

# Math 50 Final – Practice

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Name: \_\_\_\_\_

Section: \_\_\_\_\_

## Instructions

- You have 3 hours to complete the exam.
- You may have a one page (single-sided) “cheat sheet” which must be turned in with the exam, but no electronics (including calculators).
- Each problem is worth 5 points.
- Write your solutions in the boxes.
- Don’t cheat.

**Exercise 1** (Converting code to math): Consider the following code

```
x1 = np.random.normal(0,1,100)
x2 = 2*x1 + np.random.normal(0,1,100)
y = x1 + x2 + np.random.normal(0,1,100)
b1 = np.cov(y,x1)/np.var(x1)
b2 = np.cov(y,x2)/np.var(x2)
```

What are b1 and b2 (approximately)?

**Solution:**

**Exercise 2** (Joint distribution): Consider the model of a time series  $X_1, X_2, X_3, \dots$ :

$$X_{i+1}|X_i \sim \text{Normal}(1 + X_i/2, 1/3)$$

(a) Write a Python function `generatesim(L)` to generates a simulation of  $L$  steps of this time series starting with  $X_i = 0$ . The function should return a length  $L$  numpy array.

(b) After many steps, the process reaches a steady state where  $E[X_{i+1}] = E[X_i]$ . What is the distribution of  $X_i$  in steady-state?

**Exercise 3** (Regression model comparison):  $(X, Y)$  data is fit to a single-predictor regression model in statsmodels using OLS, yielding the following output:

	coef	std err	t	P> t	[0.025	0.975]
const	1.0685	0.186	5.756	0.000	0.700	1.437
x1	1.9622	0.177	11.062	0.000	1.610	2.314

A second predictor  $X_2$  is then included in the model, which yields the following output:

	coef	std err	t	P> t	[0.025	0.975]
const	1.0001	0.011	92.003	0.000	0.979	1.022
x1	0.9810	0.012	82.470	0.000	0.957	1.005
x2	2.0122	0.012	168.877	0.000	1.989	2.036

If  $X_2$  and  $X_1$  were fit to a linear regression model with  $X_2$  as the response variable, what would be the regression slope?

**Solution:**

**Exercise 4** (Sample distribution): Consider the model

$$Y_1 \sim \text{Normal}(\beta_1 X_1 + \beta_2 X_2, \sigma_\epsilon^2)$$

After fitting the model, we find  $\hat{\beta}_1 = 100$ ,  $\hat{\beta}_2 = -101$ ,  $\hat{\sigma}_\epsilon^2 = 1/4$ . The model is then fit to a different data set and it is found that  $\hat{\beta}_1 = -100$ ,  $\hat{\beta}_2 = 100.4$ .

(a) Is  $\text{cov}(X_1, X_2)$  likely to be positive or negative for the fitted data?

**Solution:**

(b) Based on this information is it possible that  $R^2$  is very close to 1?

**Solution:**

**Exercise 5 (Interactions):** Consider the the two predictor linear regression model with an interaction term:

$$Y = \beta_1 X_1 + \beta_2 X_2 + J_{1,2} X_1 X_2 + \epsilon$$

The following plot shows data generated from such a model.

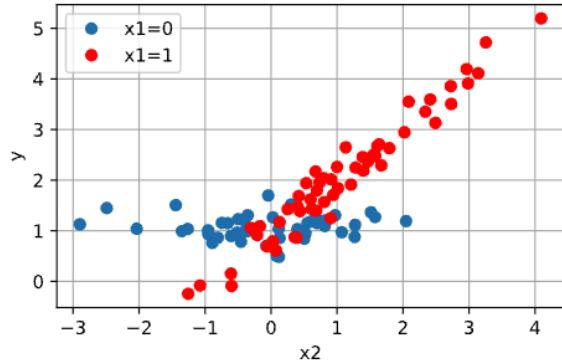


Figure 1:

What are the values of  $\beta_1$ ,  $\beta_2$  and  $J_{1,2}$ ?

**Solution:**

**Exercise 6** (Orthogonality): Consider the features  $\phi_1(x) = x^3$  and  $\phi_2(x) = x^2$ .

(a) Are these orthogonal with respect to  $X \sim \text{Uniform}(-1, 1)$ ? (in the sense that  $E[\phi_1(X)\phi_2(X)] = 0$ )

(b) What is an example of a distribution for  $X$  such that  $\phi_1$  and  $\phi_2$  are not orthogonal?

**Exercise 7** (Bayesian posterior): Consider a the Bayesian model  $\sigma_\epsilon$  and  $\beta_1$ , but unknown intercept with Normal priors:

$$\beta_0 \sim \text{Normal}(0, \tau_0^2) \quad (1)$$

$$Y|X, \beta \sim \text{Normal}(\beta_0 + \beta_1 X, \sigma_\epsilon^2) \quad (2)$$

Calculate the posterior of  $\beta_0$ .

**Exercise 8** (Missing data): You are given data with predictors  $X_1, X_2$ . You want to fit a linear regression model

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \epsilon$$

but some of the  $X_2$  values are have been corrupted and are not reliable. One idea to handle this is called *imputation* and involves generating the missing values  $X_2$ .

