Tourism Data Analysis

31 July 2019

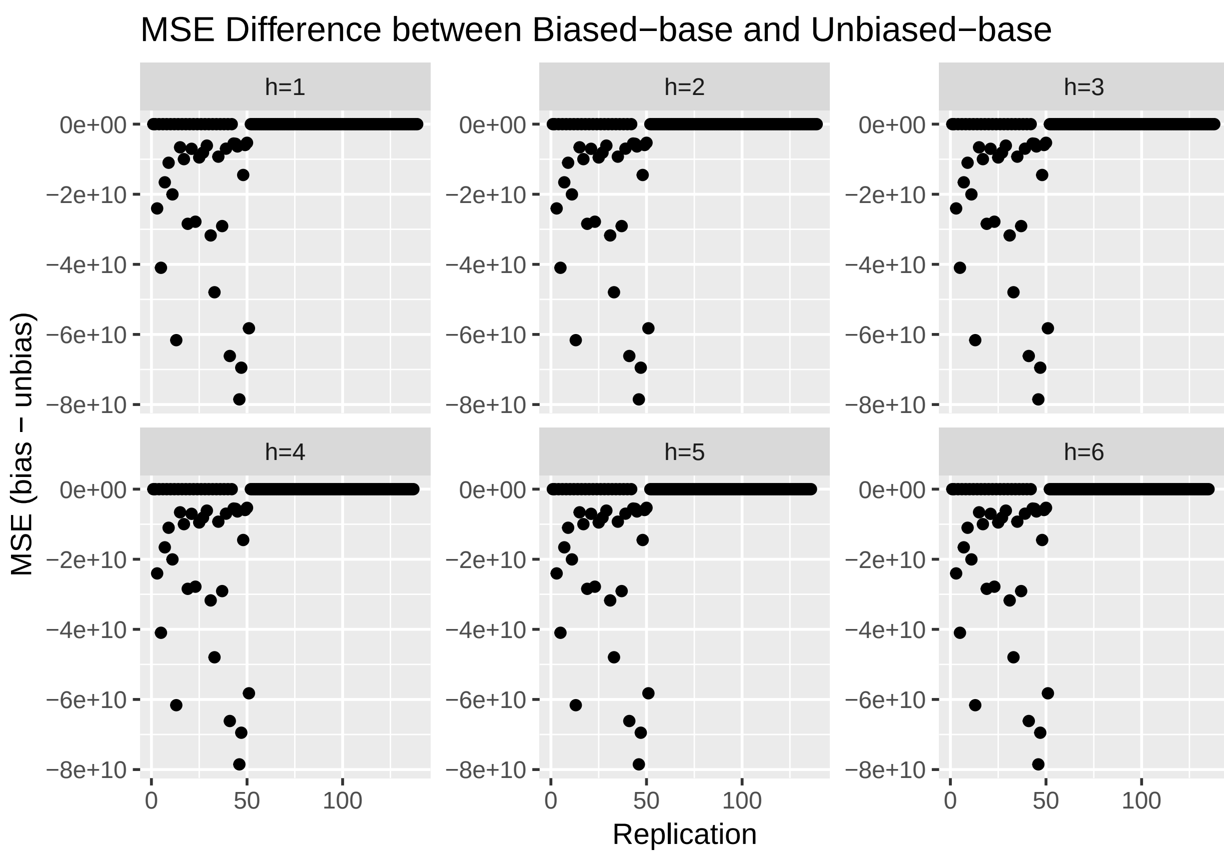
Bias adjusted forecasts are given as follows:

$$y_t = \begin{cases} \exp x_t[1 + \frac{\sigma_h^2}{2}] & \text{if } \lambda = 0 \\ \\ (\lambda x_t + 1)^{1/\lambda}[1 + \frac{\sigma_h^2(1-\lambda)}{2(\lambda x_t + 1)^2}] & \text{Otherwise} \end{cases}$$

For BoxCox transformed data (Using the BoxCox function in the forecast package)

In this exercise I have used the `BoxCox.lambda()` function in forecast package to automatically find a proper transformation for each series.

	h=1		h=2		h=3		h=4	
R-method	Biased	Unbiased	Biased	Unbiased	Biased	Unbiased	Biased	Unbia
Base	12278.62	5.170645e+09	13171.69	5.170730e+09	13853.12	5.208223e+09	15940.78	5.246292e-
Bottom-up	17982.19	2.068269e+10	17861.05	2.068446e+10	18480.28	2.083190e+10	20500.91	2.098719e-
MinT(Shrink)	10187.03	9.899359e+03	11507.51	1.080718e+04	12402.17	1.179984e+04	15529.77	1.401968e-
OLS	11830.03	3.793202e+09	12833.82	3.793271e+09	13516.04	3.820789e+09	15618.33	3.848752e-
WLS	15728.03	1.402450e+04	15930.56	1.370782e+04	16638.94	1.450090e+04	18910.95	1.625339e-

