#### EVML3

# FEATURE DATA EXPLORATION HANDS-ON

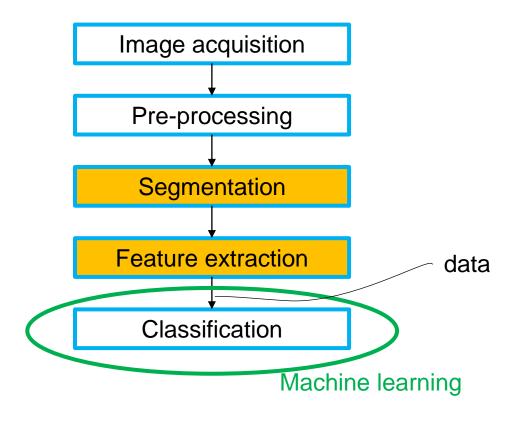
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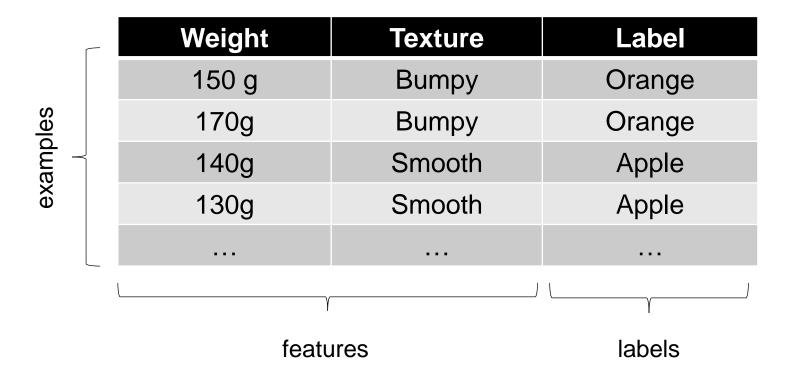
#### **CONTENTS**

- Basic segmentation and feature extraction
- Splitting your data
- Exploratory data analysis
- Feature engineering
- Data preparation

## A JUMP-START TO DATA 2

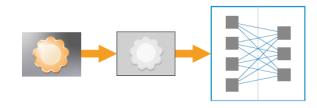


## TRAINING DATA

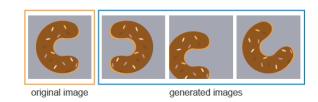


### **GENERAL TIPS ON DATA**

- Reduction of the image size
- Minimize variance
   (If the avoidable differences to the inspected images are reduced, less image data is needed to train an algorithm
- Static ambient conditions such as stable lighting, a consistent monochrome background, fixed positioning of the inspected objects and unchanging orientation



• Increase in the number and variance of the training data, e.g. by generating additional training data, or so-called augmentation.



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#### **BASIC SEGMENTATION EXAMPLE**

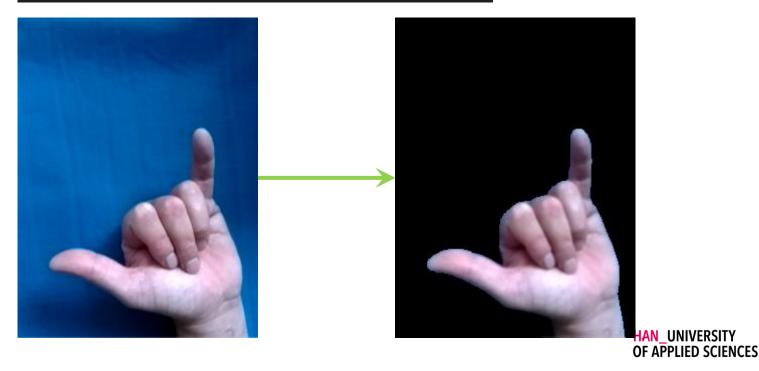
segment.py
 create segmentation function in a module

```
6 ∨ def maskBlueBG(img):
         """ Asssuming the background is blue, segment the image and return a
             BW image with foreground (white) and background (black)
         # Change image color space
         img hsv = cv.cvtColor(img, cv.COLOR BGR2HSV)
         # Note that 0≤V≤1, 0≤S≤1, 0≤H≤360 and if H<0 then H←H+360
12
         # 8-bit images: V < 255 V, S < 255 S, H < H / 2 (to fit to 0 to 255)
         # see https://docs.opencv.org/4.5.3/de/d25/imgproc color conversions.html#color convert rgb hsv
         # Define background color range in HSV space
         light blue = (75,125,0) # converted from HSV value obtained with colorpicker (150,50,0)
         dark blue = (140,255,255) # converted from HSV value obtained with colorpicker (250,100,100)
         light blue = (0,0,0) # converted from HSV value obtained with colorpicker (150,50,0)
         dark blue = (255,50,255) # converted from HSV value obtained with colorpicker (250,100,100)
         # Mark pixels outside background color range
         mask = ~cv.inRange(img hsv, light blue, dark blue)
         return mask
```

