Business Forecasting

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Understand and explain your model output

For Mean_forecast output is

```
##          Point Forecast   Lo 80    Hi 80    Lo 95    Hi 95
## Feb 2018       88.84722 69.0691 108.6253 58.55708 119.1374
## Mar 2018       88.84722 69.0691 108.6253 58.55708 119.1374
## Apr 2018       88.84722 69.0691 108.6253 58.55708 119.1374
## May 2018       88.84722 69.0691 108.6253 58.55708 119.1374
## Jun 2018       88.84722 69.0691 108.6253 58.55708 119.1374
```

The point forecast for February to June 2018 is `88.84722`, suggesting a stable expected value of approximately `88.85` based on historical data. The 80% prediction interval ranges from `69.0691` to `108.6253`, indicating confidence in this range for actual values. The wider 95% interval spans from `58.55708` to `119.1374`, reflecting increased uncertainty. This output highlights the potential variability in actual outcomes and the importance of considering prediction intervals. Overall, it emphasizes the need for informed decision-making by quantifying uncertainty in forecasts.

For Naïve forecast model

```
##          Point Forecast    Lo 80    Hi 80     Lo 95    Hi 95
## Feb 2018       129.4048 119.4651 139.3445 114.20331 144.6063
## Mar 2018       129.4048 115.3479 143.4617 107.90665 150.9030
## Apr 2018       129.4048 112.1887 146.6209 103.07505 155.7346
## May 2018       129.4048 109.5254 149.2842  99.00182 159.8078
## Jun 2018       129.4048 107.1789 151.6307  95.41324 163.3964
```

The naive forecast for February to June 2018 predicts a constant value of `129.4048`, reflecting stability without expected changes. The 80% prediction intervals range from approximately `107.18` to `151.63`, indicating confidence in this range for actual values. Wider 95% intervals span from `95.41` to `163.40`, highlighting greater uncertainty. While this simple model is useful for quick assessments, it may miss underlying trends and variability. Therefore, it should be complemented with more advanced models to enhance forecasting accuracy.

For Rw forecast

```
##          Point Forecast    Lo 80    Hi 80     Lo 95    Hi 95
## Feb 2018       129.5485 119.5853 139.5116 114.31118 144.7858
## Mar 2018       129.6922 115.5844 143.7999 108.11624 151.2681
## Apr 2018       129.8359 112.5358 147.1359 103.37767 156.2940
## May 2018       129.9795 109.9781 149.9810  99.39000 160.5691
## Jun 2018       130.1232 107.7330 152.5134  95.88035 164.3661
```

The random walk forecast from February to June 2018 shows a slight upward trend, with point forecasts rising from `129.5485` in February to `130.1232` in June. The 80% prediction intervals for February range from `119.5853` to `139.5116`, indicating confidence in actual values falling within this range. The wider 95% intervals, spanning from `114.31118` to `144.7858`, reflect greater uncertainty. This output highlights the importance of considering both expected values and their variability in decision-making. Overall, it provides a framework for understanding potential risks based on historical trends.

For snaive forecast model

```
##          Point Forecast    Lo 80     Hi 80    Lo 95     Hi 95
## Feb 2018        99.4901 94.80499 104.17521 92.32484 106.65536
## Mar 2018       101.0396 96.35449 105.72471 93.87434 108.20486
## Apr 2018        88.3530 83.66789  93.03811 81.18774  95.51826
## May 2018        92.0805 87.39539  96.76561 84.91524  99.24576
## Jun 2018       102.1532 97.46809 106.83831 94.98794 109.31846
```

The snaive forecast for February to June 2018 predicts point values that reflect seasonal patterns, with forecasts ranging from `88.3530` in April to `102.1532` in June. The 80% prediction intervals provide a range of confidence for actual values, with February's bounds from `94.80499` to `104.17521`. Wider 95% intervals, such as `92.32484` to `106.65536` for February, reflect greater uncertainty. The model captures seasonal variations effectively, indicating fluctuations in expected outcomes. Overall, it emphasizes the importance of considering seasonality in time series forecasting for better decision-making.

For MA5_forecast

The moving average values from 1985 to 2017 show a smoothed representation of the data, reducing fluctuations and highlighting trends over time. For example, early years show steady increases, peaking in the mid-2000s, while later years reflect a more stable pattern with slight variations. The absence of data for January 2018 suggests that the moving average calculation requires prior data points. This approach helps identify underlying trends without being overly influenced by short-term volatility. Overall, the moving average serves as a useful tool for analyzing long-term patterns in the dataset.

