EAS 509 Project 2

jayyoges

2023-11-27

Project 2

Importing the data

```
data = read.csv('oil.csv')
head(data)
```

```
##         date dcoilwtico
## 1 2013-01-01         NA
## 2 2013-01-02      93.14
## 3 2013-01-03      92.97
## 4 2013-01-04      93.12
## 5 2013-01-07      93.20
## 6 2013-01-08      93.21
```

```
str(data)
```

```
## 'data.frame':    1218 obs. of  2 variables:
##  $ date      : chr  "2013-01-01" "2013-01-02" "2013-01-03" "2013-01-04" ...
##  $ dcoilwtico: num  NA 93.1 93 93.1 93.2 ...
```

```
data <- data %>% setNames(c('Date', 'Price'))
data$Date <- as.Date(data$Date)
```

Phase 1: EDA & Data Cleaning

Checking for missing values in the data

```
# How many missing values?
missing_values <- sum(is.na(data))

# Print the number of missing values
cat("Number of missing values in the entire data frame:", missing_values, "\n")
```

```
## Number of missing values in the entire data frame: 43
```

```
# Check for missing values in each column
missing_values_per_column <- sapply(data, function(x) sum(is.na(x)))

# Print the number of missing values for each column
cat("Number of missing values per column:\n")
```

```
## Number of missing values per column:
```

```
print(missing_values_per_column)
```

```
##  Date Price
##     0    43
```

We have 43 missing values for oil price

```
# Identify rows with missing values in a specific column
rows_with_missing_values <- which(is.na(data$dcoilwtico))

# Print the rows with missing values
cat("Rows with missing values in column 'dcoilwtico':\n")
```

```
## Rows with missing values in column 'dcoilwtico':
```

```
print(rows_with_missing_values)
```