Explain how you could implement imputation assuming you are a given dataframe with rows  $Y, X_1, X_2, C$  where  $C = 1$  for the rows with corrupted data and  $C = 0$  otherwise. What assumptions are being made for the procedure to be unbiased?

**Solution:**

## Solutions

1.  $b_1$  is the regression coefficient with only  $X_1$  as a predictor and the regression coefficient  $\beta_{1,2}$  of  $X_1$  on  $X_2$  is given to be 2 as well as  $\beta_1 = \beta_2 = 1$ . Thus we have  $b_1 = 1+2 = 3$ . The regression coefficient of  $X_2$  on  $X_1$  is  $\beta_{2,1} = \text{cov}(X_1, X_2)/\text{var}(X_2) = \text{var}(X_1)\beta_{1,2}/(2^2 + 1) = 1 \times 2/5 = 2/5$ . Hence  $b_2 = 1 + 2/5 = 7/5$ .

2. (a) One valid implementation:

```
def generatesim(L):
    X = np.zeros(L)
    for i in range(1,L):
        X[i] = 1.0 + 0.5*X[i-1] + np.random.normal(0.0, np.sqrt(1/3))
    return X
```

(b) In steady-state we have the marginals are equal so  $\mu_X = E[X_{i+1}] = 1 + E[X_i]/2 = 1 + \mu_X/2$ . Thus  $\mu_X = 2$ . Similarly  $\sigma_X^2 = \sigma_X^2/4 + 1/3$ . Thus  $\sigma_X^2 = 4/9$  and  $X_i \sim \text{Normal}(2, 4/9)$ .

3. We are given the single predictor regression coefficient  $\hat{\beta}'_1 \approx 2$  and the two predictor model coefficients  $\hat{\beta}_1 \approx 1$ ,  $\hat{\beta}_2 \approx 2$ . Using  $\hat{\beta}'_1 = \hat{\beta}_1 + \hat{\beta}_2\beta_{1,2}$  we deduce the coefficient of  $X_1$  with  $X_2$  as the response variable, denoted  $\beta_{1,2}$  here, is  $\beta_{1,2} \approx 1/2$ .

4. (a) This suggests the  $\hat{\beta}_1$  and  $\hat{\beta}_2$  are negatively correlated and therefore  $X_1$  and  $X_2$  are positively correlated, hence  $\text{cov}(X_1, X_2) > 0$ . (b) Yes, because even though we know  $\hat{\sigma}_\epsilon^2$  we aren't given  $\sigma_Y^2$ , which could be quite large especially with such large values of  $\hat{\beta}_i$ .

5.  $\beta_2$  is the slope of  $X_2$  vs.  $Y$  when  $X_1 = 0$ , which is approximately 0 in the plot.  $\beta_2 + J_{1,2}$  is the slope when  $X_1 = 1$ , which appears to be 1.  $\beta_1$  is the expected difference in  $Y$  between  $X_1 = 0$  and  $X_1 = 1$  groups when  $X_2 = 0$ , which appears to be 0. In summary,  $\beta_1 = \beta_2 = 0$  and  $J_{1,2} = 1$ .

6. (a) With  $X \sim \text{Unif}(-1, 1)$ ,

$$E[\phi_1(X)\phi_2(X)] = E[X^5] = \int_{-1}^1 x^5 \cdot \frac{1}{2} dx = 0, \quad (3)$$

so they are orthogonal. (b) Any non-symmetric distribution makes  $E[X^5] \neq 0$ . For example, if  $X \sim \text{Unif}(0, 1)$ ,

$$E[X^5] = \frac{1}{6} \neq 0, \quad (4)$$

so they are not orthogonal.

7. The (frequentist) estimator  $\hat{\beta}_0 = \bar{Y} - \beta_1 \bar{X}$ . This is Normal when conditioned on  $\beta_0$ :  $\hat{\beta}_0 | \beta_0 \sim \text{Normal}(\beta_0, \hat{\sigma}_\epsilon^2/N)$ . If we invert this regression model we get

$$\beta_0 | \hat{\beta}_0 \sim \text{Normal} \left( \hat{\beta}_0 \frac{\tau^2}{\tau^2 + \hat{\sigma}_\epsilon^2/N}, \frac{\tau^2 \hat{\sigma}_\epsilon^2/N}{\tau^2 + \hat{\sigma}_\epsilon^2/N} \right) \quad (5)$$

8. Using rows with  $C = 0$ , fit

$$X_2 = \alpha_0 + \alpha_1 X_1 + \zeta, \quad (6)$$

and estimate  $\hat{\sigma}_\zeta^2 \approx \text{var}(\zeta)$ . For each  $C = 1$  row,

$$\tilde{X}_2 = \hat{\alpha}_0 + \hat{\alpha}_1 X_1 + \tilde{\zeta}, \quad \tilde{\zeta} \sim \text{Normal}(0, \hat{\sigma}_\zeta^2). \quad (7)$$

Then we fit

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 \tilde{X}_2 + \epsilon \quad (8)$$

on the completed data. We have assumed  $C$  is independent of  $X_1$  and  $X_2$ .