

Forecasting of Kids Revenue

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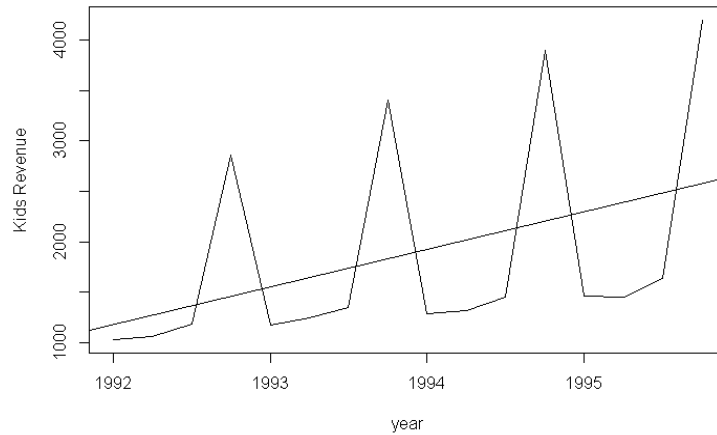
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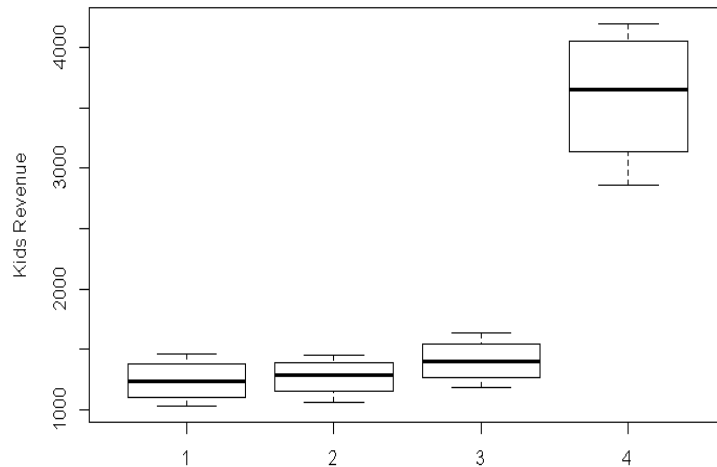
Exploratory Data Analysis

- The year on year trend clearly shows that the revenue has been increasing without fail.
- A Spike in revenue in fourth quarter of every year is observed.

