# TIME SERIES ANALYSIS FINAL PROJECT

111024509 陳冠霖

111024519 宇晉賢



### DATA

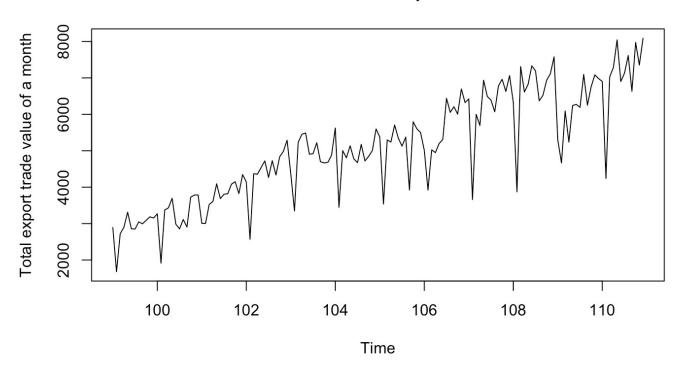
- 民國99年至112年出口貿易總額
- 資料來源:財政部統計資料庫
- Training data: 民國99年1月至民國110年12月
- Testing data: 民國111年1月至民國112年5月



## DATA

• 時間序列圖

#### Time series plot

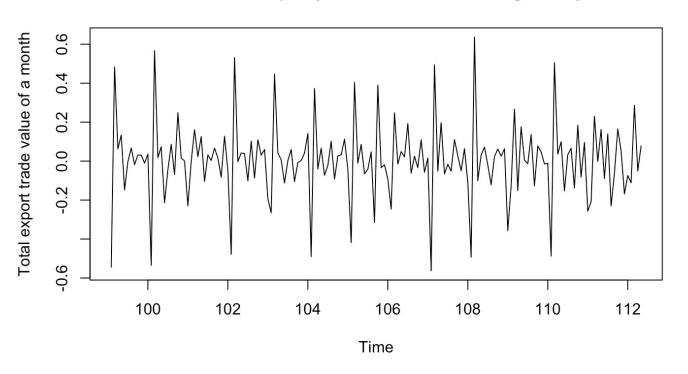




## DATA

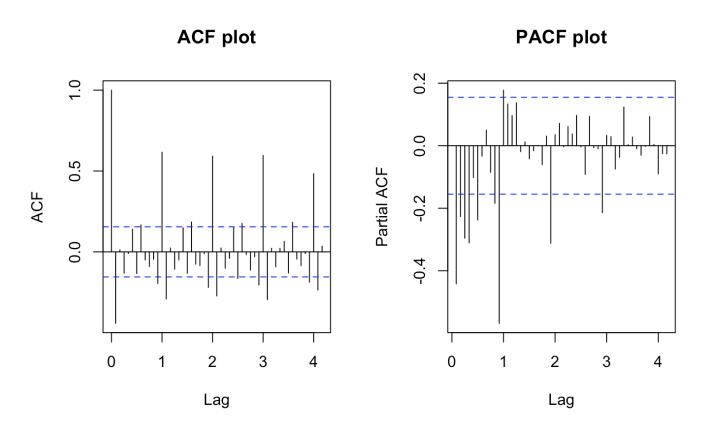
• 先進行一階差分

#### Time series plot(first difference and log scale)





## DATA ACF/PACF





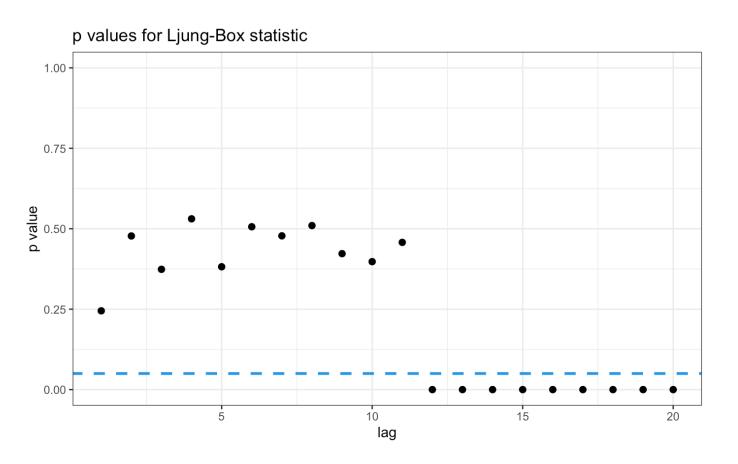
## ARIMA(0,1,1)

