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# Semester One 2022 Examination Period

Examination Period						
Faculty of Business & Economics						
EXAM CODES:	ETF3231/ETF523	ETF3231/ETF5231 - PAPER 1				
TITLE OF PAPER:	<b>Business Forecas</b>	Business Forecasting				
EXAM DURATION:	2 hours 40 minut	es				
READING TIME:	0 minutes					
✓ Caulfield	_	Parkville	Peninsula South Africa			
This includes books, notes writing on any part of you	not have in your possession , paper, electronic device/s, r r body. Any authorised items our person will be deemed to	nobile phone, sr are listed below	nart watch/devic . Items/materials	e, calculator, pencil case, or		
	s are to be removed from the aterial for personal use or to s					
	above instructions, or attempressity (Council) Regulations, of ions.					
AUTHORISED MATERIALS						
OPEN BOOK		√ YES	□NO			
CALCULATORS Only HP 10bII+ or Casio	FX82 (any suffix) calculator pern	√ YES mitted	□NO			
SPECIFICALLY PERMITTE if yes, items permitted a		YES	√ NO			
Candidat	es must complete this section	n if required to v	write answers wi	thin this paper		
STUDENT ID:	STUDENT ID: DESK NUMBER:					

The exam contains FIVE questions. ALL questions must be answered. The exam is worth 100 marks in total.

### **SECTION A**

Write about a quarter of a page each on any **four** of the following topics. Clearly state if you agree or disagree with each statement.

- 1. Events like COVID-19 show that forecasting is never a good idea because the future is too unpredictable.
- 2. Taking logarithms of the data is useful for stabilizing the variance of a time series.
- 3. Regression models are better than ARIMA models because the coefficients are more interpretable.
- 4. The best forecasting model has white noise residuals.
- 5. Choosing a model using the AICc is better than choosing a model on the basis of a test set because it involves all the data.
- 6. The MAPE is the best accuracy measure because it is easy to understand and is independent of the scale of the data.

Total: 20 marks

- END OF SECTION A -

### **SECTION B**

Figures 1, 2 and 3 relate to the daily page views on the OTexts website from 1 January 2018 to 10 April 2022.

1. Using Figures 1, 2 and 3, describe the daily page views on the OTexts website. Carefully comment on the interesting features of all three plots.

otexts %>%
 autoplot(Pageviews) +
 labs(subtitle = "Daily Pageviews on OTexts.com", y = "Thousands")

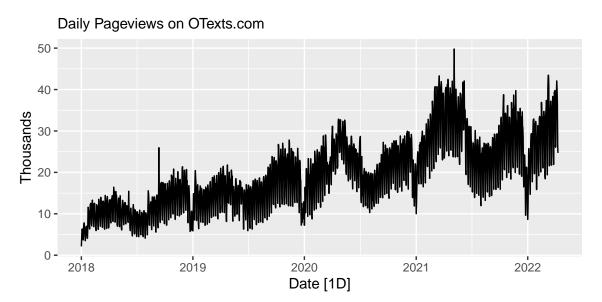


Figure 1:

```
otexts %>%
  gg_season(Pageviews, period = "year") +
  labs(subtitle = "Daily Pageviews on OTexts.com", y = "Thousands")
```

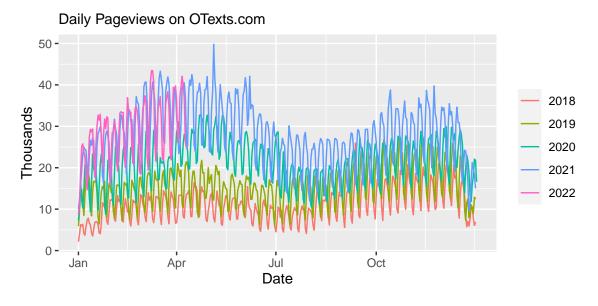


Figure 2:

```
otexts %>%
  gg_season(Pageviews, period = "week") +
  labs(subtitle = "Daily Pageviews on OTexts.com", y = "Thousands")
```

### Daily Pageviews on OTexts.com 50 -40 -2021 W43 Thousands 30 -2020 W46 2019 W48 20 -2018 W50 10 -Tuesday Wednesday Thursday Friday Saturday Monday Sunday Date