Kids Revenue per each year



Comparison of Revenue for each year

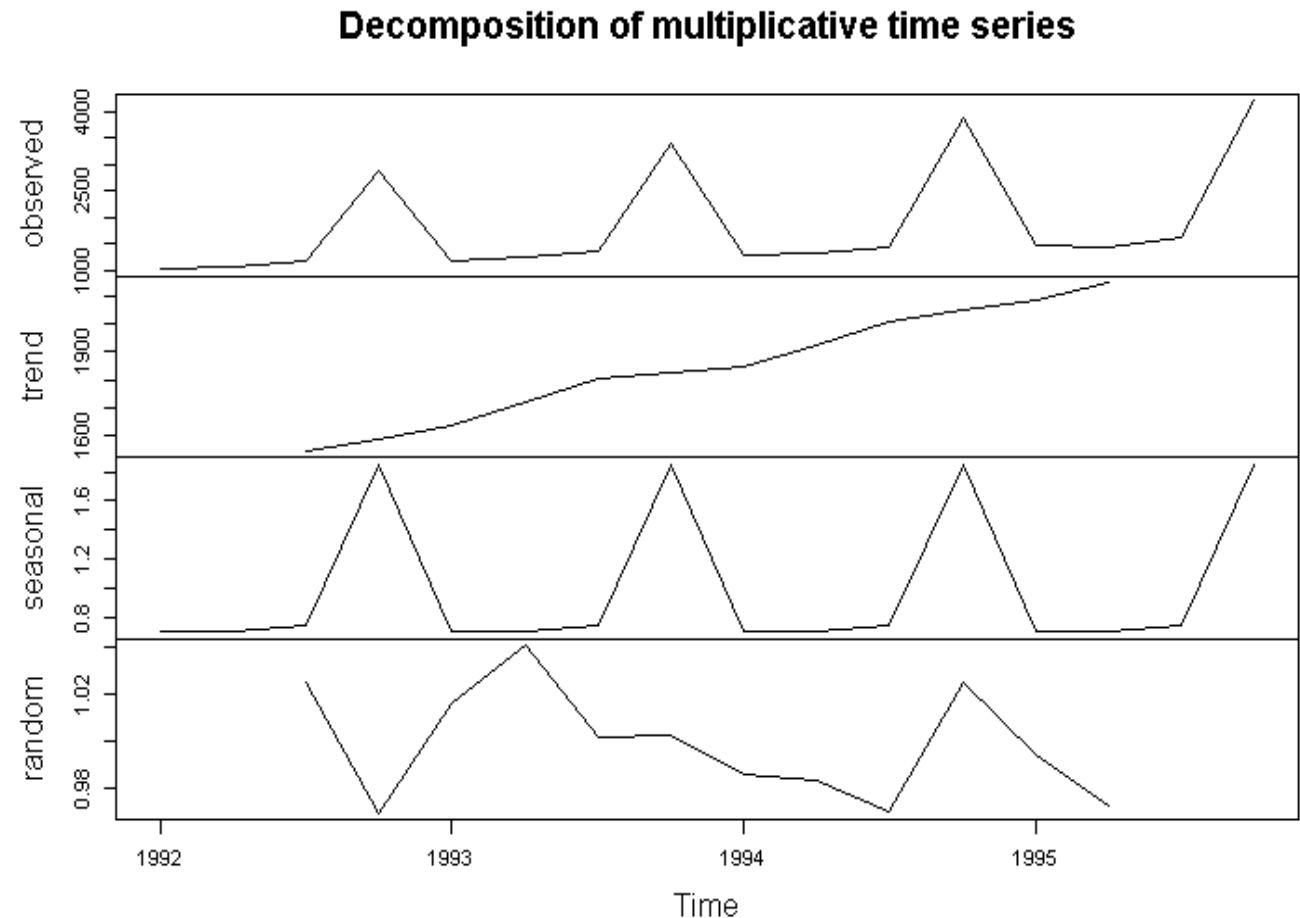


Exploratory Data Analysis

- Decomposition is a combination of level, trend, seasonality, and noise components.
- Decomposition procedures are used in time series to describe the trend and seasonal factors.
- Multiplicative Model