#### ■ 用AIC進行選模

```
Series: dats_train
ARIMA(0,1,1) with drift
Coefficients:
                drift
         ma1
      -0.9390 31.9924
s.e. 0.0933 4.3891
sigma^2 = 491650: log likelihood = -1140.01
AIC=2286.03 AICc=2286.2
                          BIC=2294.91
Training set error measures:
                                  MAE
                  ME
                         RMSE
                                           MPE
                                                   MAPE
                                                             MASE
                                                                        ACF1
Training set 7.961651 693.8349 486.5316 -1.74443 10.86456 0.8064263 0.09590838
```



## ARIMA(0,1,1) LJUNG-BOX TEST

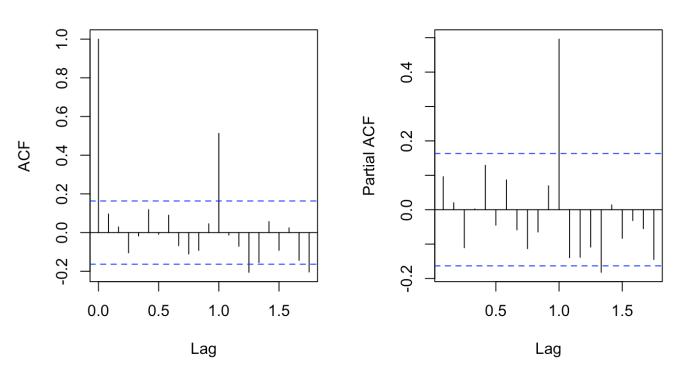




# ARIMA(0,1,1) ACF/PACF

#### Residual ACF plot of Arima(0,1,1)

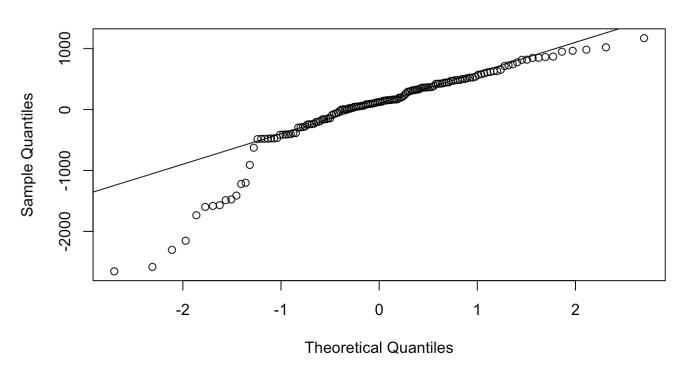
#### **Residual PACF plot of Arima(0,1,1)**





# ARIMA(0,1,1) NORMAL Q-Q

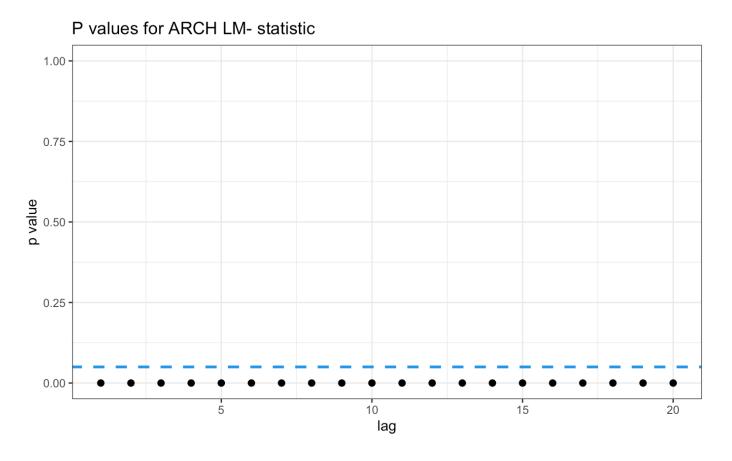






## ARIMA(0,1,1) ARCH LM TEST

所有lag下的p-value都顯示 有ARCH effect





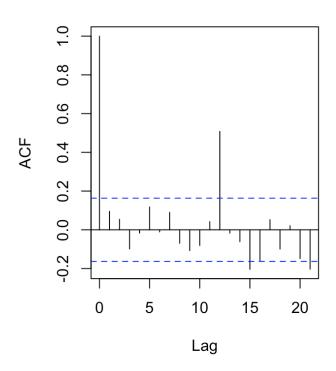
# ARIMA(0,1,1) + GARCH(1,1)

```
GARCH Model Fit
Conditional Variance Dynamics
GARCH Model : sGARCH(1,1)
Mean Model : ARFIMA(0,0,1)
Distribution : norm
Optimal Parameters
        Estimate Std. Error t value Pr(>|t|)
mu -13.852875 6.1964e+01 -0.22356 0.823098
        0.080369 8.4832e-02 0.94739 0.343439
ma1
      489.741309 1.9191e+03 0.25520 0.798572
omega
alpha1 0.023365 7.0930e-03 3.29431 0.000987
beta1 0.975635 1.7620e-02 55.37010 0.000000
```

