### Week02 Report

Wanjing Xu

# **Question 1**

a.

$$n x = 1000$$

$$\widehat{\mu}_1 = E[X] = \frac{1}{n} \sum_{i=1}^{n} x_i$$

sum of x = 1048.970390

the mean of x = 1 / 1000 \* 1048.970390 = 1.0490

$$\widehat{\mu}_{2} = E[(X - \widehat{\mu}_{1})^{2}] = \frac{1}{n-1} \sum_{i}^{n} (x_{i} - \widehat{\mu}_{1})^{2}$$

sum of  $(x-mean)^2 = 5421.793461$ 

the variance of x = 1 / 999 \* 5421.793461 = 5.4272

3) 
$$\hat{\mu}_3 = E[(\frac{X-\mu}{\sigma})^3] = \frac{u_3}{\sigma^3}$$

sum of  $(x-mean)^3 = 11117.25065592259$ 

skewness of x = sum of  $(x-mean)^3/n/sqrt(sigma_x^2) = 11117.25065592259 / 100 0 / <math>sqrt(5.421793461199845^3) = 0.8806$ 

$$\hat{\mu}_4 = E[(\frac{X-\mu}{\sigma})^4] - 3 = \frac{u_4}{\sigma^4} - 3$$

sum of  $(x-mean)^4 = 767884.148133907$ 

kurtosis of x = sum of  $(x-mean)^4/n/sigma_x^2 = 465.9228484697776 / 1000 / 5.4 21793461199845^2 = 26.1222$ 

excess kurtosis of x = kurtosis of x - 3 = 23.1222

b. I chose python pandas and numpy statistical packages. I calculate the difference between x and its mean and the power for the difference from 2 to 4. The second part involves four moments calculated by normalized formula and by pandas.

```
(x-mean)^3
                          (x-mean)^2
                                                    (x-mean)^4
                  x-mean
     0.922177 -0.126794
0
                            0.016077
                                        -0.002038
                                                      0.000258
     1.791781 0.742810
                            0.551767
                                         0.409858
                                                      0.304447
     0.397551 -0.651419
                            0.424347
                                         -0.276428
                                                      0.180071
     3.564269 2.515298
                            6.326725
                                        15.913600
                                                     40.027451
    -0.691414 -1.740385
                            3.028938
                                        -5.271517
                                                      9.174467
995 -2.913057 -3.962027
                           15.697660
                                       -62.194556
                                                    246.416523
996 2.845173 1.796203
997 1.663335 0.614365
                            3.226344
                                         5.795168
                                                     10.409296
                            0.377444
                                         0.231888
                                                      0.142464
    2.344441
                            1.678243
                                         2.174114
                                                      2.816499
               1.295470
    1.164175 0.115204
                                                      0.000176
                            0.013272
                                         0.001529
```

[1000 rows x 5 columns]
mean\_x is 1.0489703904839585
var\_x is 5.427220681681682
skewness of x is 0.8806086425277363
kurtosis\_x is 26.122200789989733
ex\_kurtosis\_x is 23.122200789989733
pandas mean is 1.0489703904839585
pandas variance is 5.421793461199845
pandas skewness is 0.8806086425277365
pandas kurtosis is 26.122200789989733

C.

My statistical package is unbiased. Compared four moments calculated by normalized formula and by pandas, the results are the same.

# Question 2

OLS beta is 0.7753; OLS intercept is -0.0874; OLS standard deviation of residuals is 1.0038

MLE beta is 0.7753; MLE intercept is -0.0874; MLE standard deviation of residuals is 1.0038

Beta and standard deviation of residuals are the same under the OLS and MLE given the assumption of normality.

		OLS Reg	ress	ion Res	ults		
Dep. Varia	========= able:		у	R-squa	red:		0.346
Model:		C	LS	Adj. R	-squared:		0.342
Method: Date: Time: No. Observations:		Least Squar	es	F-stat	istic:		104.6
		u, 25 Jan 20	24	Prob (	F-statistic)	:	5.59e-20
		15:03:	27	Log-Li	-284.54		
		200		AIC:			573.1
Df Residua	als:	1	98	BIC:			579.7
Df Model:			1				
Covariance	e Type:	nonrobu	st				
	coef	std err		t	P> t	[0.025	0.975]
const	-0.0874	0.071	-1.	.222	0.223	-0.228	0.054
х	0.7753	0.076	10.	226	0.000	0.626	0.925
Omnibus:		11.9	22	Durbin	-Watson:		2.023
Prob(Omnib	ous):	0.0	03	Jarque	-Bera (JB):		16.685
Skew:		0.3	87	Prob(J	B):		0.000238
Kurtosis:		4.1	84	Cond.	No.		1.09