Figure 3:

2. Figure 4 was created using the code below. Why has a logarithm been used? Comment on the choice of the window argument in each term. What would you expect if the window values were substantially changed?

```
otexts %>%
model(STL(log(Pageviews) ~ trend(window = 99) +
    season(period = "week", window = 99) +
    season(period = "year", window = 9),
    robust = TRUE
)) %>%
components() %>%
autoplot()
```

## STL decomposition

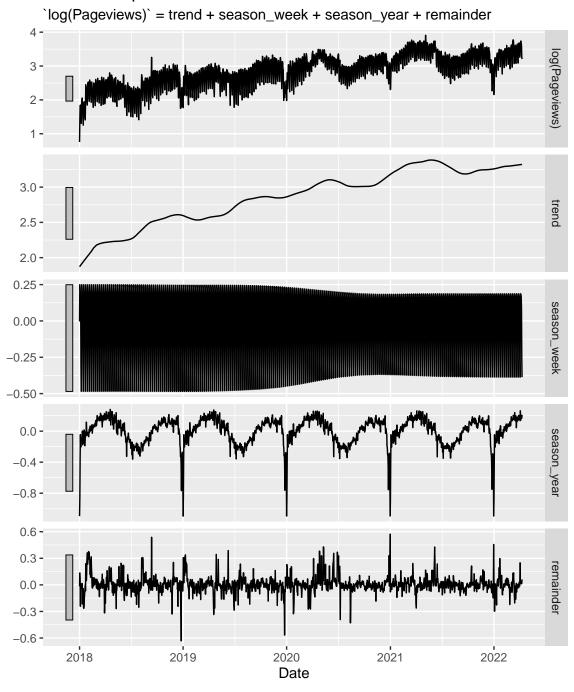


Figure 4:

- 3. You have been asked to provide forecasts for the next four weeks for OTexts pageviews.
  - Consider applying each of the methods and models below. Comment, in a few words each, on whether each one is appropriate for forecasting the data. No marks will be given for simply guessing whether a method or a model is appropriate without justifying your choice.

Start your response by stating: suitable or not suitable.

- (a) Seasonal naïve method using annual seasonality.
- (b) Seasonal naïve method using weekly seasonality.
- (c) An STL decomposition on the log transformed data combined with an ETS to forecast the seasonally adjusted component, and seasonal naïve methods for both seasonal components.
- (d) Holt-Winters method with damped trend and multiplicative weekly seasonality.
- (e) ETS(A,N,A).
- (f) ETS(M,A,M) with annual seasonality.
- (g) ARIMA $(2,2,2)(0,0,0)_7$  applied to the log transformed data.
- (h) ARIMA $(0,1,1)(0,1,1)_7$  applied to the log transformed data.
- (i) Regression with time and Fourier terms for both weekly and annual seasonality.
- (j) Dynamic regression on the log transformed data with Fourier terms for the annual seasonality and a seasonal ARIMA model to handle the weekly seasonality and other dynamics.

10 marks

Total: 20 marks

- END OF SECTION B -

### **SECTION C**

The output below shows the results of fitting an ETS model to the Pageviews variable.

```
fit <- otexts %>%
  model(ETS(Pageviews))
report(fit)
## Series: Pageviews
## Model: ETS(M,A,M)
##
     Smoothing parameters:
       alpha = 0.5737414
##
       beta = 0.0001000033
##
##
       gamma = 0.1266783
##
##
     Initial states:
##
        1[0]
                   b[0]
                             s[0]
                                       s[-1]
                                                s[-2]
                                                          s[-3]
                                                                   s[-4]
    3.605899 0.1449521 0.6318171 0.7210449 1.035443 1.163588 1.300494 1.20237
##
##
        s[-6]
    0.9452431
##
##
##
     sigma^2:
               0.0101
##
##
        AIC
                AICc
                           BIC
## 13337.34 13337.54 13401.58
```

1. Write down the observation and state equations for the model, specifying which is the observation equation, what parameters have been optimized, and explaining why this particular model was chosen.