## **BASIC SEGMENTATION EXAMPLE**

segment.py

```
# mask background
mask = maskBlueBG(img)
masked_img = cv.bitwise_and(img, img, mask=mask)
```



extract.py or fetch\_data.py

import our segmentation function from module

```
5 from segment import maskBlueBG
```

segment the image and do a bit of denoising

```
# mask background
img_BW = maskBlueBG(img)

# perform a series of erosions and dilations to remove any small regions of noise
img_BW = cv.erode(img_BW, None, iterations=2)
img_BW = cv.dilate(img_BW, None, iterations=2)
```

extract.py or fetch\_data.py

get some features from contour

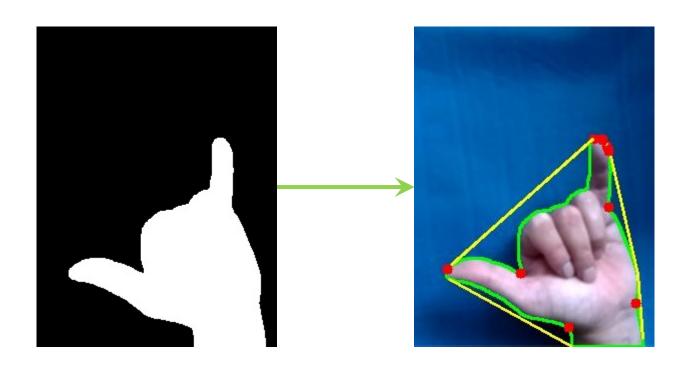
```
# find largest contour
contour = getLargestContour(img_BW)

# extract features
features, defects = getContourFeatures(contour)
print("[INFO] contour features: {}".format(features))
```

using standard OpenCV functions to find perimeter, area, etc.

You can do much better than this!!

03\_extract.py or 04\_fetch\_data.py



extract.py or fetch\_data.py

```
>>> gestures.feature_names
['area', 'perimeter', 'aspect_ratio', 'extent']
```

```
>>> gestures.unique_targets
array(['hang_loose', 'ignore', 'paper', 'rock', 'scissors'], dtype='<U10')</pre>
```

```
>>> gestures.target
['hang_loose', 'hang_loose', 'hang loose', 'han
```

## TRAINING AND TEST SETS: SPLITTING DATA

- training set—a subset to train a model.
- test set—a subset to test the trained model.
- You could imagine slicing the single data set as follows:

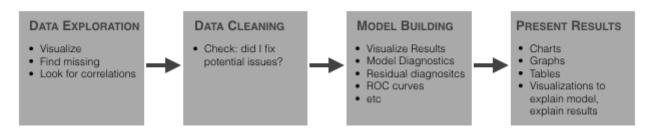


- Make sure that your test set meets the following two conditions:
  - Is large enough to yield statistically meaningful results.
  - Is representative of the data set as a whole. In other words, don't pick a test set with different characteristics than the training set.

#### **EXPLORATORY DATA ANALYSIS**

- Initial investigations on data to discover patterns
- Spot anomalies, and to check assumptions
- Summary statistics and graphical representations.