Notes: [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

	Genera	alized Linea	r Mod	lel Regr	ession Resu	ilts	
Dep. Varia	ble:		у	No. Ob	servations:		200
Model:			GLM	Df Res	iduals:		198
Model Fami	ly:	Gauss	ian	Df Mod	el:		1
Link Funct	ion:	ident	ity	Scale:			1.0177
Method:		I	RLS	Log-Li	kelihood:		-284.54
Date:	TI	nu, 25 Jan 2	024	Devian	ce:		201.51
Time:		15:11	:56	Pearso	n chi2:		202.
No. Iterat	ions:		3	Pseudo	R-squ. (CS	i):	0.4072
Covariance	Type:	nonrob	ust		*		
	coef	std err	=====	z	P> z	[0.025	0.975]
const	-0.0874	0.071	-1	.222	0.222	-0.228	0.053
x	0.7753	0.076	10	.226	0.000	0.627	0.924

b.

Estimated Parameters - t distribution: log\_likelihood\_t is 281.2934031796488

mle beta: 0.675

mle\_intercept: -0.0973

df: 7.1598 sigma: 0.8551

Estimated Parameters - under normality: log\_likelihood\_n is 284.53756305442874

mle\_beta: 0.7753

mle\_intercept: -0.0874

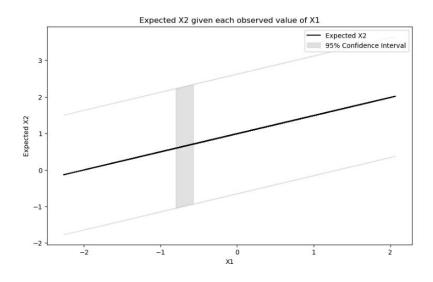
sigma: 1.0038

AIC for t-distribution model: 570.5868

AIC for normal distribution model: 575.0751

The fitted parameters among MLE under normality assumption is slightly different than under T distribution assumption. An additional parameter under T distribution assumption allows greater adaptability for modeling. Sigma is smaller under T distribution assumption, suggesting that the t distribution model may have less variability in the errors than the normal distribution model. Compared with log likelihood values, MLE under T distribution assumption has a lower value, which shows a better fit. Similarly, the t-distribution model has a smaller AIC (570.5868), which has a better fit compared to the normal distribution model (575.0751).

c.  $X = [X1, \ X2] \ \text{follows the multivariate normal distribution}.$  When we plot the conditional mean of X2, X2 follows the normal distribution given the observed value of X1.



Assume 
$$\in N N(0, 6^2 In)$$

$$f(y|\beta, 6^2) = \prod_{i=1}^n f(y_i|\beta, 6^2) = \prod_{i=1}^n \frac{1}{\sqrt{2\pi}6^2} e^{-\frac{|y_i - M_i|^2}{2\pi 2}} M_i = E(y_i) = X_i'\beta$$

$$= (2\pi 6^2)^{\frac{1}{2}} e^{-\frac{|y_i - M_i|^2}{2\pi 2}} M_i = E(y_i) = X_i'\beta$$

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$$= (2\pi 6^2)^{\frac{1}{2}} e^{-\frac{|y_i - M_i|^2}{2\pi 2}} M_i = E(y_i)^2 + X_i'\beta)^2$$

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$$= (2\pi 6^2)^{\frac{1}{2}} e^{-\frac{|y_i - M_i|^2}{2\pi 2}} M_i = E(y_i)^2 + X_i'\beta)^2$$

$$= (2\pi 6^2)^{\frac{1}{2}} e^{-\frac{|y_i - M_i|^2}{2\pi 2}} M_i = E(y_i)^2 + E(y_i)^2 + E(y_i)^2$$

$$= (2\pi 6^2)^{\frac{1}{2}} e^{-\frac{|y_i - M_i|^2}{2\pi 2}} M_i = E(y_i)^2 + E(y_i)^2$$