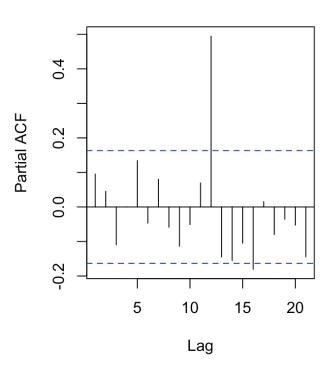


## ARIMA(0,1,1)+GARCH(1,1) ACF/PACF

#### **GARCH residual ACF**



#### **GARCH residual PACF**





## SARIMA(1,0,1)X(0,1,1)

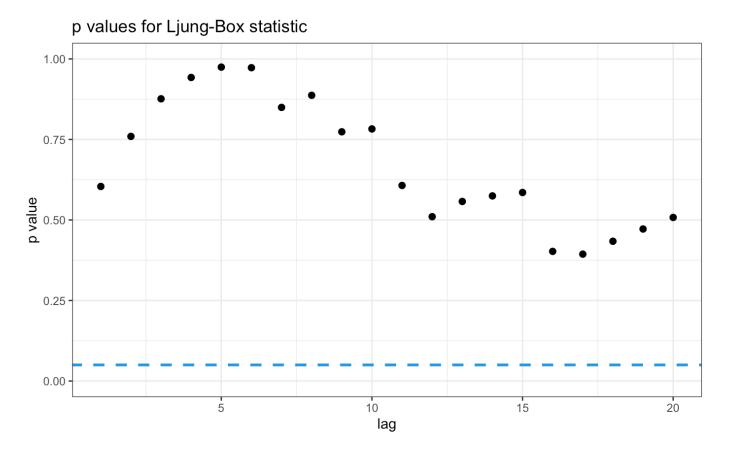
#### ■ 用AIC進行選模

```
Call:
arima(x = dats\_train, order = c(1, 0, 1), seasonal = list(order = c(0, 1, 1),
    period = 12)
Coefficients:
        ar1
                 ma1
                         sma1
      0.9975 -0.7452 -0.7752
s.e. 0.0041 0.0633 0.0768
sigma^2 estimated as 221705: log likelihood = -1005.52, aic = 2019.03
Training set error measures:
                  ME
                         RMSE
                                   MAE
                                               MPE
                                                       MAPE
                                                                 MASE
                                                                             ACF1
Training set 30.60616 450.8111 323.1846 -0.02795158 6.393399 0.5279044 -0.02532674
```



