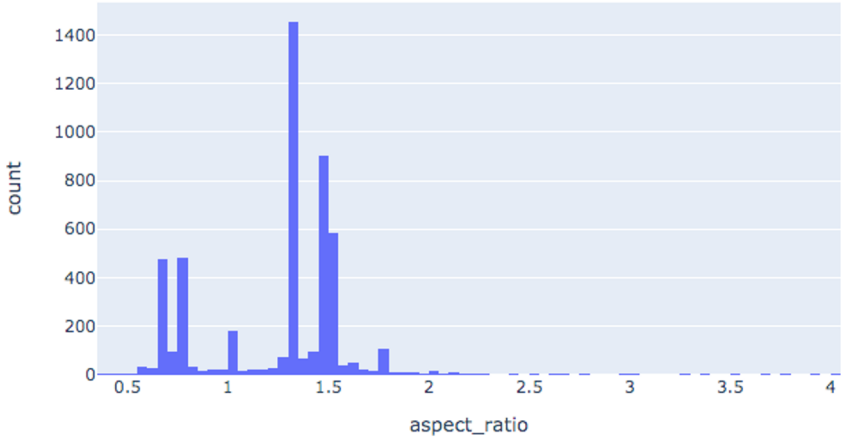

```
from easyimages import EasyImageList

Li = EasyImageList.from_folder('/Users/jcieslik/Downloads/val2017/')
Li.symlink_images()
Li.html(sample=500, size=44)
```



Aspect ratio and size

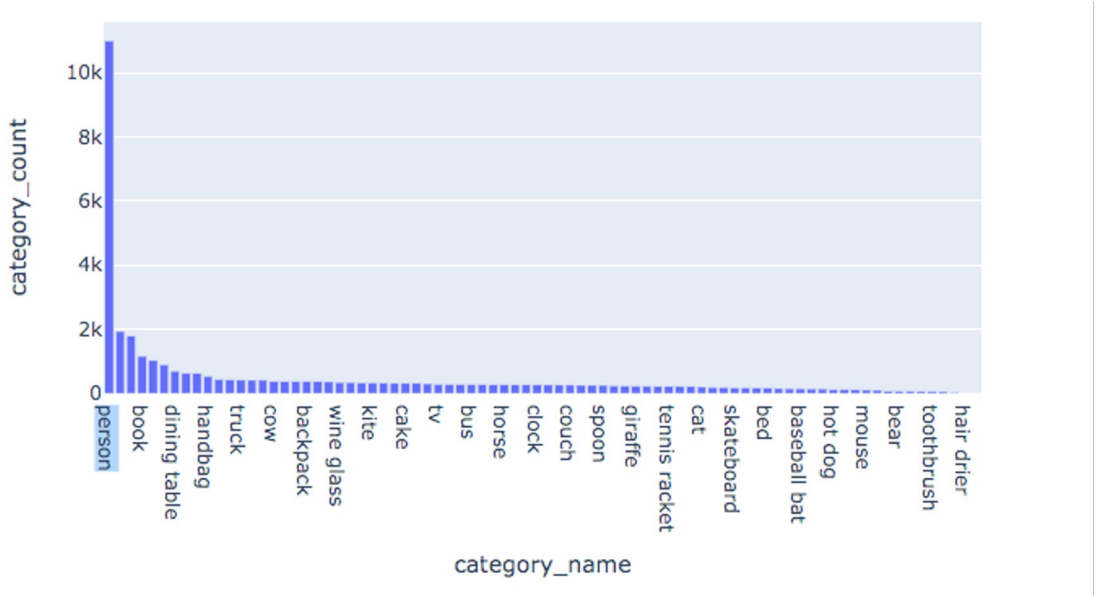
- Size or definition: W X H (1600 X 900)
- Aspect ratio: W / H (16 / 9)
- Distribution (total and per label)
  - Unimodal: resizing or not
  - Bimodal: resizing
  - Multimodal: batch training or else
- Anchor box size per label