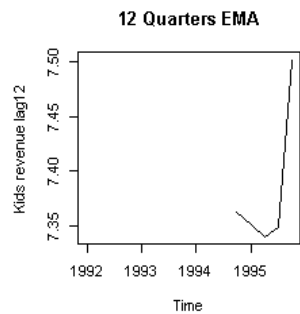
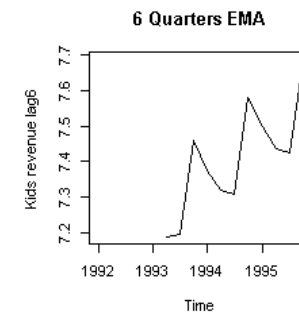
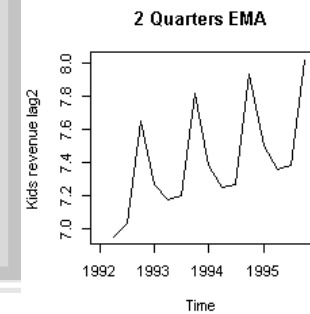
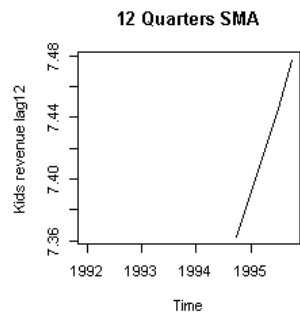
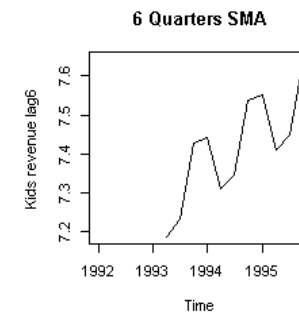
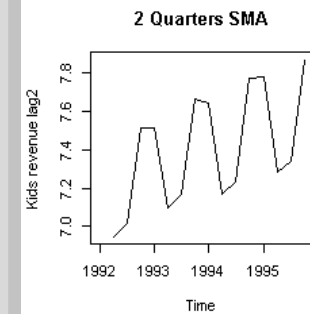
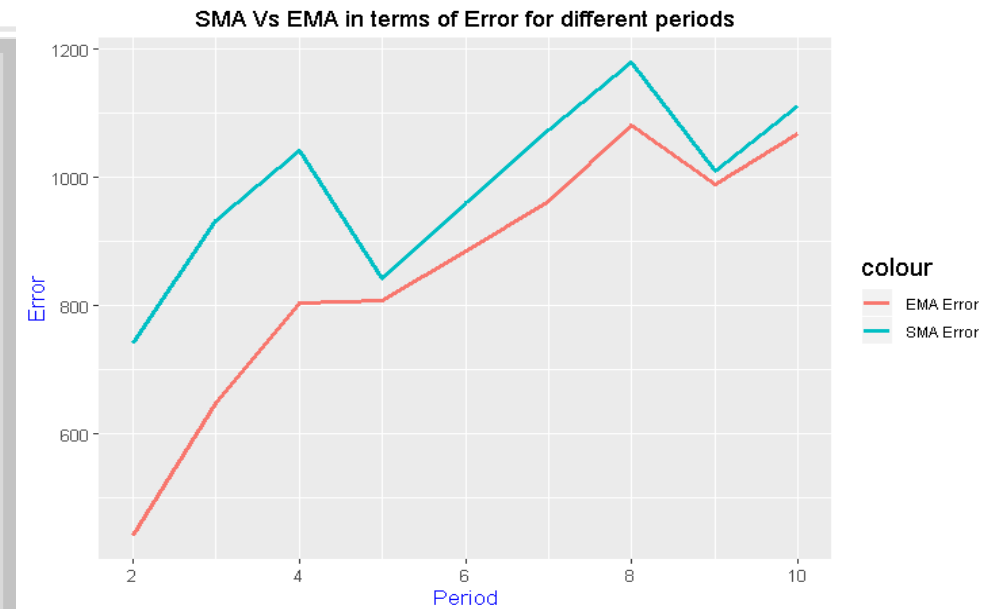
$$y(t) = \text{Level} * \text{Trend} * \text{Seasonality} * \text{Noise}$$