For MA10 Forecast

The moving average dataset from 1985 to 2017 illustrates trends in monthly values, smoothing out short-term fluctuations to reveal longer-term patterns. Values show a general upward trajectory over the years, peaking in the mid-2000s before stabilizing in the later years. The missing data points for early 1985 and 2018 highlight the need for a complete dataset to effectively calculate averages. This approach helps identify seasonal patterns and shifts in the data. Overall, the moving average serves as a valuable tool for understanding historical trends and making informed projections.

For doble moving average forecast

```
## Holt-Winters exponential smoothing with trend and additive seasonal comp
onent.
##
## Call:
## HoltWinters(x = ts_data)
##
## Smoothing parameters:
##  alpha: 0.5114631
##  beta : 0
##  gamma: 0.4937904
##
## Coefficients:
##             [,1]
## a   109.88397723
## b     0.06902204
## s1    5.17157827
## s2   -0.87042757
## s3  -12.39608137
## s4  -10.05303052
## s5    1.05754725
## s6   10.55311009
## s7    9.15800088
## s8   -1.51403696
## s9   -9.87520385
## s10  -6.88525059
## s11   8.32585970
```

```
## s12  17.44813758
```

The Holt-Winters exponential smoothing model applies an additive seasonal component to account for both trends and seasonality in the time series data. The smoothing parameters show that the level (alpha) is moderately influential, while the trend (beta) is not being adjusted (set to zero), indicating no significant trend component is detected. The seasonal smoothing parameter (gamma) is also moderately high, suggesting seasonal effects are captured effectively. The coefficients indicate the model's starting level (a), growth rate (b), and seasonal adjustments for each month, reflecting how seasonal variations influence the forecast. Overall, this model is suited for data with consistent seasonal patterns and no significant underlying trend.

For exponentially smoothing

```
## ETS(M,A,M)
##
## Call:
## ets(y = ts_data)
##
##   Smoothing parameters:
##     alpha = 0.4226
##     beta  = 6e-04
##     gamma = 0.1755
##
##   Initial states:
##     l = 62.4801
##     b = 0.0931
##     s = 1.0831 0.9238 0.9017 0.9553 1.0402 1.036
##            0.9751 0.9007 0.9278 1.0157 1.0883 1.1522
##
##   sigma:  0.0263
##
##      AIC     AICc      BIC
## 3053.850 3055.465 3121.577
```

The ETS(M,A,M) model indicates that the time series data is modeled with an error term that follows an additive trend and multiplicative seasonality. The smoothing parameters reveal that the level (alpha) has a moderate influence, while the trend (beta) is very small, suggesting a nearly constant trend. The seasonal component (gamma) is low, indicating less variability in seasonal adjustments. The initial states show the starting level (l), growth (b), and seasonal factors for each period, reflecting the seasonality's effect on the data. The AIC and BIC values suggest a good fit, with lower values indicating a better model performance.

For Holt forecast

```
##          Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
## Feb 2018       103.5511 93.35256 113.7497 87.95376 119.1485
## Mar 2018       103.6328 93.43411 113.8314 88.03527 119.2302
## Apr 2018       103.7144 93.51556 113.9132 88.11663 119.3122
## May 2018       103.7960 93.59687 113.9952 88.19776 119.3943
## Jun 2018       103.8777 93.67800 114.0773 88.27862 119.4767
## Jul 2018       103.9593 93.75890 114.1597 88.35914 119.5595
## Aug 2018       104.0409 93.83954 114.2423 88.43925 119.6426
## Sep 2018       104.1226 93.91988 114.3252 88.51890 119.7262
## Oct 2018       104.2042 93.99987 114.4085 88.59803 119.8104
## Nov 2018       104.2858 94.07948 114.4922 88.67656 119.8951
```

The Holt forecast provides projected values for the time series from February to November 2018, indicating a steady upward trend. Each point forecast remains around 103 to 104, suggesting minimal change over this period. The 80% confidence intervals (Lo 80, Hi 80) and 95% confidence intervals (Lo 95, Hi 95) provide ranges within which the actual values are likely to fall, reflecting uncertainty in the predictions. The intervals widen slightly over time, indicating increasing uncertainty as the forecast horizon extends. Overall, the model predicts stability with slight growth in the observed data.

For Simple smoothing

```
## Holt-Winters exponential smoothing without trend and without seasonal co
mponent.
##
## Call:
## HoltWinters(x = ts_data, beta = FALSE, gamma = FALSE)
##
## Smoothing parameters:
##  alpha: 0.9999339
##  beta : FALSE
##  gamma: FALSE
##
## Coefficients:
##       [,1]
```

```
## a 129.4038
```

The Holt-Winters model without trend and seasonal components indicates a very high level of smoothing with an alpha of approximately 0.9999. This suggests that the model places significant emphasis on the most recent observations, essentially tracking the data closely. The coefficient \(a\) is approximately 129.40, representing the level of the time series after accounting for smoothing. Since both trend (beta) and seasonal (gamma) components are turned off, this model is best suited for data that does not exhibit clear trends or seasonal patterns. Overall, this approach yields a simple level forecast that closely mirrors the latest data points.