- Destructive resizing
- Padding method
- Visual inspection

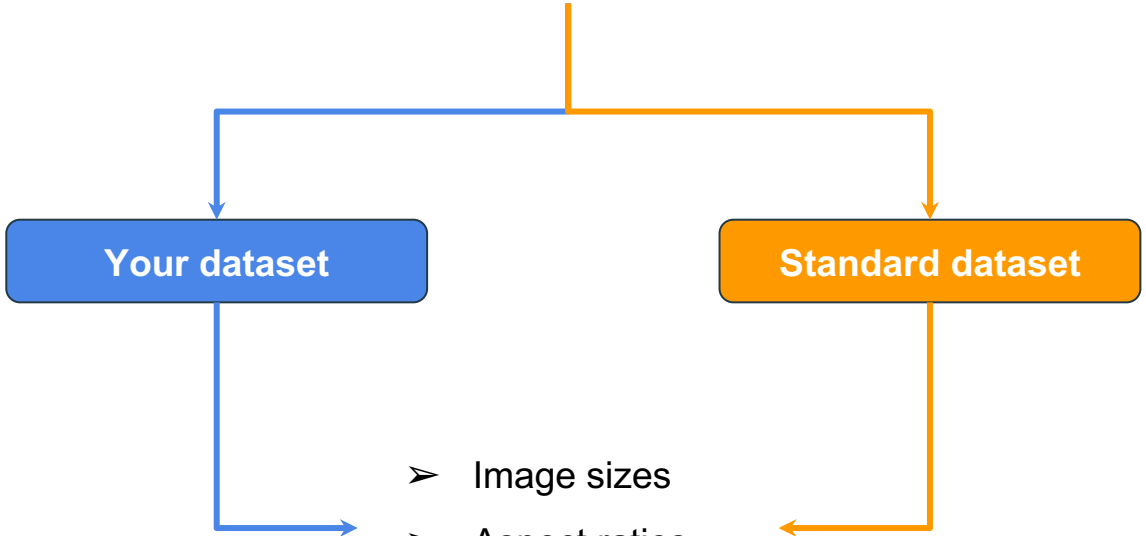
Label composition

- Oversample
- Downsample
- Update dataset
- Balance model weights



Datasets comparison

- What's your target model (architecture) ?
- Best performance obtained on which dataset ?



- Image sizes
- Aspect ratios
- Anchor box sizes

Normalisation & transformation

Increase training speed

- **Pixel Normalization**: pixel values range 0-1.
- **Pixel Centering**: pixel values have a zero mean.
- **Pixel Standardization**: pixel values have a zero mean and unit variance (gaussian distrib).
- Per image / batch / **dataset**

Increase efficiency and robustness

- **Histogram equalization**: improve feature appearance by increased contrast
- **Crop / zoom / rotations**: generate more or less possibilities
- **Denoising**: improve feature detection

- This is all theory
- Look for proofs

Feature Engineering

Algorithms

Feature notions

Characteristics

- Feature = interesting image zones
- Characteristics:
  - Repeatable
  - Distinct
  - Local (minimum neighbors impact)
- Based on gradient disruption

Algorithms

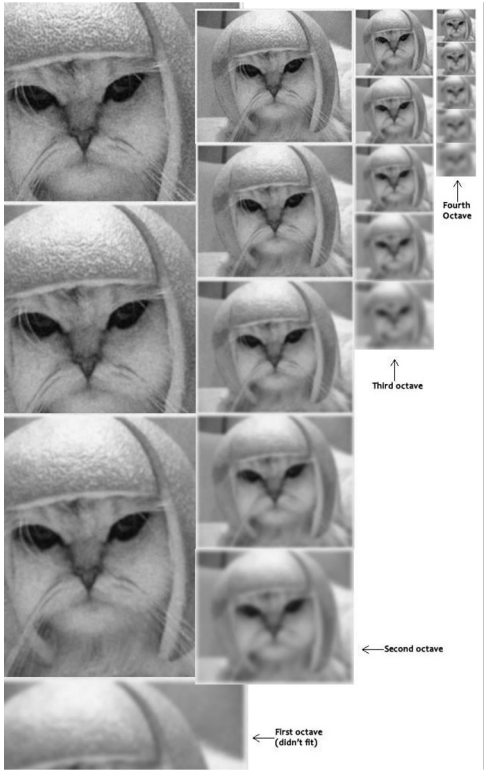
- Detectors: HARRIS, FAST
- Descriptors: BRIEF
- Both: SIFT, ORB, Conv layer