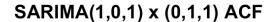
## SARIMA(1,0,1)X(0,1,1) LJUNG-BOX TEST

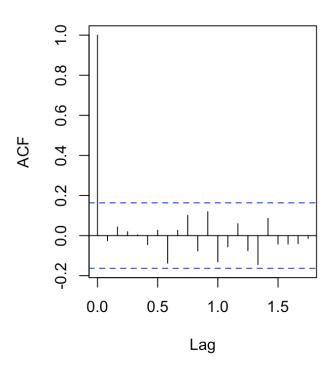
所有lag下的p-value皆顯示 符合white noise假設



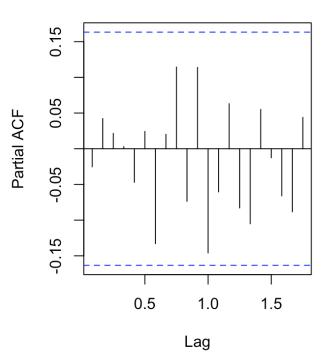


## SARIMA(1,0,1)X(0,1,1) ACF/PACF



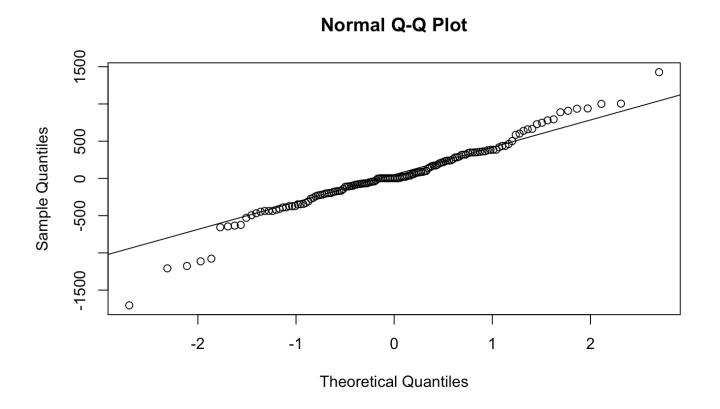


#### **SARIMA(1,0,1) x (0,1,1) ACF**





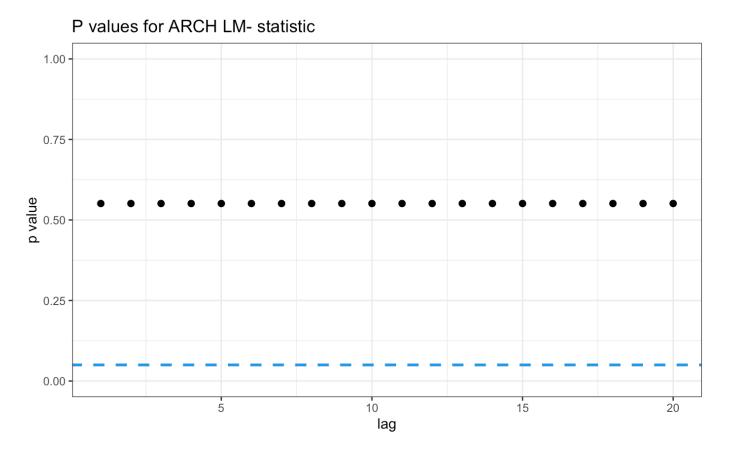
# SARIMA(1,0,1)X(0,1,1) NORMAL Q-Q





# SARIMA(1,0,1)X(0,1,1) ARCH LIM TEST

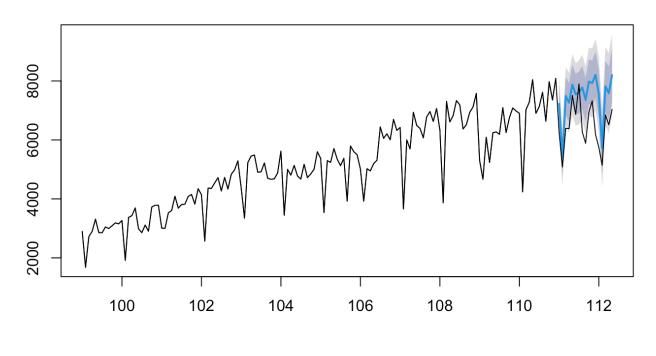
所有lag下的p-value都顯示 沒有ARCH effect

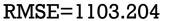




## SARIMA(1,0,1)X(0,1,1) PREDICTION

#### forcast from SARIMA(1,0,1) x (0,1,1)







# HOLT LINEAR TREND MODEL & HOLT-WINTERS SEASONAL MODEL

- 美國德州大學奧斯丁分校Charles Holt(1957)將指數平滑法納入趨勢方程式
- 他的學生Peter Winters(1960)將預測方程式改良納入季節因子,成為Holt-Winters季節 趨勢模型
- Holt Linear Trend Model: 將時間序列分為循環變化(level)與趨勢變化(trend),將兩者 指數平滑後再做線性組合
- Holt-Winters Seasonal Model: 將時間序列分為循環變化(level)、趨勢變化(trend)與
   季節變化(seasonality),將三者指數平滑後再做線性組合



## HOLT-WINTERS SEASONAL MODEL

 $0 < \alpha < 1$ 

 $0 < \beta < 1$ ,

 $0 < \gamma < 1$ .

$$Z_t = \mu_t + T_t + S_t + a_t$$
 where  $\mu_t = \text{level}, \ T_t = \text{trend}, \ S_t = \text{seasonality}$ 

$$\bar{\mu}_t = \alpha(Z_t - \bar{S}_{t-s}) + (1-\alpha)(\bar{\mu}_{t-1} + \bar{T}_{t-1}),$$

$$\bar{T}_t = \beta(\bar{\mu}_t - \overline{\mu}_{t-1}) + (1 - \beta)\bar{T}_{t-1},$$

$$\bar{S}_t = \gamma (Z_t - \bar{\mu}_t) + (1 - \gamma) \bar{S}_{t-1}, \label{eq:spectrum}$$

where  $\alpha, \beta, \gamma$  are smoothing constants

$$\hat{Z}_t(k) = \bar{\mu}_t + k\bar{T}_t + \bar{S}_{t+k-hs}, \ h = 1 + \text{int}(k/s)$$