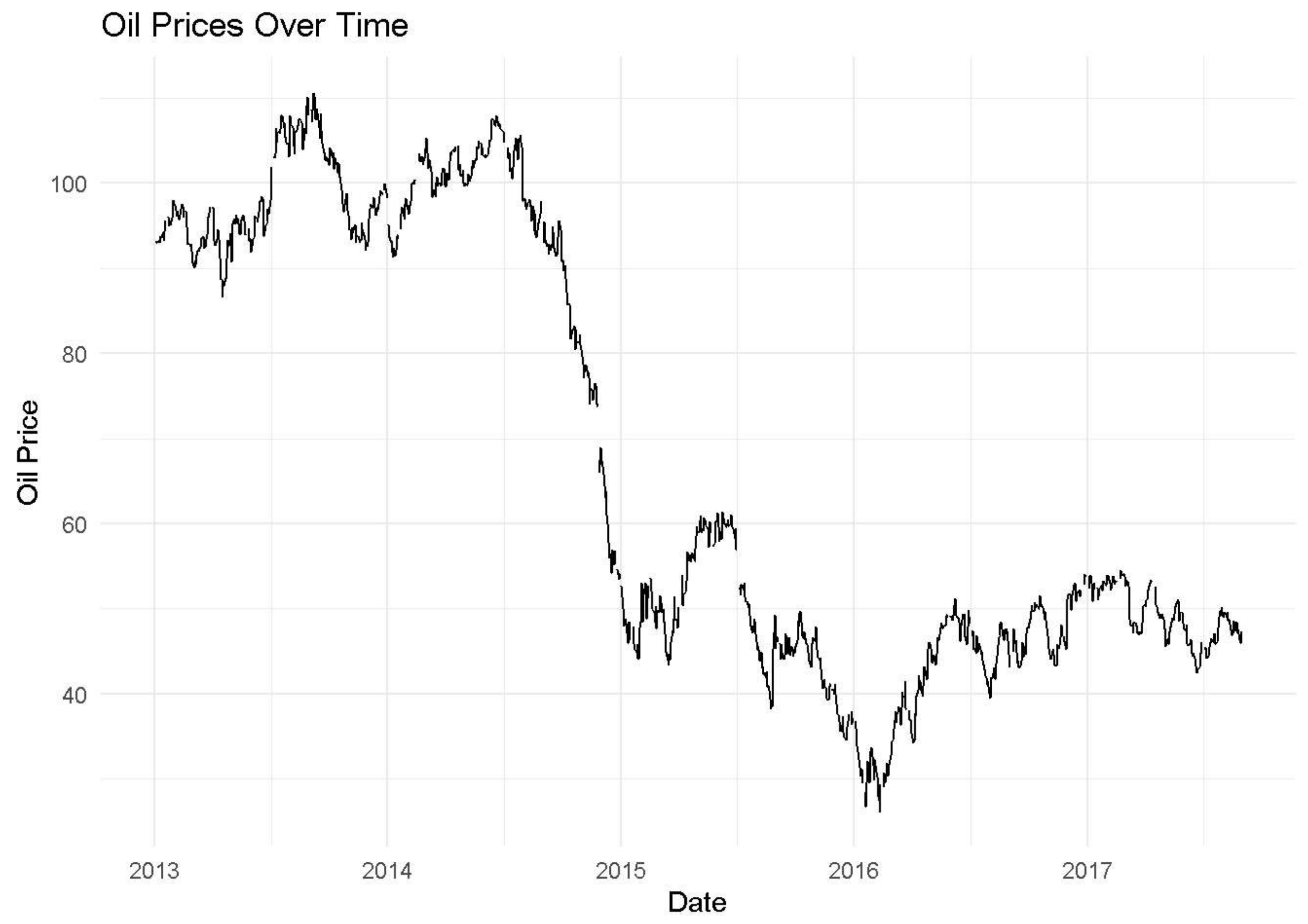
```
## integer(0)
```

Plot before imputing

```
oilplot = function(data, title = "Oil Prices Over Time") {
  ggplot(data, aes(x = Date, y = Price)) +
    geom_line() +
    labs(title = title,
        x = "Date",
        y = "Oil Price") +
    theme_minimal()
}

oilplot(data)
```

```
## Warning: Removed 1 row containing missing values (`geom_line()`).
```



Imputing the data

```
# Forward Fill
data_ffill <- data
data_ffill$Price <- na.locf(data_ffill$Price, na.rm = FALSE)

# Backward Fill
data_bfill <- data
data_bfill$Price <- na.locf(data_bfill$Price, fromLast = TRUE)

# Linear Interpolation
data_linear <- data
data_linear$Price <- na.approx(data_linear$Price, na.rm = FALSE)

# Moving Average
k <- 5
data_ma <- data
data_ma$Price <- na.fill(data_ma$Price, fill = "extend")
data_ma$Price <- rollapply(data_ma$Price, k, FUN = mean, na.rm = TRUE, fill = NA, align = 'cente
r')
```

Missing values after imputation

```
comparison_df <- data.frame(
   Date = data$Date
  ,Original = data$Price
  ,ForwardFill = data_ffill$Price
  ,BackwardFill = data_bfill$Price
  ,LinearInterpolation = data_linear$Price
  ,MovingAverage = data_ma$Price
)
```

```
sum(is.na(comparison_df$Original))
```

```
## [1] 43
```

```
sum(is.na(comparison_df$ForwardFill))
```

```
## [1] 1
```

```
sum(is.na(comparison_df$BackwardFill))
```

```
## [1] 0
```

```
sum(is.na(comparison_df$LinearInterpolation))
```

```
## [1] 1
```