Exemples of repeatable and distinct

Scale Invariant Feature Transform (SIFT)

Feature Detector

- Scale space



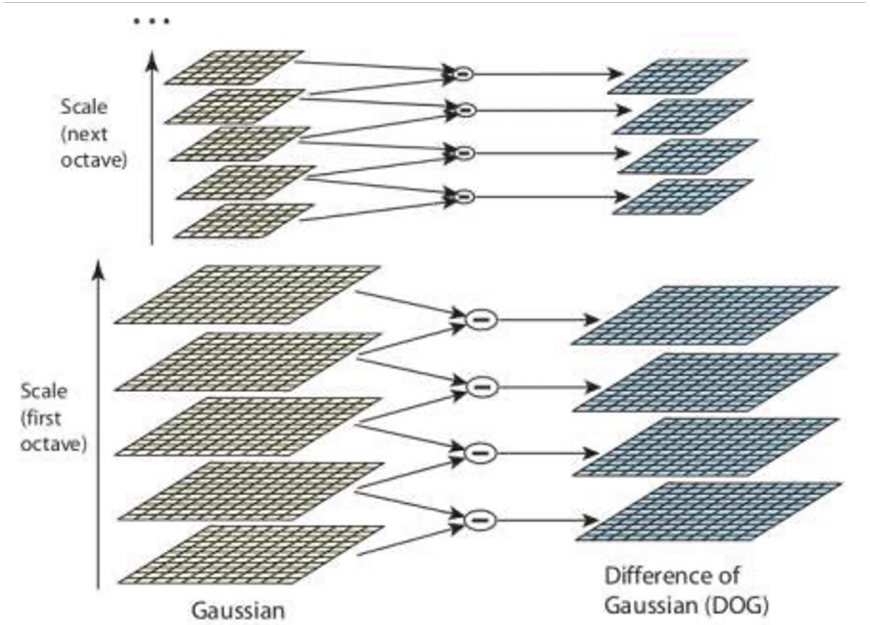
Scale Invariant Feature Transform (SIFT)

Detector

- Scale space
- Keypoints (extremes in Gaussian differences)

Descriptor

- Vectors of n dimensions
- Orientation
- Brightness normalisation
- Feature matching

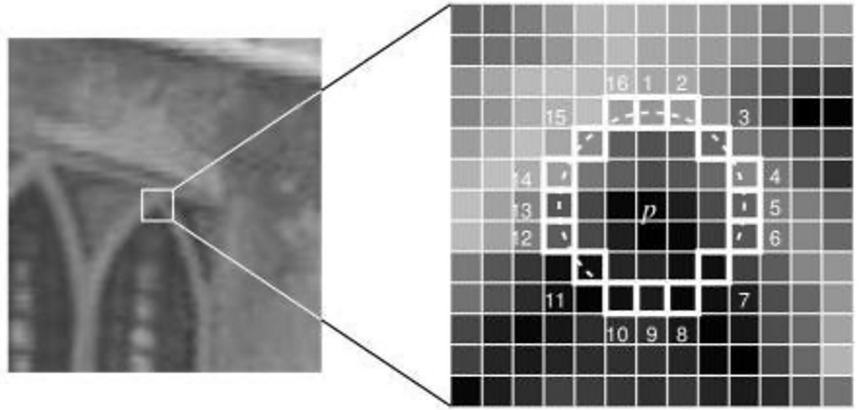


Oriented FAST and Rotated BRIEF (ORB)

