B-IT Pattern Recognition Project-I Report

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Generalities

Programming Language, Libraries:

- Implementation of the solution is in Python.
- Using NumPy, SciPy, Matplotlib modules.
- Anaconda data science platform¹ (not obligatory).



¹https://www.anaconda.com/

Task 1.1: Plotting 2D data

- Task: Plotting the data without the outliers,
- Why?
 - To deal with missing data,
 - To deal with outliers.
- How?

A Python Code Sample:

```
# Task 1.1
outlierInd = np.where( X[:,0] != -1 )
X, y = X[outlierInd], y[outlierInd]
```

Task 1.1: Plotting 2D data

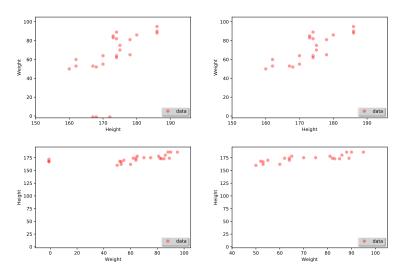


Figure 1: Removing outliers.

Task 1.1: Plotting 2D data

```
# Task 1.1
axs.set_aspect('equal')
```

same scaling from data to plot units for x and y,

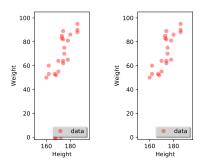


Figure 2: Plots with equal aspect ratio.

Task 1.2: Fitting a Normal Distribution on 1D Data

Task:

- Calculate the mean and standard deviation of body sizes,
- Plot the data and normal distribution.

Why?

 To be sure that body sizes are distributed accordingly to normal distribution

How?

Using ML estimation:

Normal Distribution:
$$f(x|\mu,\sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}}e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$
 Standard Deviation:
$$\sigma_{MLE} = \sqrt{\frac{1}{n}\sum_{i=1}^n(x_i-\mu)^2}$$
 Mean:
$$\mu_{MLE} = \frac{1}{n}\sum_{i=1}^n ns_i$$

Task 1.2: Fitting a Normal Distribution on 1D Data

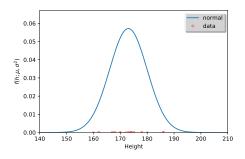


Figure 3: $\mu_h = 173.0, \sigma_h = 6.98$

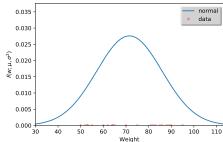


Figure 4: $(\mu_w = 71.52, \sigma_w = 14.46)$

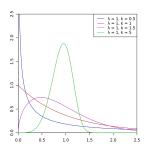


Figure 5: Weibull Distribution.

PDF of Weibull distribution:

$$f(x|\kappa,\alpha) = \frac{\kappa}{\alpha} \left(\frac{x}{\alpha}\right)^{\kappa-1} e^{-\left(\frac{x}{\alpha}\right)^{\kappa}}, \text{ if } x \geq 0 \text{ otherwise } 0.$$

where κ is the shape parameter and α is the scale parameter.

Task:

- Estimate the parameters of Weibull distribution,
- Plot the data and Weibull distribution..

■ Why?

 To have a good prediction if the Weibull distribution can be closely fitted to the observed data.

How?

- Maximum Likelihood Estimation(MLE): Estimate κ, α which makes the log-likelihood as large as possible.
- Use the function scipy.integrate.odeint.

How?

■ Maximum Likelihood Estimation(MLE): Estimate κ, α which makes the log-likelihood as large as possible.

PDF of Weibull distribution:

$$f(x|\kappa,\alpha) = \frac{\kappa}{\alpha} \left(\frac{x}{\alpha}\right)^{\kappa-1} e^{-\left(\frac{x}{\alpha}\right)^{\kappa}},$$

Log-likelihood is:

$$L(\alpha, \kappa | D) = N(\log \kappa) - \kappa \log(\alpha) + (\kappa - 1) \sum_{i} \log d_{i} - \sum_{i} (d_{i} / \alpha)^{\kappa}$$

■ Use Newton Raphson Method:

$$\begin{bmatrix} \kappa^{\mathsf{new}} \\ \alpha^{\mathsf{new}} \end{bmatrix} = \begin{bmatrix} \kappa \\ \alpha \end{bmatrix} + \begin{bmatrix} \frac{\partial^2 L}{\partial \kappa^2} \frac{\partial^2 L}{\partial \kappa \partial \alpha} \\ \frac{\partial^2 L}{\partial \kappa \partial \alpha} \frac{\partial^2 L}{\partial \alpha^2} \end{bmatrix}^{-1} \begin{bmatrix} -\frac{\partial L}{\partial \kappa} \\ -\frac{\partial L}{\partial \alpha} \end{bmatrix}$$

Run for 20 iterations.

Plot the data histogram with the scaled version of the fitted distribution.

```
def model(y, t):
          K, a = y[0], y[1]
          d_K = N / K - N * math.log(a) + sum_log_di - np.sum
                (((hist / a) ** K) * np.log(hist / a))
          d_a = (K / a) * (np.sum((hist / a) ** K) - N)
          return [d_K, d_a]

# initial condition and time points
K, a = 1., 1.
t = np.linspace(0,100,1000)
y = odeint(model,[K,a],t)
```

 Plot the data histogram with the scaled version of the fitted distribution.

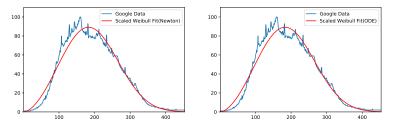


Figure 6: Data fitting with Newton Raphson Method(left) and scipy.integrate.odeint(right).