For winters forecast

```
##          Point Forecast     Lo 80    Hi 80     Lo 95    Hi 95
## Feb 2018      114.52918 111.13601 117.9224 109.33977 119.7186
## Mar 2018      108.55558 104.83273 112.2784 102.86197 114.2492
## Apr 2018       97.24437  93.21861 101.2701  91.08751 103.4012
## May 2018       99.62374  95.31620 103.9313  93.03593 106.2115
## Jun 2018      110.75363 106.18153 115.3257 103.76121 117.7460
## Jul 2018      120.29207 115.46980 125.1144 112.91704 127.6671
## Aug 2018      119.01676 113.95655 124.0770 111.27784 126.7557
## Sep 2018      108.46048 103.17294 113.7480 100.37388 116.5471
## Oct 2018      100.26812  94.76251 105.7737  91.84802 108.6882
## Nov 2018      103.42439  97.70895 109.1398  94.68338 112.1654
## Dec 2018      118.74998 112.83205 124.6679 109.69929 127.8007
## Jan 2019      128.03697 121.92317 134.1508 118.68672 137.3872
## Feb 2019      115.80012 109.24777 122.3525 105.77916 125.8211
## Mar 2019      109.82653 103.09658 116.5565  99.53396 120.1191
## Apr 2019       98.51531  91.61226 105.4184  87.95800 109.0726
## May 2019      100.89468  93.82268 107.9667  90.07899 111.7104
## Jun 2019      112.02457 104.78750 119.2616 100.95642 123.0927
## Jul 2019      121.56302 114.16448 128.9616 110.24793 132.8781
## Aug 2019      120.28770 112.73108 127.8443 108.73084 131.8446
## Sep 2019      109.73143 102.01988 117.4430  97.93764 121.5252
## Oct 2019      101.53906  93.67558 109.4025  89.51291 113.5652
## Nov 2019      104.69533  96.68273 112.7079  92.44112 116.9495
## Dec 2019      120.02092 111.86186 128.1800 107.54272 132.4991
```

```
## Jan 2020      129.30791 121.00491 137.6109 116.60957 142.0063
```

The forecast from the Holt-Winters model indicates a variety of projected values from February 2018 to January 2020, reflecting the underlying patterns in the data. The point forecasts show fluctuations, with the highest forecast in January 2020 at approximately 129.31, suggesting a potential upward trend. The 80% and 95% confidence intervals provide ranges for these forecasts, indicating the level of uncertainty; for example, the 95% interval for January 2020 spans from about 116.61 to 142.01. Some months, such as February 2018, show a high forecast (114.53) followed by notable declines in subsequent months, indicating volatility. Overall, the model captures both the level and variability of the time series, helping to inform decision-making.

Pick an accuracy measure, compare your models, and state the best model based on the accuracy comparison

```
accuracy(naive_forecast)
##                     ME      RMSE       MAE         MPE      MAPE      MASE
ACF1
## Training set 0.1436859 7.756005 6.586275 -0.2059819 7.305277 2.307787 0.
3745347
accuracy(mean_forecast)
##                        ME      RMSE       MAE       MPE      MAPE     MASE
ACF1
## Training set 5.440818e-15 15.36844 12.59313 -3.26063 15.09589 4.41255 0.
8627791
accuracy(snaive_forecast)
##                    ME      RMSE       MAE       MPE     MAPE MASE       ACF1
## Training set 1.277674 3.655813 2.853935 1.495417 3.14802    1 0.5157808
accuracy(es_forecast)
##                      ME      RMSE       MAE            MPE      MAPE       MAS
E
## Training set 0.04313688 2.450764 1.862419 0.0004651161 2.035931 0.652579
3
##                   ACF1
## Training set 0.2033935
accuracy(holt_forecast)
##                   ME      RMSE       MAE         MPE      MAPE      MASE
ACF1
## Training set -0.2033 7.917794 6.632971 -1.010092 7.464721 2.324149 0.501
7449
accuracy(winters_forecast)
```

```
##                            ME      RMSE       MAE           MPE      MAPE       MAS
E
## Training set 0.04583001 2.593804 2.040593 -0.005969128 2.270192 0.715010
4
##                        ACF1
## Training set 0.1989171
```

The Exponential Smoothing (ETS) model emerges as the top performer across all accuracy metrics, indicating it is the most dependable for forecasting in this context. The Holt-Winters model also demonstrates strong performance, though it is marginally less accurate than ETS. In contrast, the Mean model displays the poorest performance overall.