# HOLT LINEAR TREND MODEL & HOLT-WINTERS SEASONAL MODEL

#### Holt Linear Trend

```
Call:
HoltWinters(x = dat_train, gamma = FALSE)
Smoothing parameters:
alpha: 0.5091814
beta : 0.2107366
gamma: FALSE
```

#### Coefficients:

[,1] a 7840.9744 b 129.2519

#### Holt-Winters Seasonal

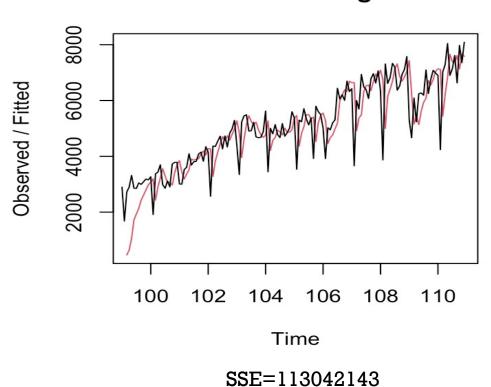
Call:

```
HoltWinters(x = dat_train, seasonal
Smoothing parameters:
 alpha: 0.2164627
 beta: 0
 gamma: 0.2481529
Coefficients:
           [,1]
a 7164.0203695
     23.6976981
   0.9942581
      0.6682512
      1.0366536
s3
      1.0009350
s4
      1.1040573
      1.0331569
      1.0371040
s7
      1.0589817
s8
      0.9840298
s9
      1.0754349
s10
      1.0642417
s11
       1.0973951
s12
```

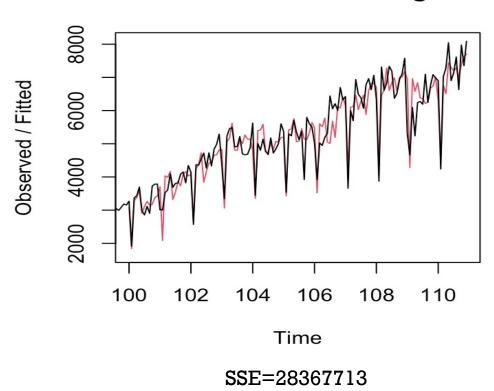


# HOLT LINEAR TREND MODEL & HOLT-WINTERS SEASONAL MODEL

#### **Holt filtering**



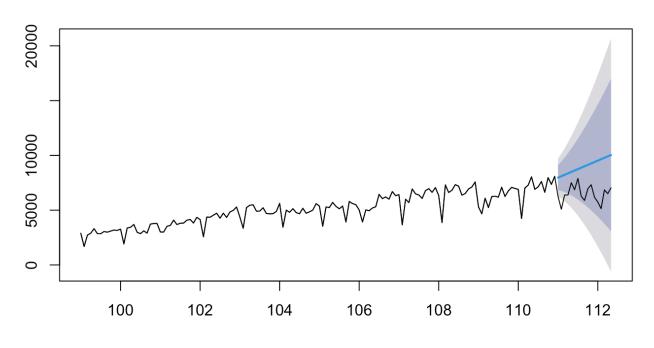
#### **Holt-Winters filtering**





## HOLT LINEAR TREND MODEL PREDICTION

#### **Forecasts from HoltWinters**

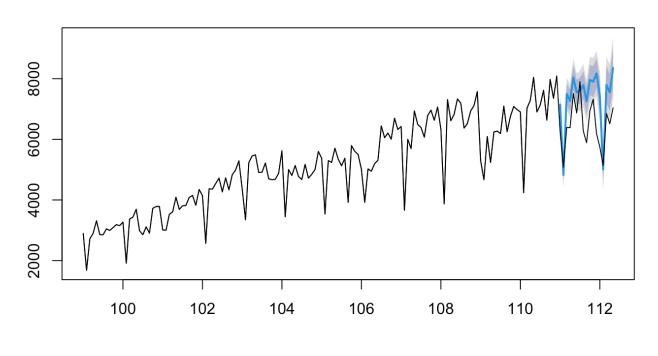


RMSE=2691.283



### HOLT-WINTERS SEASONAL MODEL PREDICTION

#### **Forecasts from HoltWinters**







## CONCLUSION

model	SARIMA	HOLT	HOLT-WINTERS
RMSE	1103.204	2691.283	1078.029

從模型結果可以看出季節性對此data的重要性!