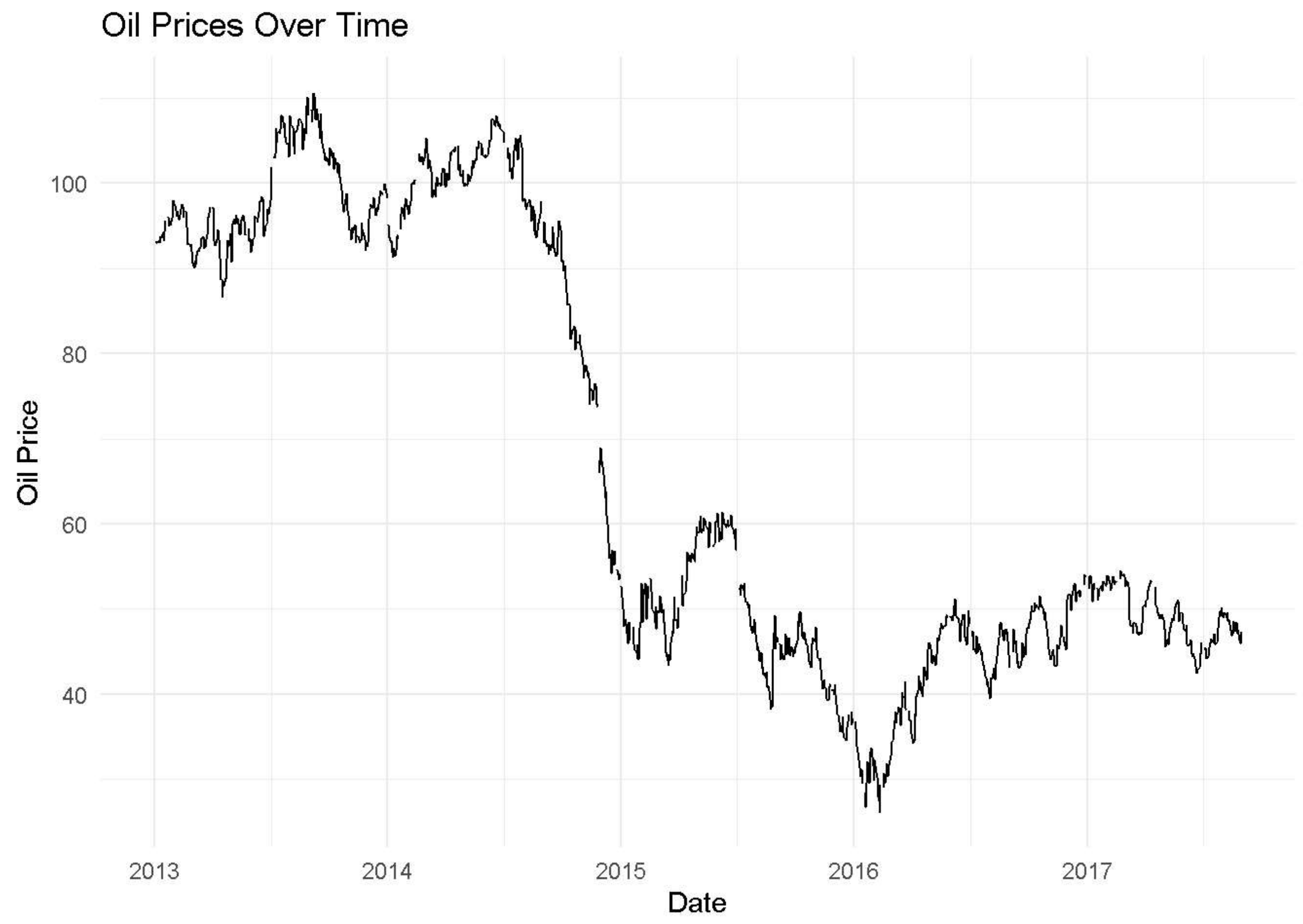
```
sum(is.na(comparison_df$MovingAverage))
```

```
## [1] 4
```