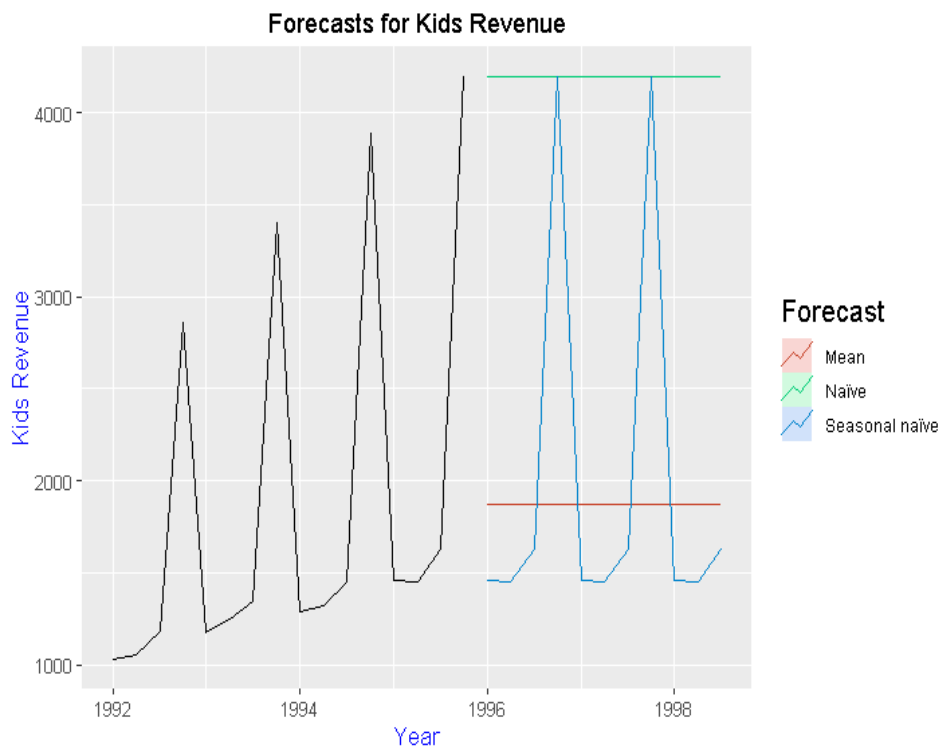
- We can see that the trend and seasonality information extracted from our data shows that revenue increases overtime.



Using Moving Average

- SMA gives overall trend based on average of historical values in a given time frame.
- Moving averages smoothens the kids revenue data to form a trend, they do not predict price direction, but rather define the current direction with a lag.
- EMA gives higher weightage to recent revenue, while the SMA assigns equal weightage to all values.