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$$= (2\pi 6^2)^{\frac{1}{2}} e^{-\frac{|y_i - M_i|^2}{2\pi 2}} M_i = E(y_i)^2 + E(y_i)^2$$

$$= (2\pi 6^2)^{\frac{1}{2}} e^{-\frac{|y_i - M_i|^2}{2\pi 2}} M_i = E(y_i)^2 + E(y_i)^2$$

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$$= (2\pi 6^2)^{\frac{1}{2}} e^{-\frac{|y_i - M_i|^2}{2\pi 2}} M_i = E(y_i)^2 + E(y_i)^2$$

$$= (2\pi 6^2)^{\frac{1}{2}} e^{-\frac{|y_i - M_i|^2}{2\pi 2}} M_i = E(y_i)^2 + E(y_i)^2$$

$$= (2\pi 6^2)^{\frac{1}{2}} e^{-\frac{|y_i - M_i|^2}{2\pi 2}} M_i = E(y_i)^2 + E(y_i)^2$$

$$= (2\pi 6^2)^{\frac{1}{2}} e^{-\frac{|y_i - M_i|^2}{2\pi 2}} M_i = E(y_i)^2 + E(y_i)^2$$

$$= (2\pi 6^2)^{\frac{1}{2}} e^{-\frac{|y_i - M_i|^2}{2\pi 2}} M_i = E(y_i)^2 + E(y_i)^2$$

$$= (2\pi 6^2)^{\frac{1}{2}} e^{-\frac{1}{2}} M_i = E(y_i)^2 + E$$

### Question 3

Among AR models, the order 3 has the smallest AIC (1436.660) which means a better fit. Among MA models, the order 3 has the smallest AIC (1536.868) which means a better fit. Compared with AR(3), AR(3) has the smaller AIC (1436.660), which is the best of fit.

AR(1) p=1 d=0 q=0

Dep. Varia	hle:		x No.	Observations:		500
Model:		ARIMA(1, 0,				-819.328
Date:		u, 25 Jan 20		221101211000		1644.656
Time:		22:50:				1657.299
Sample:			0 HQIC			1649.617
		- 5	500			
Covariance	Type:	C	pg			
	coef	std err	Z	P> z	[0.025	0.975]
const	2.1258	0.070	30.473	0.000	1.989	2.263
ar.L1	0.2019	0.045	4.512	0.000	0.114	0.290
sigma2	1.5517	0.105	14.743	0.000	1.345	1.758
Ljung-Box	(L1) (Q):		2.51	Jarque-Bera (	JB):	1.
Prob(Q):			0.11	Prob(JB):		0.
Heteroskedasticity (H):			1.37	Skew:		-0.
Prob(H) (to	wo-sided):		0.04	Kurtosis:		2.

Warnings

[1] Covariance matrix calculated using the outer product of gradients (complex-step).

# AR(2) p=2 d=0 q=0

# SARIMAX Results

Dep. Varia	ble:		x No.	Observations:	H	500
Model:		ARIMA(2, 0,	0) Log	Likelihood		-786.540
Date:	Т	hu, 25 Jan 20	024 AIC			1581.079
Time:		22:52	:05 BIC			1597.938
Sample:			0 HQI	C		1587.694
Covariance	Type:	(	opg			
	coef	std err	Z	P> z	[0.025	0.975]
const	2.1270	0.049	43.663	0.000	2.032	2.222
ar.L1	0.2732	0.042	6.486	0.000	0.191	0.356
ar.L2	-0.3505	0.043	-8.068	0.000	-0.436	-0.265
sigma2	1.3603	0.094	14.455	0.000	1.176	1.545
 Ljung-Box	(L1) (Q):		15.51	Jarque-Bera	(JB):	3.1
Prob(Q):			0.00	Prob(JB):		0.2
Heteroskedasticity (H):		1.20	Skew:		-0.1	
Prob(H) (t	wo-sided):		0.24	Kurtosis:		2.6

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).