Data Plots After Imputation

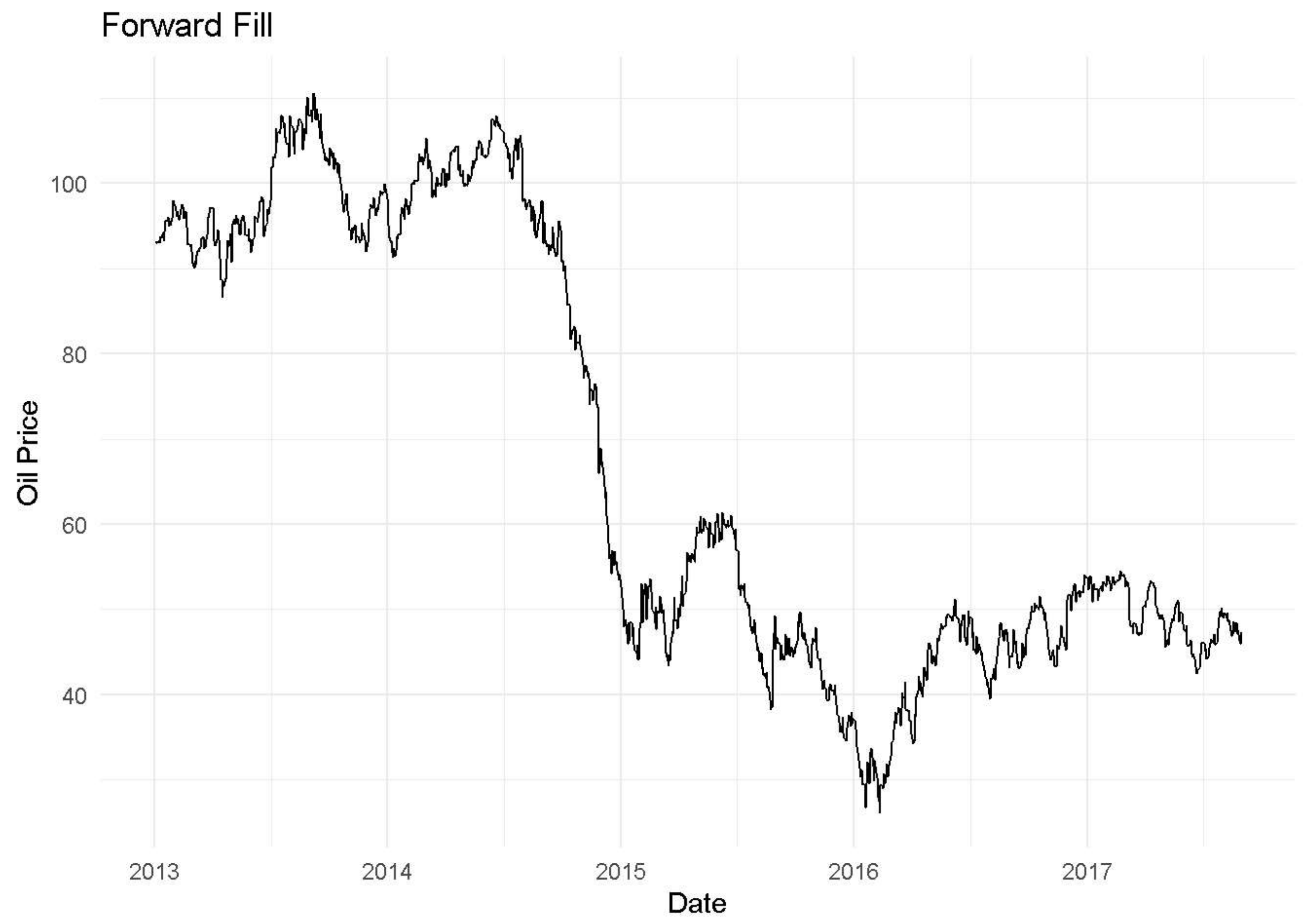
```
oilplot(data)
```

```
## Warning: Removed 1 row containing missing values (`geom_line()`).
```