- Open source
- Fastest
- Most efficient

Detector (FAST)

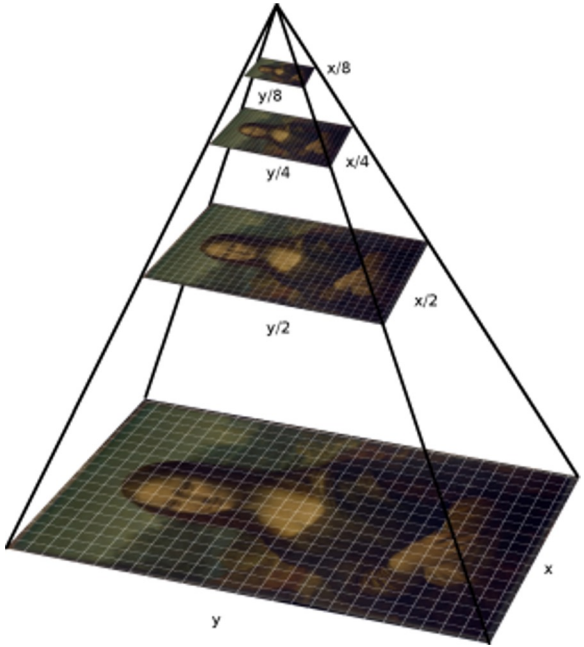
- > 8 pixels darker / lighter = feature



Oriented FAST and Rotated BRIEF (ORB)

Detector (FAST)

- > 8 pixels darker / lighter = feature
- Orientation based on multiscale pyramid



Oriented FAST and Rotated BRIEF (ORB)

Descriptor (BRIEF)

- Binary vector of 128 to 512 bits
- Feature matching

Dimensionality Reduction

Why and how ?

Purpose

- 1 pixel = 1 variable
- 64 x 64 pixels = **4096** variables !
- Features detectors = too many variables !

Can we get rid of some of them ?

Code exemple: https://www.kaggle.com/hamishdickson/preprocessing-images-with-dimensionality-reduction

Variance

- How far from the mean
- Low = all points are similar
- High = Very different points

Assumptions:

- Background and object = high variance
- I can delete some pixels and keep high variance