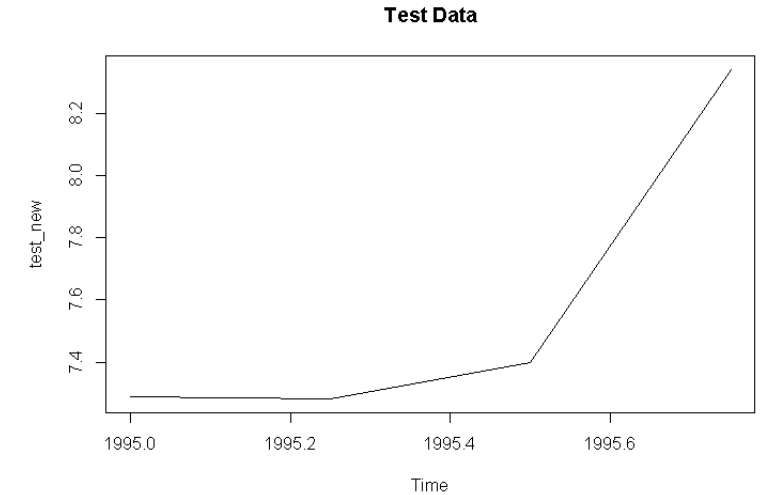
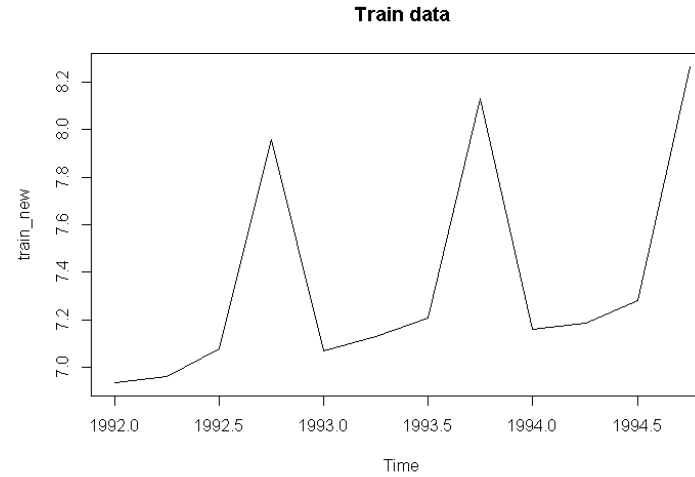


Naïve Methods

- **Naïve Forecast** : Method uses the most recent observation for forecasting. In our case forecast value for the revenue is \$4200 (in millions) . Since it is the last observation.
- **Seasonal Naïve** : Method uses the last value from the same season for forecasting
- **Mean** : Method is the Mean of historical data, mean revenue forecasted for current data is \$1874 (in million)

```
> forecast_seasonalnaive
      Point Forecast      Lo 80      Hi 80      Lo 95      Hi 95
1996 Q1          1462  1126.1704  1797.830   948.3929  1975.607
1996 Q2          1452  1116.1704  1787.830   938.3929  1965.607
1996 Q3          1631  1295.1704  1966.830  1117.3929  2144.607
1996 Q4          4200  3864.1704  4535.830  3686.3929  4713.607
1997 Q1          1462   987.0652  1936.935   735.6499  2188.350
1997 Q2          1452   977.0652  1926.935   725.6499  2178.350
1997 Q3          1631  1156.0652  2105.935   904.6499  2357.350
1997 Q4          4200  3725.0652  4674.935  3473.6499  4926.350
```

ARIMA Model



- **ARIMA** :Autoregressive Integrated Moving Averages
- Present data contains revenue information of 4 years across the 4 quarters.
- First 3 years data has been taken for training and last 1 year data has been taken for testing.
- Calculating AR and MA part required stationary time series data which is achieved in I through differencing.

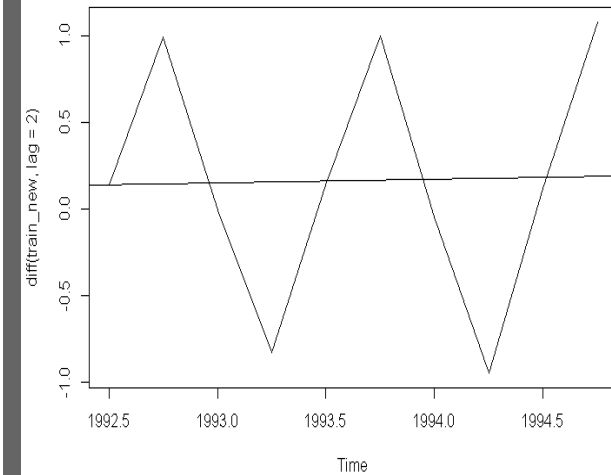
ARIMA Model: Integrated

- We have applied logarithmic transformation to stabilize the variance in the data
- Based on the plots we could see that the data shows the variation in the plot.
- Differencing can help to stabilize the time series data by eliminating the trend and seasonality.
- In Kids revenue we converted data to stationary. By differencing the data with lag 1
- ADF Test with p – value (0.01) less than 0.05, also confirms that differenced data is stationary.

