- 1.
- a) Students' accumulative GPA can be a possible target variable.
- b) It is continuous.
- c) Students' GRE score. Students' ILETS or TOEFL score can also be a variable.
- d) A linear model should be reasonable for the data. I expect the model as a increasing linear function. The student with higher GRE score should have higher GPA.
- 2.

a)
$$x_bar = (0 + 1 + 2 + 3 + 4) / 5 = 2$$

 $y_bar = (0 + 2 + 3 + 8 + 17) / 5 = 6$

b)
$$s_x^2 = 2.5$$

 $s_y^2 = 46.5$
 $s_y^2 = 8$

c) The least squares parameters are beta_0 and beta_1.

beta_1 =
$$s_xy / s_x^2 = 3.2$$

beta_0 = y_bar - beta_1 * x_bar = -0.4

- d) When x = 2.5, y = 7.6
- 3.

a)
$$\ln z(t) \approx \ln z_0 e^{-\alpha t}$$

$$\ln z(t) \approx -\alpha t + \ln z_0$$
 Now z 0 and a appeared linearly.

b) RSS = $\sum_{i=1}^{n} (\ln z(t)_i - \ln z(t_i))^2 = \sum_{i=1}^{n} (\ln z(t)_i + \alpha t_i - \ln z_0)^2$ By replacing $\ln z(t)_i$ with y_i , t_i with $-x_i$, $\ln z_0$ with β_0 and α with β_1 , we got RSS = $\sum_{i=1}^{n} (y_i - \beta_0 - \beta_1 x_i)^2$, which is exactly the same as the original model.

We know the solution to the original model are

$$\beta_1 = \frac{S_{xy}}{S_{xx}}, \ \beta_0 = \bar{y} - \beta_1 \bar{x}$$

By replacing variables back, we got

$$\alpha = -\frac{S_{t \ln z(t)}}{S_{tt}}, \ \ln z_0 = \overline{\ln z(t)} + \alpha \overline{t}, \ z_0 = \overline{z(t)} + e^{\alpha t}$$

```
import numpy as np
 2
 3
     def fit_linear(t, zt):
         x = -t
 5
         y = zt
 6
7
         xm = np.mean(x)
         ym = np.mean(y)
 8
         syx = np.mean((y - ym) * (x - xm))
9
        sxx = np.mean((x - xm) ** 2)
10
        beta1 = syx/sxx
11
        beta0 = ym - beta1 * xm
12
        yhat = beta0 + beta1 * x
13
        RSS = np.sum((y - yhat) ** 2)
14
15
        alpha = beta1
16
17
        lnz0 = beta0
18
         z0 = np.exp(lnz0)
19
        return alpha, z0, RSS
```

4.

a) RSS =
$$\sum_{i=1}^{n} (y_i - \hat{y}_i)^2 = \sum_{i=1}^{n} (y_i - \beta x_i)^2$$

b)
$$\frac{\partial RSS}{\partial \beta} = \sum_{i=1}^{n} 2x_i^2 \beta - 2x_i y_i$$

When $\frac{\partial RSS}{\partial \beta} = 0$, RSS has the minimum value.

Let
$$\frac{\partial RSS}{\partial \beta} = 0$$
, $\beta = \sum_{i=1}^{n} \frac{y_i}{x_i}$