6 marks

2. Figure 5 shows the components of the model. Explain what has been plotted, and how these plots relate to the equations shown earlier. Explain how the values of beta and gamma shown earlier correspond to features of these plots.

```
fit %>%
  components() %>%
  autoplot()
```

### ETS(M,A,M) decomposition

Pageviews = (lag(level, 1) + lag(slope, 1)) \* lag(season, 7) \* (1 + remainder)

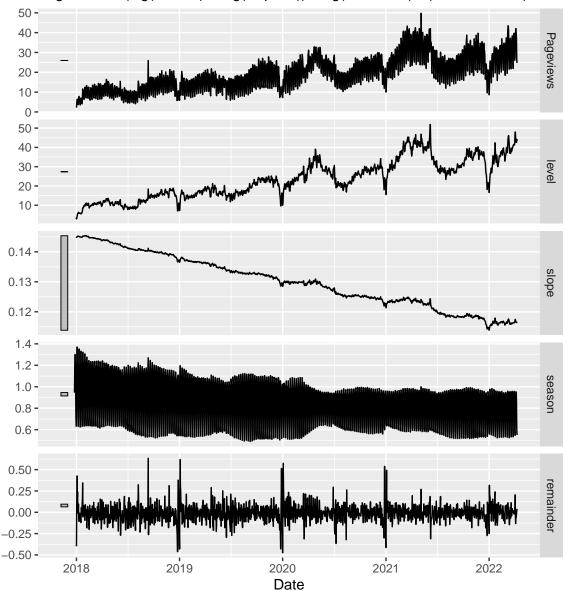


Figure 5:

3. How have the annual and weekly seasonalities been handled by this ETS model?

3 marks

4. Comment on the large residuals seen at the end of each year, and the dip in the level at the end of each year. What is causing these?

2 marks

5. Do you expect this model to produce good forecasts for the next 3 weeks? What about for the next 12 months? Explain.

4 marks

Total: 20 marks

### **SECTION D**

It is decided to fit a dynamic regression model to the data, with Fourier terms to handle the annual seasonality, and a seasonal ARIMA error to handle the weekly seasonality.

```
fit arima <- otexts %>%
 model(
    dr = ARIMA(log(Pageviews) ~ fourier(period = "year", K = 4) + PDQ(period = "week"))
report(fit arima)
## Series: Pageviews
## Model: LM w/ ARIMA(1,0,2)(2,1,1)[7] errors
## Transformation: log(Pageviews)
##
## Coefficients:
##
            ar1
                     ma1
                               ma2
                                      sar1
                                              sar2
                                                        sma1
##
         0.8858
                -0.1213 -0.1750 0.1600
                                            0.0247
                                                     -0.9046
         0.0236
                  0.0361
                           0.0341 0.0307
                                                      0.0182
## s.e.
                                            0.0298
##
         fourier(period = "year", K = 4)C1_365
##
                                         0.0071
## s.e.
                                         0.0318
##
         fourier(period = "year", K = 4)S1 365
##
                                         0.0928
## s.e.
                                         0.0319
##
         fourier(period = "year", K = 4)C2 365
##
                                        -0.1580
## s.e.
                                         0.0251
##
         fourier(period = "year", K = 4)S2_365
##
                                        -0.0818
## s.e.
                                         0.0255
         fourier(period = "year", K = 4)C3_365
##
##
                                        -0.0440
## s.e.
                                         0.0228
##
         fourier(period = "year", K = 4)S3 365
##
                                         0.0183
## s.e.
                                         0.0229
##
         fourier(period = "year", K = 4)C4 365
##
                                         -0.0575
## s.e.
                                         0.0208
##
         fourier(period = "year", K = 4)S4 365
##
                                         0.0018
## s.e.
                                         0.0209
##
## sigma^2 estimated as 0.009012:
                                    log likelihood=1456.1
## AIC=-2882.21
                  AICc=-2881.9
                                  BIC=-2801.98
```

1. Write down the model using backshift notation.

2. Comment on the model diagnostics shown in Figure 6 and the output below. How might the model be improved? Do you think the resulting forecasts will be reliable?