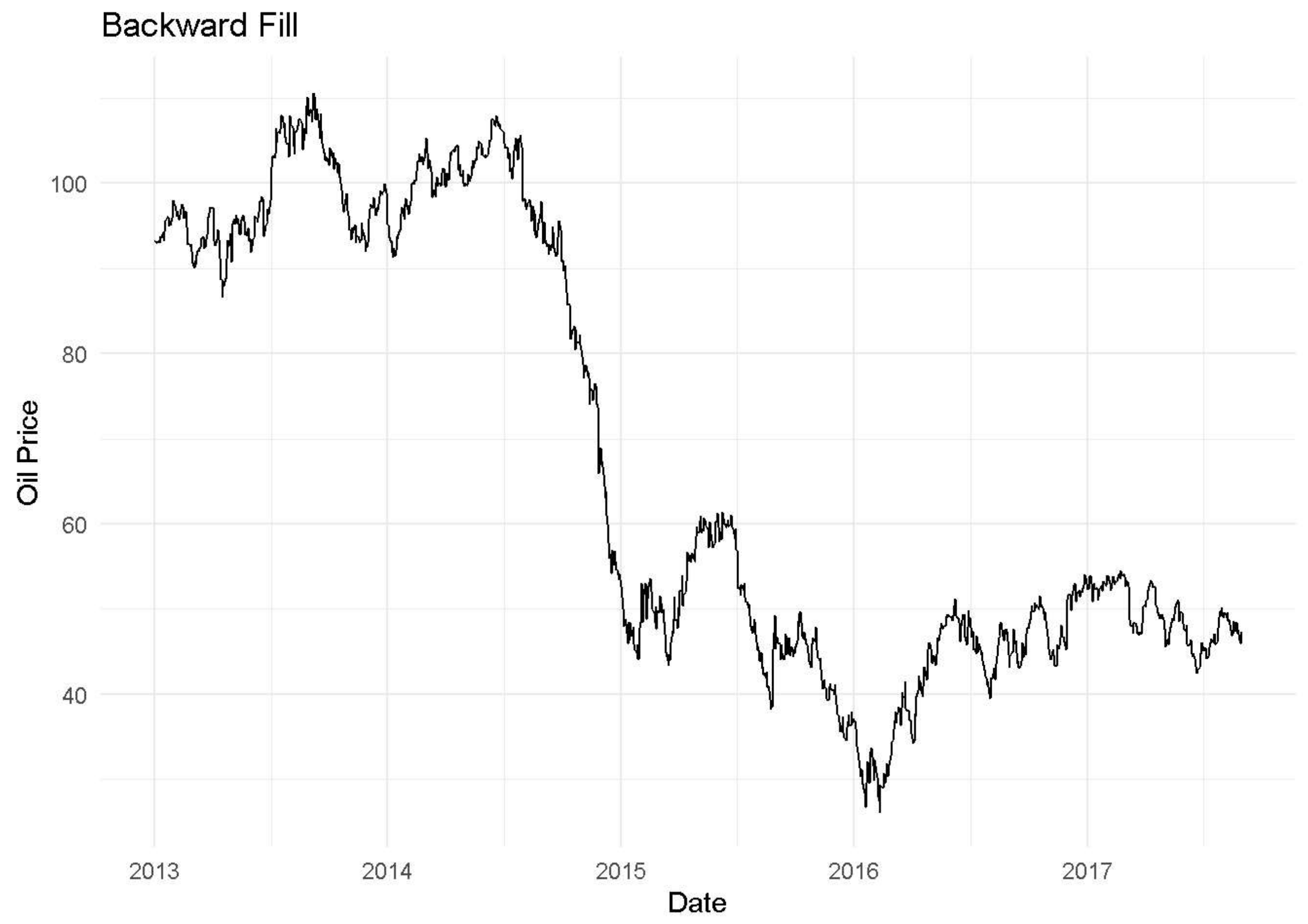


```
oilplot(data_ffill, "Forward Fill")
```

```
## Warning: Removed 1 row containing missing values (`geom_line()`).
```