Example

Vector(10): 2, 3, 3, 3, 4, **4**, 4, 5, 5, **6**

Variance = s^2 = 1.4333333
Mean = 3.9

Vector(9): 2, 3, 3, 3, 4, 4, 5, 5, 6

Variance = s^2 = 1.6111111
Mean = 3.9

14.3%

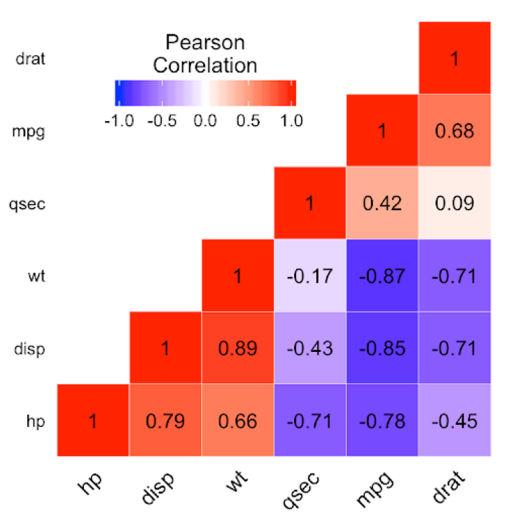
Vector(9): 2, 3, 3, 3, 4, 4, 4, 5, 5

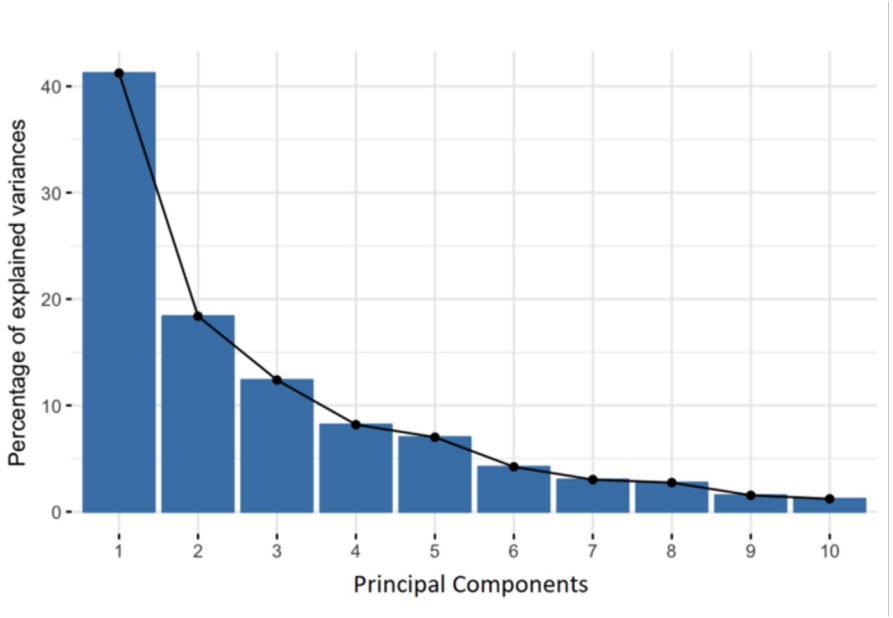
Variance = s^2 = 1
Mean = 3.7

28.6%

Principal Component Analysis

- Reduce the number of variables of a data set, while preserving as much information as possible
- Requires **dataset pixel standardization**





t-SNE

Steps:

- Probability of difference in high dimension
- Probability of difference in low dimension

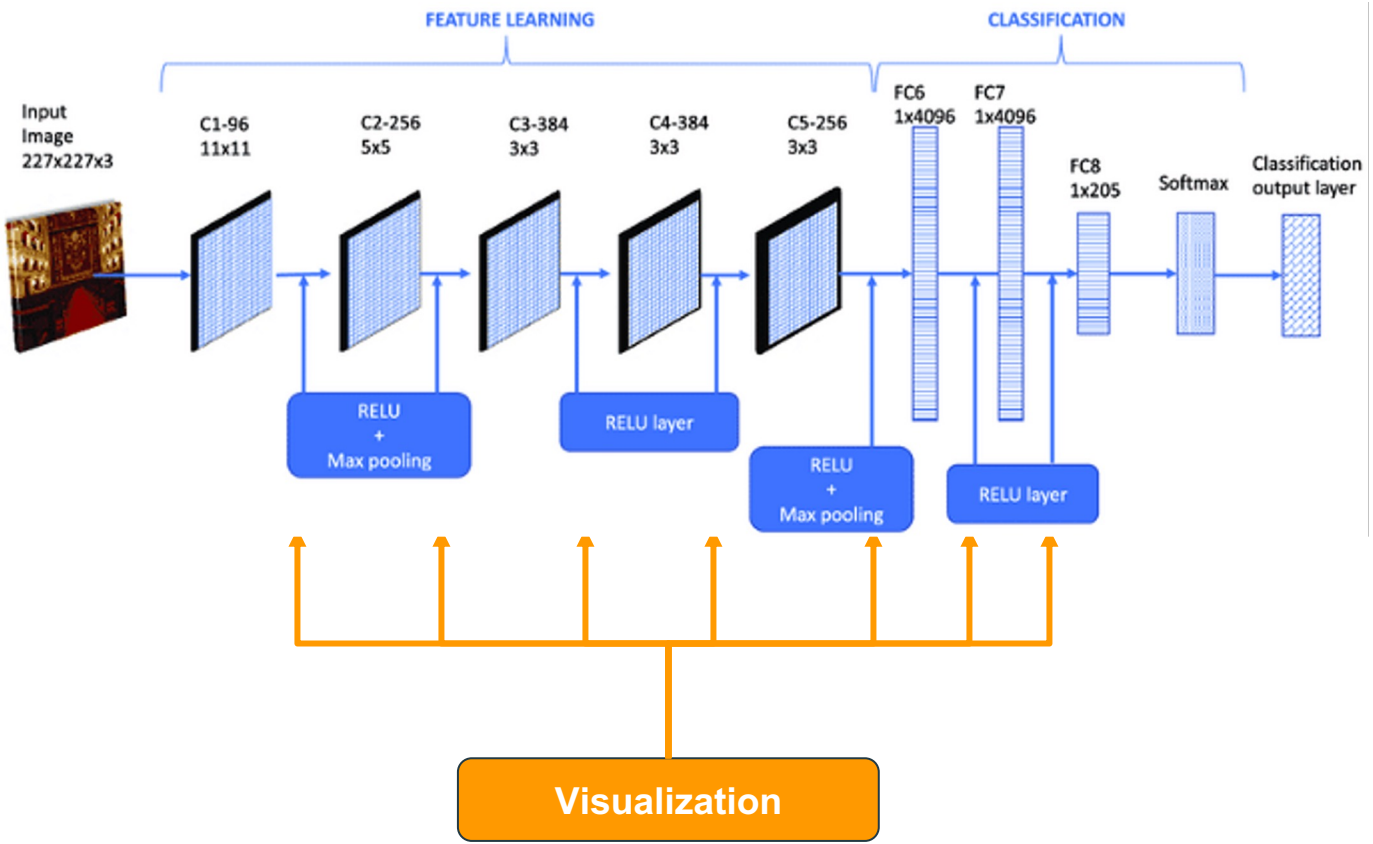
- Hyperparameters
- Computationally expensive