5 marks

```
augment(fit_arima) %>%

gg_tsdisplay(.innov, "histogram")
```

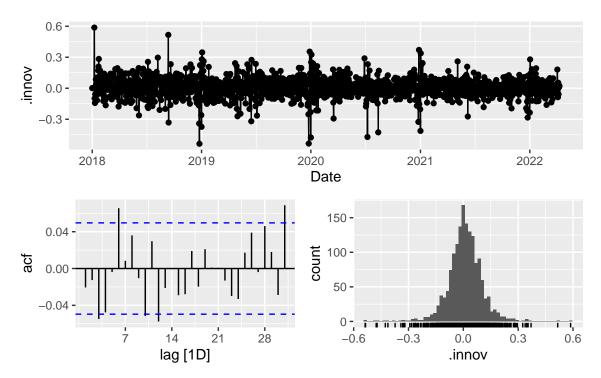


Figure 6:

3. Figure 7 shows forecasts with prediction intervals for the next four weeks, along with the data from 2022. The forecasts appear to have no trend. Why is that? If you wanted to include a *local* trend, how would you modify the model?

```
fit_arima %>%
  forecast(h = "4 weeks") %>%
  autoplot(otexts %>% filter(year(Date) == 2022)) +
  labs(title = "Data and forecasts for 2022")
```

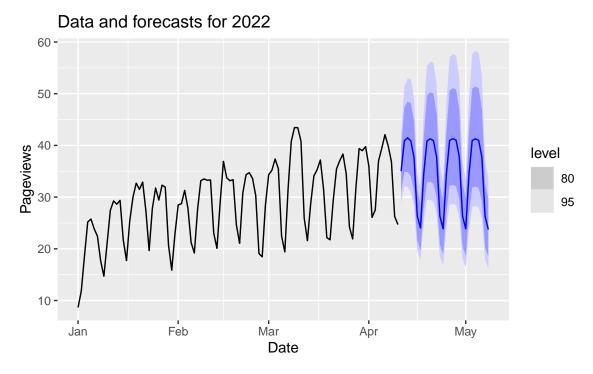


Figure 7:

4. The one-step-ahead forecast is 35.0 pageviews. Give a 95% prediction interval assuming Gaussian innovation residuals.

4 marks

5. It is thought that pageviews will be higher during teaching semesters. How would you modify this model to allow for a semester effect?

2 marks

Total: 20 marks

- END OF SECTION D -

### **SECTION E**

1. You decide to compare three different models on this data set: (a) the ETS model from Section C; (b) the dynamic regression model from Section D; and (c) the STL decomposition shown in Figure 4 with ETS applied to the seasonally adjusted data, and seasonal naive methods applied to both seasonal components.

The following code uses a test set of the last 4 weeks to compare the three models, along with two benchmark methods.

```
fit <- otexts %>%
  head(-28) %>%
 model(
   ets = ETS(Pageviews),
   dr = ARIMA(log(Pageviews) ~ fourier(period = "year", K = 4) +
                                PDQ(period = "week")),
   stl = decomposition model(
            STL(log(Pageviews) \sim trend(window = 99) +
                  season(period = "week", window = 99) +
                  season(period = "year", window = 9),
                  robust = TRUE),
            ETS(season_adjust)
   ),
   naive = NAIVE(Pageviews),
   snaive = SNAIVE(Pageviews ~ lag("week"))
 )
fc <- fit %>%
 forecast(h = 28)
 accuracy(otexts, measures=list(RMSE=RMSE, MAPE=MAPE)) %>%
 arrange(RMSE)
```

What do you conclude from the above output about the five models? Explain the two accuracy measures used. Why is the naive method so bad?

4 marks

2. An alternative approach to comparing the forecast accuracy of models would be to use time series cross-validation. Explain the concept of time series cross-validation. You may use an annotated diagram.

3. You decide the snaive model is good enough even though it is not as accurate as the first three models. Let the observations be  $y_1, \ldots, y_T$  and the residual variance be denoted by  $\sigma^2$ . Write down the forecast distribution for an h-step forecast. What assumptions have you made?

5 marks

4. OTexts also needs forecasts of the maximum monthly traffic that could arise, in order to make sure their internet server will cope with the extreme demand. They want to choose an internet plan that allows for a maximum of *P* pageviews per month, and they are happy to allow a 1% chance of being above this level. Explain how you would choose *P* based on forecasts over the next 12 months.

5 marks

Total: 20 marks

- END OF SECTION E -