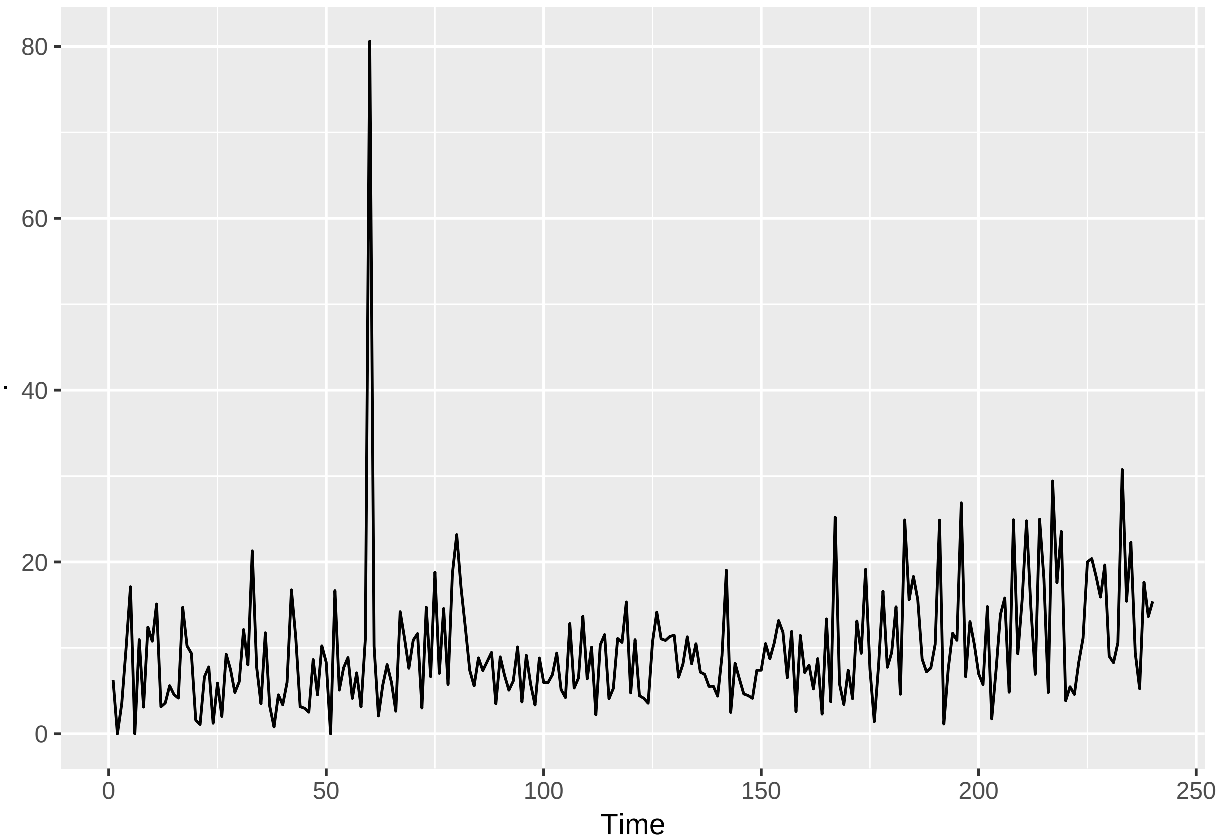


The above graph shows the difference between the MSE of `Base-biased forecasts` and `Base-unbiased forecasts`. As we can see, this difference is very large for some of the replications which courses the large average MSE in unbiased-base forecasts shown in the table 1.

However an important thing to notice here is that although the unbiased base forecasts are terrible, MinT has adjusted these through the reconciliation. In fact the MinT reconciled unbiased forecasts are even better than the MinT reconciled biased forecasts.

We have also noticed that the based-bias adjusted forecasts are going worst for only one variable which is `Adelaide Hills`. If we visualise this time series we get,

```
AllTS %>%
  dplyr::select(`Adelaide Hills`) %>%
  as.ts() %>%
  autoplot()
```



We can see this variable has a very unusual observation which might be an outlier. To avoid this, I have replaced this observation with the average of it's adjacent observations. Then I have refitted the models for automatically chosen BoxCox transformed data and back-transformed and back-transformed bias-adjusted forecasts were obtained. The results are as follows.

	h=1		h=2		h=3		h=4		h
R-method	Biased	Unbiased	Biased	Unbiased	Biased	Unbiased	Biased	Unbiased	Biased
Base	12211.93	161607.44	13171.58	243382.99	13852.99	268664.87	15940.66	325216.31	15535.03
Bottom-up	17861.25	15549.44	17859.03	14901.96	18473.08	15607.21	20498.29	17214.97	20339.64
MinT(Shrink)	10202.61	10025.34	11508.72	10827.99	12411.10	11812.91	15528.58	14033.35	14617.11
OLS	11765.67	135167.10	12833.74	204657.51	13515.97	225108.83	15618.28	272250.83	15210.38
WLS	15636.09	13980.72	15930.46	13715.41	16636.62	14492.72	18910.67	16259.52	18754.80

These results also shows that, even though the bias-adjusted based forecasts are worst than that of biased base forecasts, the MinT reconicilation is outperforming.

For Log transformed data

In this exercise I have used only the log transformation. As we can see from the results, the bias adjusted forecasts are outperforming biased forecasts as we would expect.

	h=1		h=2		h=3		h=4		h=
R-method	Biased	Unbiased	Biased	Unbiased	Biased	Unbiased	Biased	Unbiased	Biased
Base	12369.306	12172.307	12926.70	12708.52	14156.00	13950.30	15396.09	15063.25	15492.90
Bottom-up	17250.633	15349.826	17276.24	15049.39	17951.51	15514.18	19772.43	17148.44	20004.22
MinT(Shrink)	9381.599	9299.624	11297.88	11228.62	12456.07	12286.74	13420.79	13225.14	13665.27
OLS	11886.503	11708.234	12574.79	12377.98	13792.53	13620.81	15021.11	14714.86	15139.72
WLS	14938.728	13775.262	15159.62	13830.53	15981.18	14505.29	17950.12	16258.10	18173.51