

# Homework 8

Math 87

## 1 How effective is regression?

In this exercise, you will investigate the quality of an linear least squares regression as a function of the amount of noise in your data.

- To sample from this line, one could uniformly sample  $x$  from  $[0, N]$  and then apply the transformation  $m * x + b$  to each sample, defining a new random variable that samples along the line  $y = mx + b$ . Since these samples lie exactly on the line, we should only need two samples to reconstruct the line.
- As  $\sigma$  increases, we will expect the required number to approximate the line to increase.
- Below is sample code to solve this problem: The code generates a chosen number of samples (here set to 100000) from the “noisy line” with a prescribed variance (we use  $\sigma = 0.1$ ). Then the code computes the least squares regression for the sampled data. One may then plot the samples and solution lines using matplotlib.

### Sampling

```
import numpy as np
from scipy import optimize
import matplotlib.pyplot as plt
s = np.random.uniform(0,10,100000)
def generategauss(n, sigma):
    eta=np.random.normal(0, sigma, n)
    return eta

M=generategauss(len(s),0.1)

y=3*s+4+M
J=np.ones(len(s))
A=[]
for i in np.arange(len(s)):
    A.append([s[i],1])
np.linalg.solve(
np.matmul(np.transpose(A),A),np.matmul(np.transpose(A),y5))
```

One should see that as  $\sigma$  increases, a greater number of samples is needed to approximate the line correctly.

## 2 Polynomial curve fitting

Given a set of observations in the form  $(x_i, y_i)$ , we can represent the problem of fitting an  $n$ -degree polynomial as a matrix equation. Let the polynomial be of the form:

$$f(x) = a_n x^n + a_{n-1} x^{n-1} + \dots + a_1 x + a_0$$

1. The general matrix equation for fitting the observations to an  $n$ -degree polynomial is:

$$\begin{bmatrix} 1 & x_1 & x_1^2 & \dots & x_1^n \\ 1 & x_2 & x_2^2 & \dots & x_2^n \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & x_m & x_m^2 & \dots & x_m^n \end{bmatrix} \begin{bmatrix} a_0 \\ a_1 \\ \vdots \\ a_n \end{bmatrix} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_m \end{bmatrix}$$

Here,  $m$  is the number of observations.

2. To test the formula, we can use Python with libraries like NumPy and Matplotlib. Below is an example code snippet:

#### Fitting

```
import numpy as np
import matplotlib.pyplot as plt

# Given data
x = np.array([0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1])
y = np.array([3.66711, 4.06035, 4.41999, 4.69781, 4.82905,
              4.54028, 4.38693, 3.17306, 1.40012, -1.0748])

M=len(x)

degrees = [1, 2, 3, 4, 5]
plt.scatter(x, y, label='Data', color='k')

for degree in degrees:
    # Fit polynomial
    A=np.array([[pow(x[i],k) for k in range(degree+1)]
                for i in range(M)])
    coefficients = np.linalg.lstsq(A,y, rcond=None)[0]
    # Compute predicted values
    y_pred = A@coefficients

    # Compute residual errors
    residuals = y - y_pred

    # Print results
    print(f"Degree-{degree}-Polynomial-Coefficients:-{coefficients}")
    print(f"Residual-Errors:-{residuals}")

    # Plot the data and the fitted polynomial
    plt.plot(x, y_pred, label=f'Degree-{degree}-Polynomial-Fit')
plt.xlabel('x')
plt.ylabel('y')
plt.legend()
plt.show()
```

| x        | 0.1     | 0.2     | 0.3     | 0.4     | 0.5     | 0.6     | 0.7    | 0.8     | 0.9     | 1.0     |
|----------|---------|---------|---------|---------|---------|---------|--------|---------|---------|---------|
| degree=1 | -1.6180 | -0.8081 | -0.0317 | 0.6628  | 1.2107  | 1.3386  | 1.6020 | 0.8048  | -0.5514 | -2.6097 |
| degree=2 | 0.4661  | -0.1134 | -0.3791 | -0.3793 | -0.1787 | -0.0507 | 0.5599 | 0.4575  | 0.1433  | -0.5256 |
| degree=3 | -0.0488 | 0.0582  | 0.0499  | 0.0007  | -0.0316 | -0.1978 | 0.1800 | 0.0284  | -0.0283 | -0.0107 |
| degree=4 | -0.0069 | 0.0071  | 0.0104  | 0.0077  | 0.0103  | -0.1560 | 0.1869 | -0.0111 | -0.0795 | 0.0311  |
| degree=5 | 0.0115  | -0.0359 | 0.0135  | 0.0414  | 0.0287  | -0.1744 | 0.1532 | -0.0141 | -0.0365 | 0.0127  |

Table 1: Residual error at each point

The resulting residuals are given in table 1 and coefficients are as follows:

degree=1:  $a_0 = 5.7018$ ,  $a_1 = -4.1670$

degree=2:  $a_0 = 1.8810$ ,  $a_1 = 14.9371$ ,  $a_2 = -17.3673$

degree=3:  $a_0 = 3.6339$ ,  $a_1 = -0.6099$ ,  $a_2 = 16.3416$ ,  $a_3 = -20.4297$

degree=4:  $a_0 = 3.3014$ ,  $a_1 = 3.6520$ ,  $a_2 = 0.7472$ ,  $a_3 = 0.8795$ ,  $a_4 = -9.6860$

degree=5:  $a_0 = 2.8628$ ,  $a_1 = 10.8827$ ,  $a_2 = -37.2112$ ,  $a_3 = 85.7427$ ,  $a_4 = -94.0380$ ,  $a_5 = 30.6735$