# WE USE DATA ANALYSIS AND VISUALIZATION AT EVERY STEP OF THE MACHINE LEARNING PROCESS

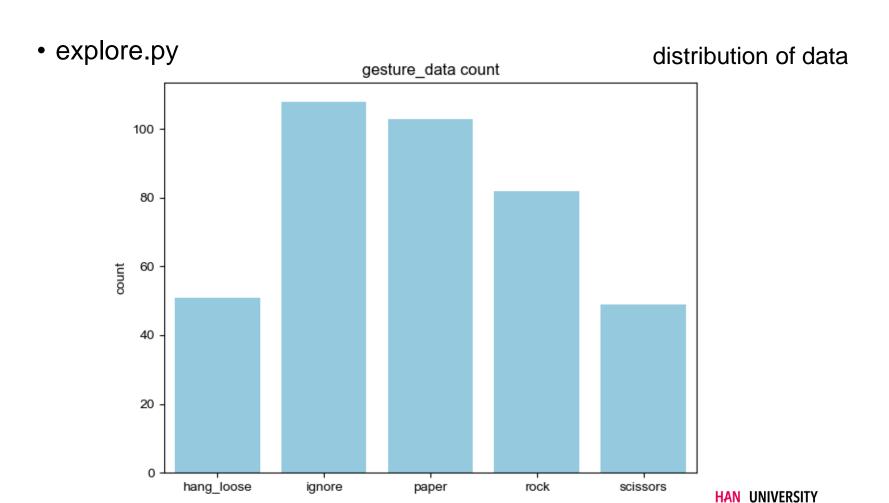


Source: Stanford: Statistical reasoning MOOC

explore.py

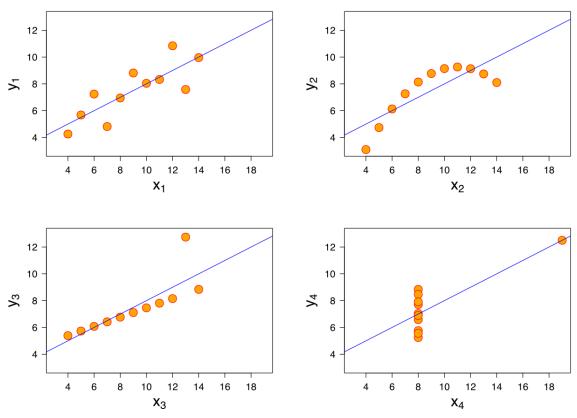
```
import numpy as np
from fetch data import fetch data
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.model selection import train test split
import matplotlib.pyplot as plt
import seaborn as sns
if name == " main ":
    """feature exploration"""
    data path = r'G:\My Drive\data\gesture data'
    # fetch the data
    gestures = fetch data(data path)
    # encode the categorical labels
    le = LabelEncoder()
    coded labels = le.fit transform(gestures.target)
    # partition the data into training and testing splits using 75% of
    # the data for training and the remaining 25% for testing
    (trainX, testX, trainY, testY) = train test split(gestures.data, coded labels,
    test size=0.25, stratify=gestures.target)#, random state=42)
                                                                                         RSITY
```

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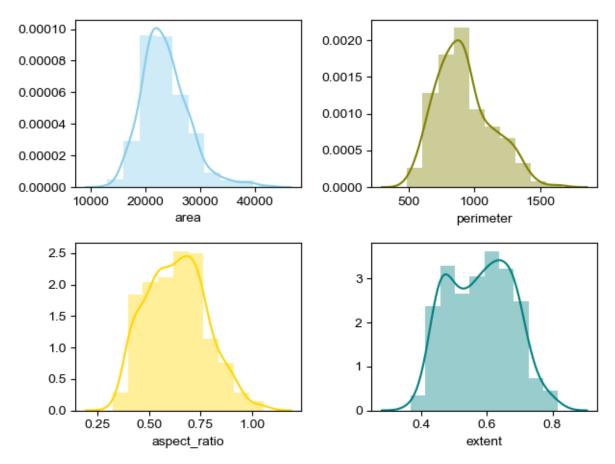
## **ANSCOMBE'S QUARTET**



Source: By Anscombe.svg: Schutz(label using subscripts): Avenue - Anscombe.svg, CC BY-SA 3.0, https://commons.wikimedia.org/w/index.php?curid=9838454