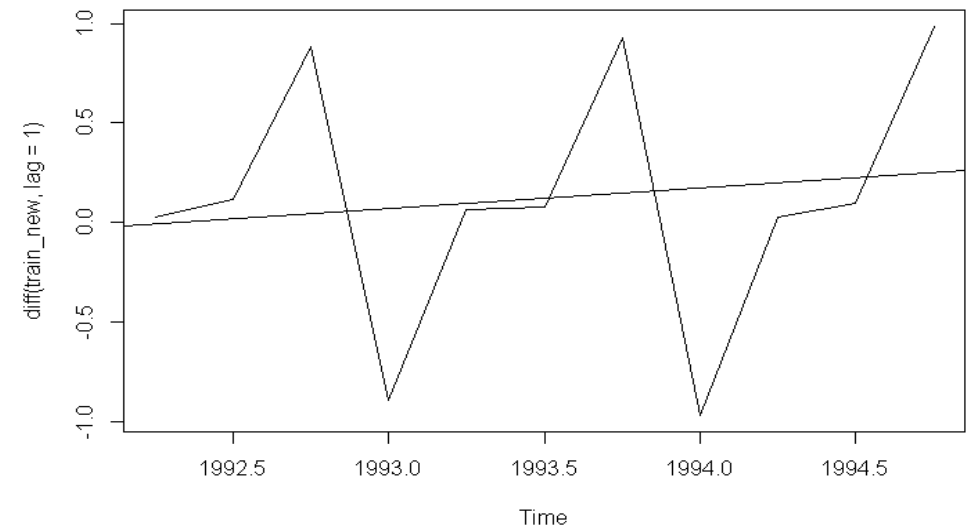
Train Data with no differencing



Train Data differencing with lag 2

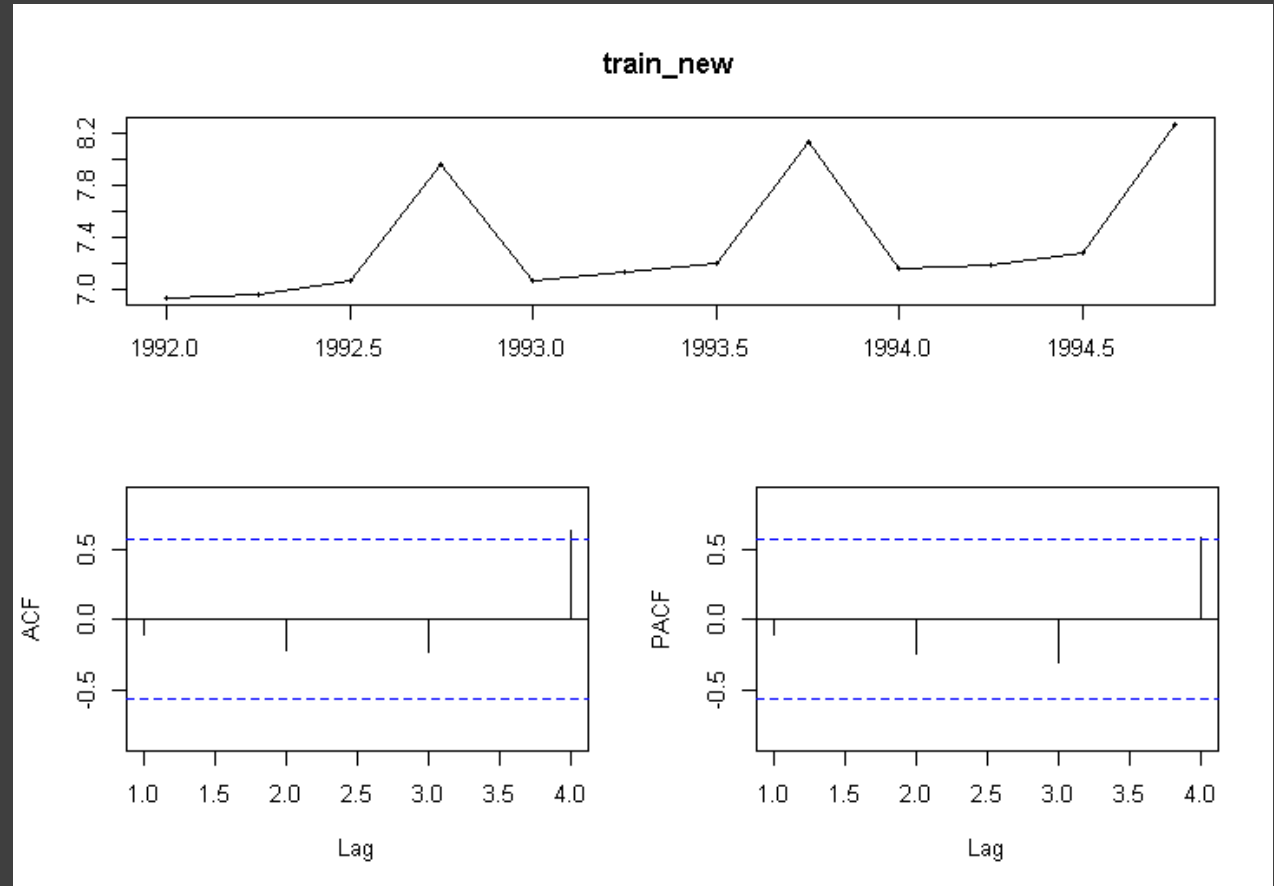


Train Data differencing with lag 1



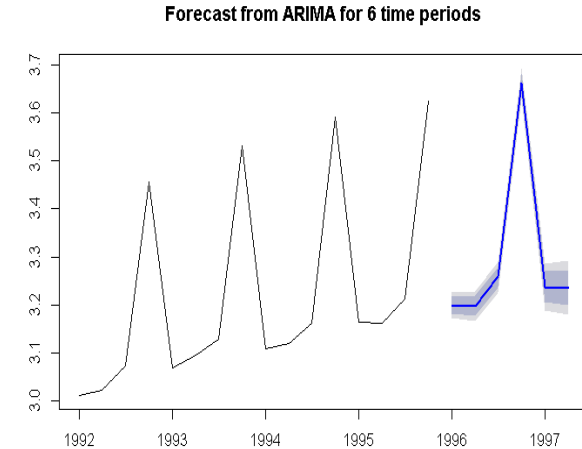
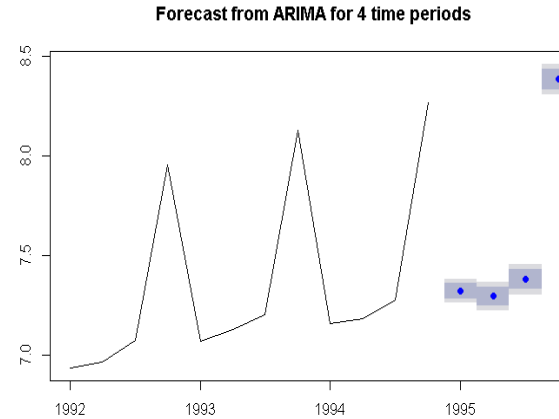
ACF and PACF Values:

- **p**: The number of lag observations included in the model, also called the lag order.
- **q**: The size of the moving average window, also called the order of moving average.
- From ACF we can see that lag of 4 has strong correlation between values of the same variable across observations.
- From PACF, we can see that lag of 4 shows that there is strong association between two variables while adjusting for effect.
- ARIMA Model – (4,1,4)



ARIMA Model Forecasting

- Using p, d, q Values, we calculated the Test RMSE on year 1995 for 4 quarters.
- We have forecasted revenue for the next 6 quarters Q1 1996 – Q2 1997.