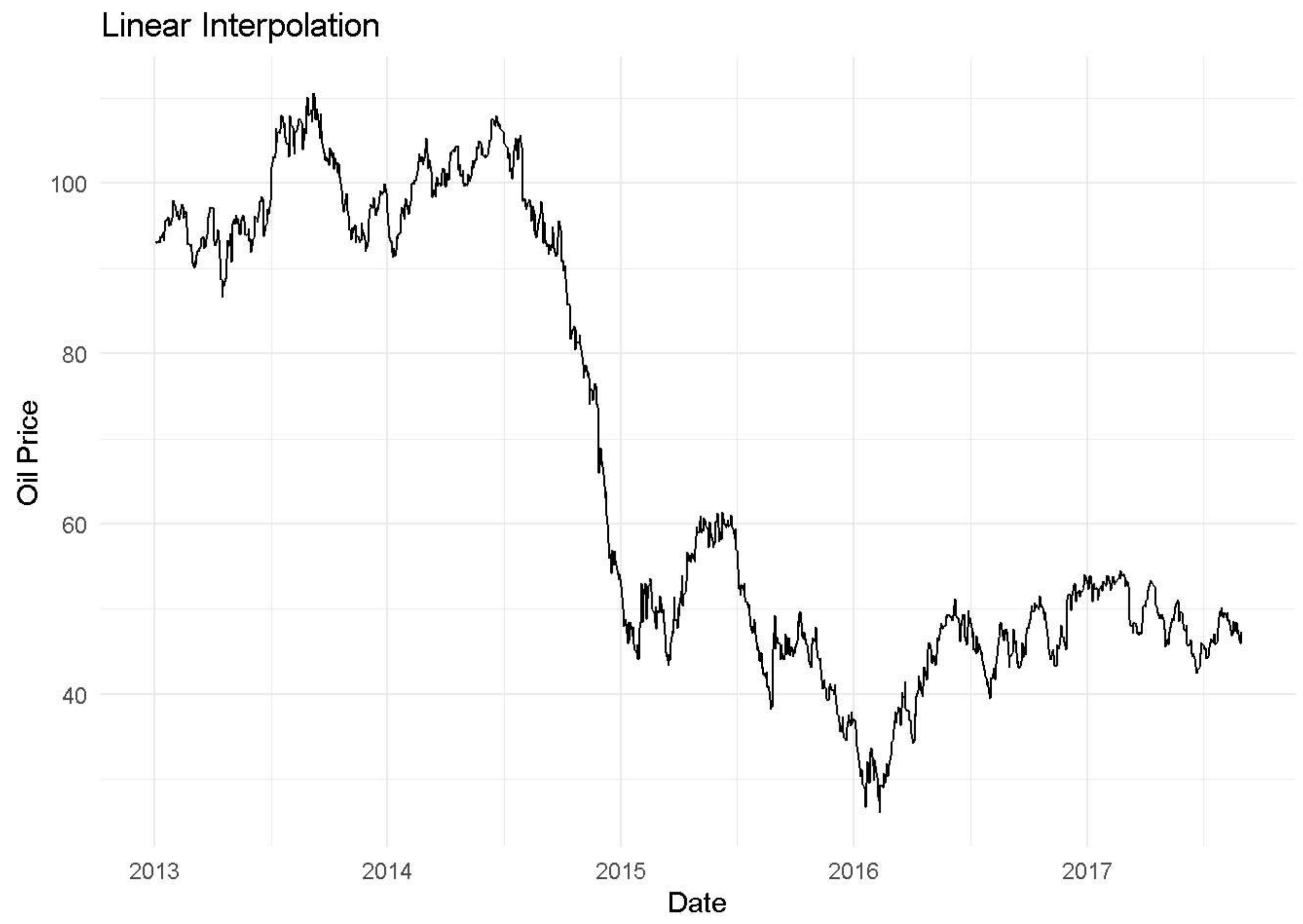


```
oilplot(data_bfill, "Backward Fill")
```