# AR(3) p=3 d=0 q=0

### SARIMAX Results

Dep. Variab	۵۰			x	No	Observations:		500
Model:	ie.	ARIMA(	3 0			Likelihood	100	-713.330
Date:	т	hu, 25			AIC	LIKCCINOOU		1436.660
Time:		iiu, 25			BIC			1457.733
Sample:			22.5		HQI			1444.929
Samp te:				500	пұт	•		1444.929
Covariance 1	Гуре:		1.77	opg				
	coef	std	err		z	P> z	[0.025	0.975]
const	2.1209	0.	085	24.	990	0.000	1.955	2.287
ar.L1	0.4515	0.	040	11.	179	0.000	0.372	0.531
ar.L2	-0.4887	0.	037	-13.	104	0.000	-0.562	-0.416
ar.L3	0.5047	0.	040	12.	769	0.000	0.427	0.582
sigma2	1.0132	0.	068	14.	939	0.000	0.880	1.146
Ljung-Box (l	1) (Q):		====	0.	02	Jarque-Bera	(JB):	0
Prob(Q):				0.	90	Prob(JB):		0
Heteroskedas	sticity (H)	:		1.	04	Skew:		-0
Prob(H) (two	-sided):			0.	81	Kurtosis:		2

Warnings: [1] Covariance matrix calculated using the outer product of gradients (complex-step).

# MA(1) p=0 d=0 q=1

### SARIMAX Results

Dep. Variable	e:	ARIMA(0, 0,			No.	Observations:	50 -780.70		
Model:					Log	Likelihood			
Date:	Т	hu, 25	Jan 2	024	AIC			1567.404	
Time:			22:53	3:49 I	BIC			1580.047	
Sample:			-	0 I 500	HQIC			1572.365	
Covariance T	ype:			opg					
	coef	std	err		z	P> z	[0.025	0.975]	
const	2.1236	0.	.085	25.0	028	0.000	1.957	2.290	
ma.L1	0.6434	0.	034	18.8	347	0.000	0.577	0.710	
sigma2	1.3282	0.	090	14.	782	0.000	1.152	1.504	
Ljung-Box (L:	1) (Q):			11.	73	Jarque-Bera	(JB):		1.18
Prob(Q):				0.0	00	Prob(JB):			0.55
Heteroskedasi	ticity (H)	:		1.3	39	Skew:		: <del>:</del>	-0.02
Prob(H) (two-	-sided):			0.0	04	Kurtosis:			2.77

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).

# MA(2) p=0 d=0 q=2

# SARIMAX Results

Dep. Variab	ole:		x No.	Observations:		500	
Model:		ARIMA(0, 0,	<ol> <li>Log</li> </ol>	Likelihood		-764.971	
Date:	Т	hu, 25 Jan 20	024 AIC			1537.941	
Time:		22:53	49 BIC			1554.800	
Sample:			0 HQI	C		1544.556	
		- 5	500				
Covariance	Type:	(	opg				
	coef	std err	Z	P> z	[0.025	0.975]	
const	2.1255	0.060	35.199	0.000	2.007	2.244	
ma.L1	0.4344	0.044	9.775	0.000	0.347	0.522	
ma.L2	-0.2306	0.047	-4.949	0.000	-0.322	-0.139	
sigma2	1.2473	0.086	14.558	0.000	1.079	1.415	
======= Ljung-Box (	L1) (Q):		0.02	Jarque-Bera	(JB):	1	1.67
Prob(Q):	0000000 0000 0000 <del>0</del> 000000		0.88	Prob(JB):		0	0.43
Heteroskeda	sticity (H)	:	1.28	Skew:		-0	0.03
Prob(H) (tw	o-sided):		0.11	Kurtosis:		2	2.72

Warnings: [1] Covariance matrix calculated using the outer product of gradients (complex-step).

# MA(3) p=0 d=0 q=3

# SARIMAX Results

Dep. Varial	ole:		x No.	Observations:		500
Model:		ARIMA(0, 0,	3) Log	Likelihood		-763.434
Date:	T	hu, 25 Jan 20	24 AIC			1536.868
Time:		22:55	35 BIC			1557.941
Sample:			0 HQIC			1545.137
		- 5	500			
Covariance	Type:	(	opg			
	coef	std err	z	P> z	[0.025	0.975]
const	2.1259	0.059	35.880	0.000	2.010	2.242
ma.L1	0.5582	0.045	12.333	0.000	0.469	0.647
ma.L2	-0.2286	0.053	-4.308	0.000	-0.333	-0.125
ma.L3	-0.1531	0.048	-3.216	0.001	-0.246	-0.060
sigma2	1.2394	0.085	14.592	0.000	1.073	1.406
Ljung-Box	(L1) (Q):		1.60	Jarque-Bera	(JB):	1
Prob(Q):			0.21	Prob(JB):		0
Heteroskeda	asticity (H)	:	1.25	Skew:		-0
Prob(H) (tv	vo-sided):		0.15	Kurtosis:		2

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).