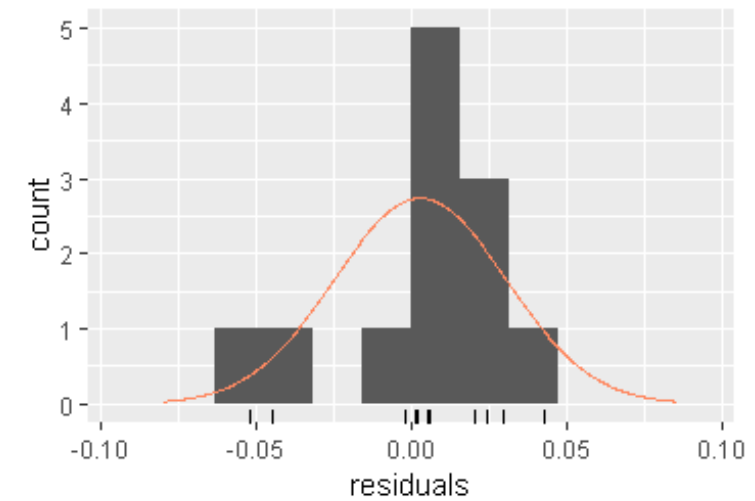
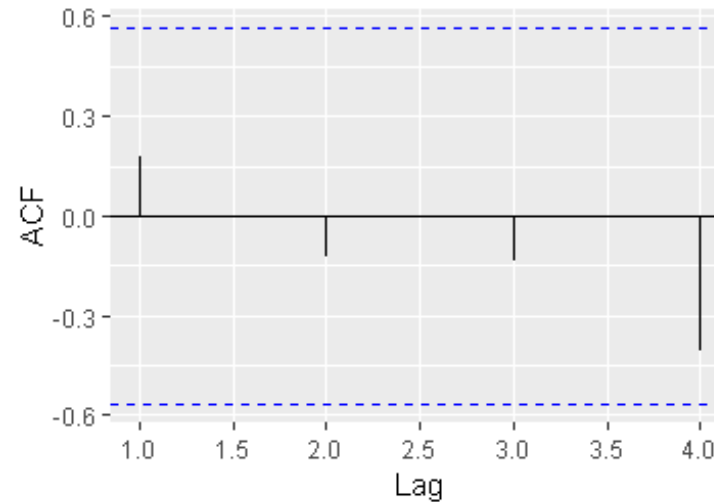
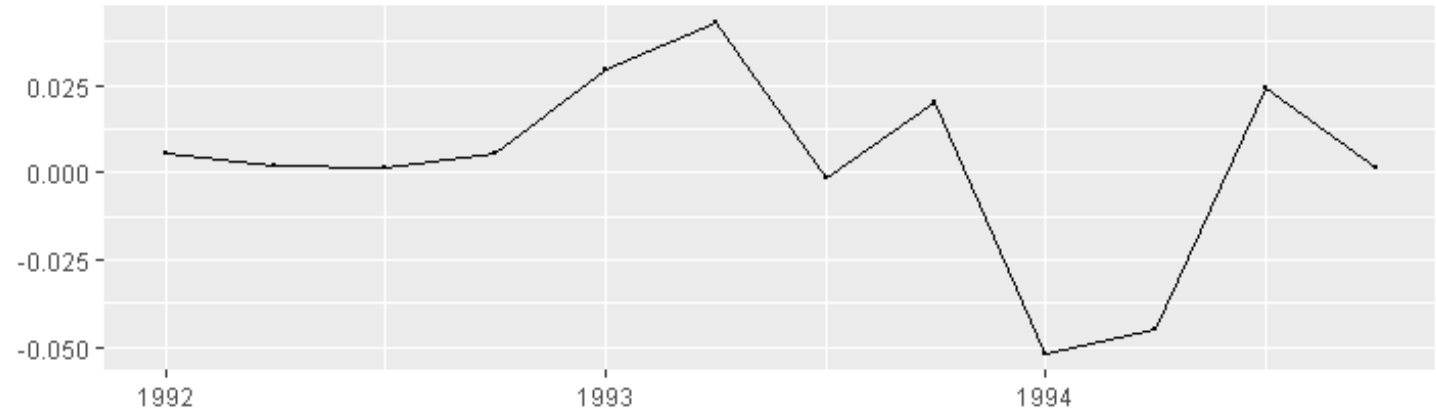
QuarterYear	Revenue(in million \$)	Predicted
Q1-95	1462	1481.312
Q2-95	1452	1440.49
Q3-95	1631	1568.2
Q4-95	4200	4278.52
RMSE		51.51375

```
> 10^pred$pred
      Qtr1    Qtr2    Qtr3    Qtr4
1996 1582.233 1577.702 1812.492 4583.581
1997 1727.559 1719.674
> |
```

Using ARIMA Model

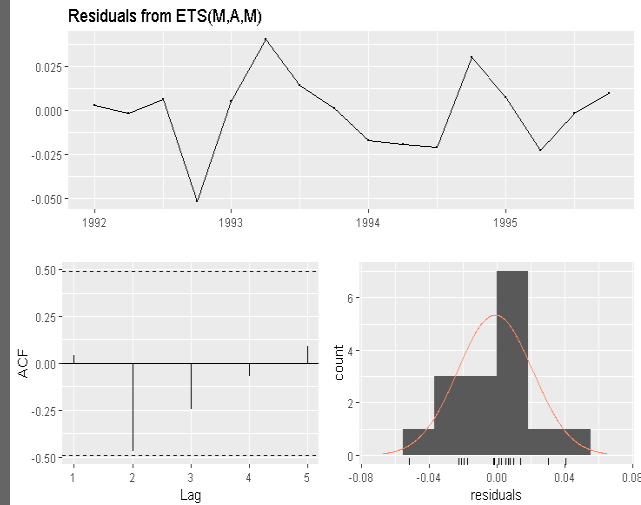
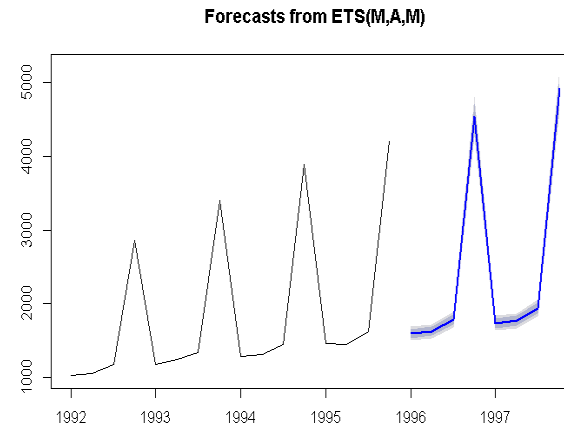
- **Residual errors:**
 - Amount of variability in a dependent variable (DV) that is "left over" after accounting for the variability explained by the predictors
 - We can see that the distribution does have a Gaussian look, that shows that errors are randomly distributed.
 - From the residual ACF plot, we could see that there is no correlation among the residuals.
 - As there are no spikes outside the insignificant zone for ACF plots, we can conclude that residuals are random with no information or juice in them.