9

UMAP:

- Slightly better projection than t-SNE
- Much faster

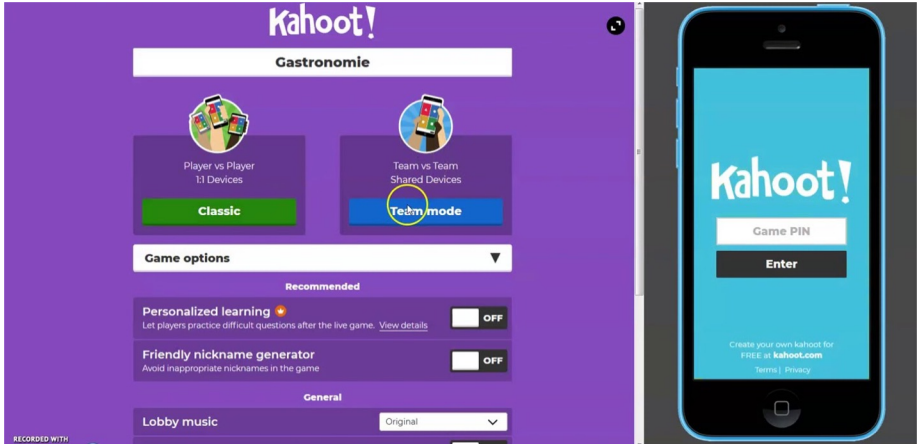
Use Case


FEATURE LEARNING
CLASSIFICATION
Input
Image
227x227x3
C1-96
11x11
C2-256
5x5
C3-384
3x3
C4-384
3x3
C5-256
3x3
FC6
1x4096
FC7
1x4096
FC8
1x205
Softmax
Classification
output layer
RELU
+
Max pooling
RELU layer
RELU
+
Max pooling
RELU layer
Visualization

Exercices

Real cases

Quizz Kahoot !



- Link: https://kahoot.it/
- Pin: **08400066**

Compete: digit recognizer

Link: kaggle.com/c/digit-recognizer

- **Create your team !**
- **Define your strategy**
- **Submit your model**

Ai design: dataset / concept

- Select a dataset or an app idea
- Create your team !
- Define your strategy
- Prototype and test

Google Dataset Search Beta

Search for Data Sets

kaggle

OpenML