explore.py

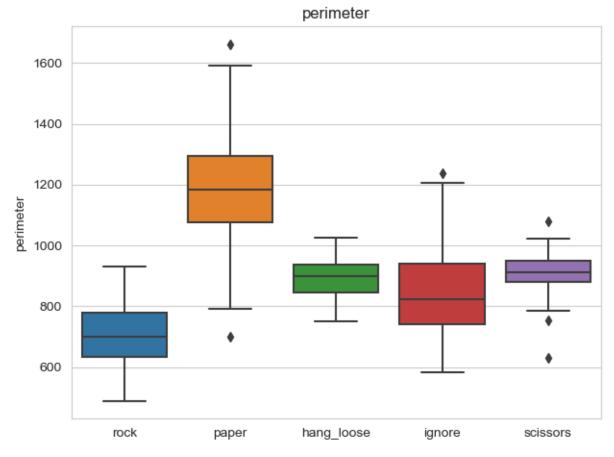
Total feature histograms



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explore.py

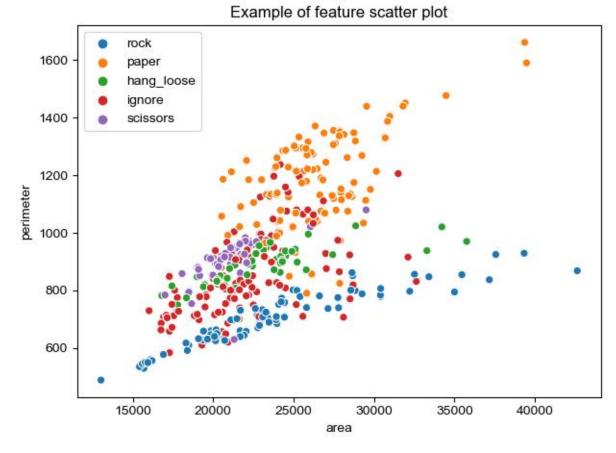
Boxplot of a single feature



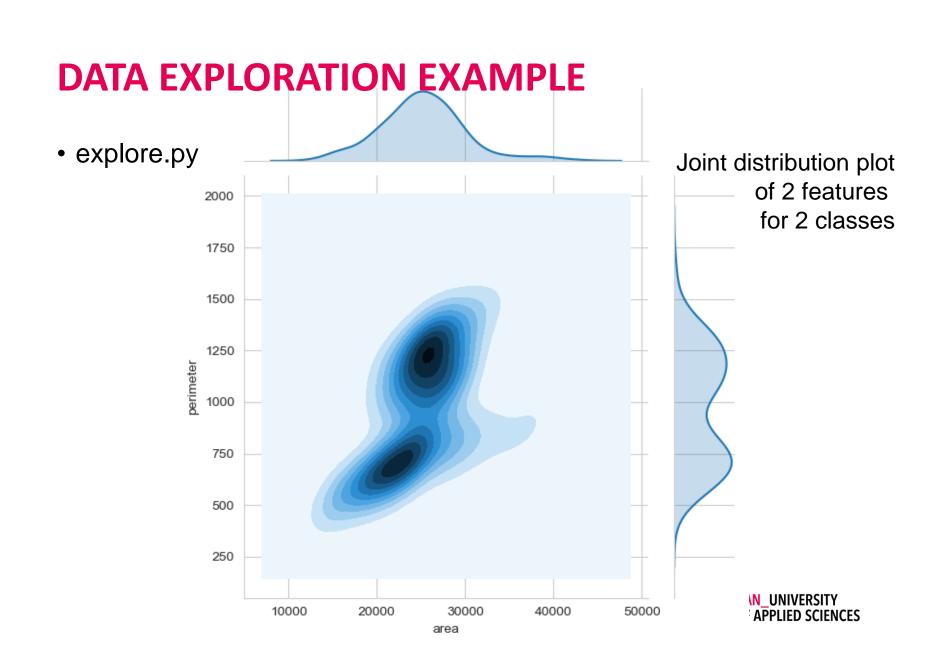


explore.py

Scatterplot of 2 features



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explore.py



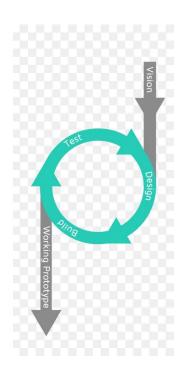
Feature correlation heatmap

See: https://www.statology.org/how-to-read-a-correlation-matrix/



#### **FEATURE ENGINEERING**

- Based on your explorations:
  - Select features
  - Decompose features (e.g. area -> length, width)
  - Extract features (e.g. aggregate, combinations)
  - Add promising transformations of features (e.g., log(x), sqrt(x),  $x^2$ , etc.).
- Propose new features?
- Adjust data acquisition?
- Remember that machine learning is an iterative process!



#### **MORE ON FEATURE SELECTION**

- Possible strategy
  - Create many, many features,
  - Use automated process to select best
  - E.g. using scikit learn feature selection module

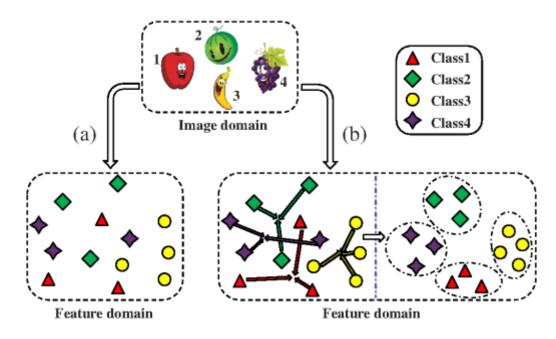
https://scikit-learn.org/stable/modules/feature\_selection.html

 Alternatively, use regularization techniques, we'll get to that in another lesson



## **QUALITIES OF GOOD FEATURES**

- Informative
- Discriminating
- Independent
- Nearly unique



Source: https://www.spiedigitallibrary.org/ContentImages/Journals/JEIME5/26/1/013023

NB feature scaling may be required



#### DATA PREPARATION

- Data cleaning:
  - Fix or remove outliers (optional)
  - Fill in missing values (e.g., with zero, mean, median...) or drop their rows (or columns).
- Feature computation:
  - Selection
  - Transformation
- Feature scaling:
  - Standardize or normalize features.

#### **EXAMPLE OF FEATURE SCALING**

explore.py

```
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn model selection import train test split

# Data preparation (note that a pipeline would help here)
trainX = StandardScaler().fit_transform(trainX)
```

• See <a href="https://scikit-learn.org/stable/auto\_examples/preprocessing/plot\_all\_scaling.html">https://scikit-learn.org/stable/auto\_examples/preprocessing/plot\_all\_scaling.html</a>
for more inspiration



## **EXAMPLE OF FEATURE SCALING**

• explore.py