Residuals from ARIMA(4,1,4)



ETS Model

- ETS is an approach for detecting additive errors and seasonal structures with prediction of interval coverages.
- In the current data, we built ETS (M,A,M) Multiplicative Holt-Winter's method with Multiplicative Errors.
- We have compared Error for ETS and ARIMA Model using cross validation, ARIMA Model gives less error compared to ETS.

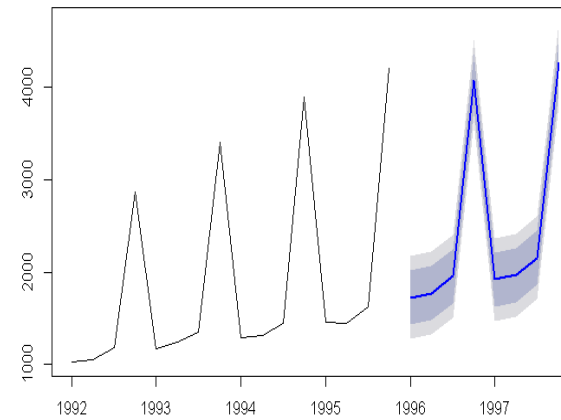


```
> mean(eterror^2, na.rm=TRUE)
[1] 8405885
> mean(arimaerror^2, na.rm=TRUE)
[1] 93955.99
> |
```

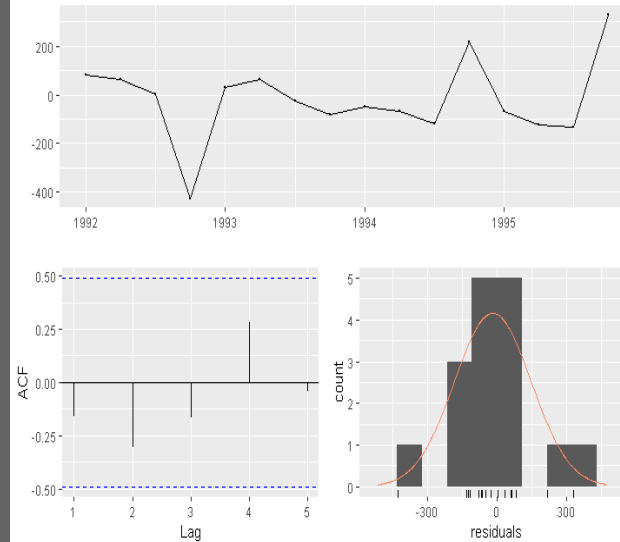
Holt Winter Model

- Holt Winter also known as Triple Exponential Smoothing Method.
- Holt Winter additive is an extension of Holt exponential smoothing that captures seasonality.

Forecasts from Holt-Winters' additive method



Residuals from Holt-Winters' additive method



```
> forecast(hw(kids_ts, h = 8))
      Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
1996 Q1      1723.594 1430.954 2016.235 1276.040 2171.149
1996 Q2      1772.144 1479.503 2064.784 1324.589 2219.698
1996 Q3      1956.510 1663.870 2249.151 1508.956 2404.065
1996 Q4      4066.387 3773.746 4359.028 3618.832 4513.942
1997 Q1      1918.367 1625.726 2211.008 1470.811 2365.922
1997 Q2      1966.916 1674.275 2259.557 1519.360 2414.472
1997 Q3      2151.283 1858.642 2443.924 1703.727 2598.839
1997 Q4      4261.160 3968.518 4553.801 3813.603 4708.717
> |
```

Recommendations

- For given set of data , we have built and compared multiple time series forecasting techniques.
- From the error comparison table we can arrive to the conclusion that **ARIMA** model gives less RMSE, so it's the best fit for the given data.

Model	RMSE	MAPE
Moving Average - 2	740	55.2
Exponential Average - 2	441	25.4
Naïve	1481	51.1
SNaive	262	10.9
Mean	1032	46.7
ETS	53.2	2.34
HW - Additive	161	5.7
ARIMA	51.5	1.96

Code

The following files has the code for entire project –

- Code to Build ARIMA Model - Forecasting_Kids_ARIMA.R
- Code for EDA and other modelling techniques (Naïve, SMA, EMA, ETS and HW) at Forecasting_KidsRevenue.R