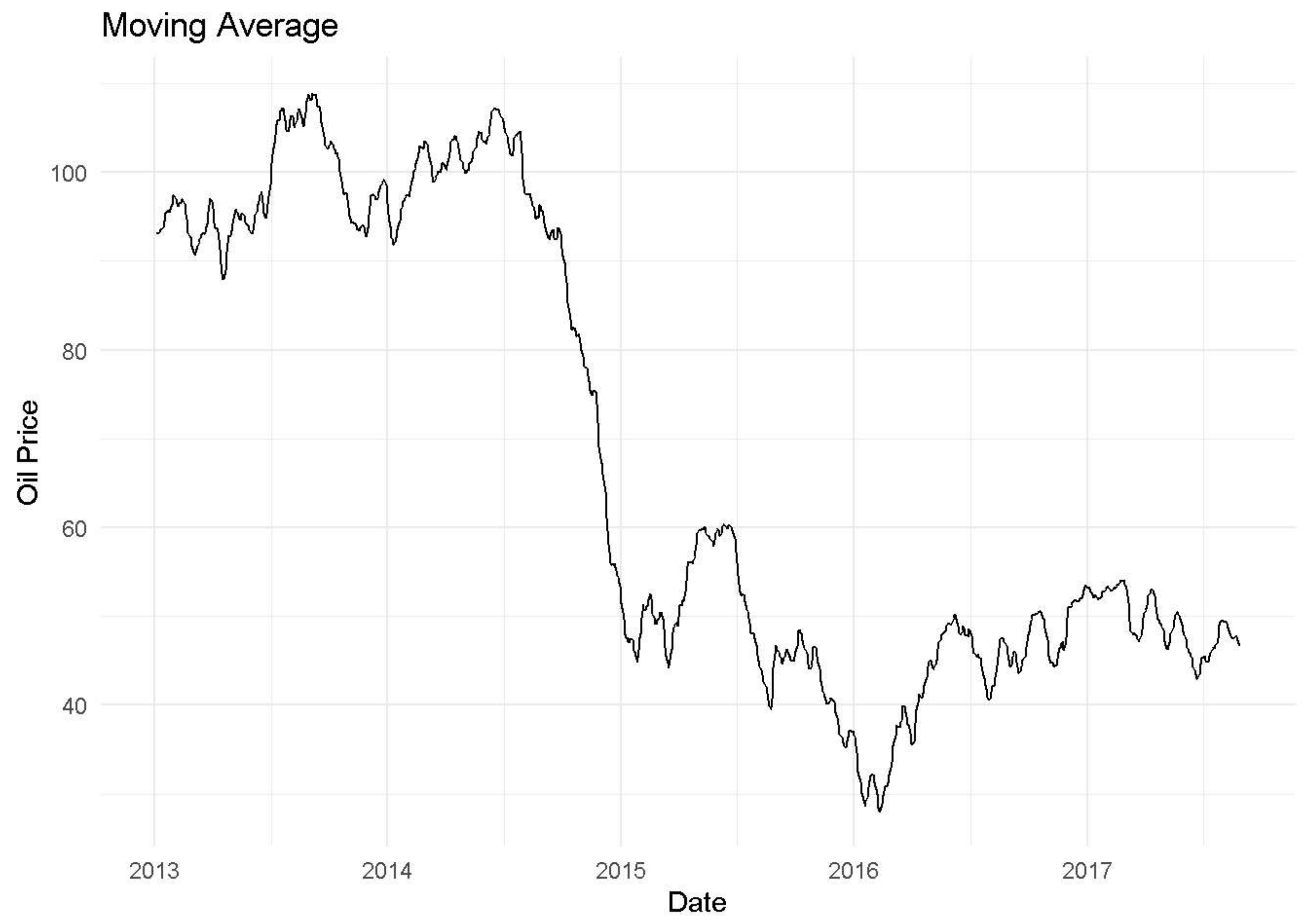
```
oilplot(data_linear, "Linear Interpolation")
```

```
## Warning: Removed 1 row containing missing values (`geom_line()`).
```



```
oilplot(data_ma, "Moving Average")
```

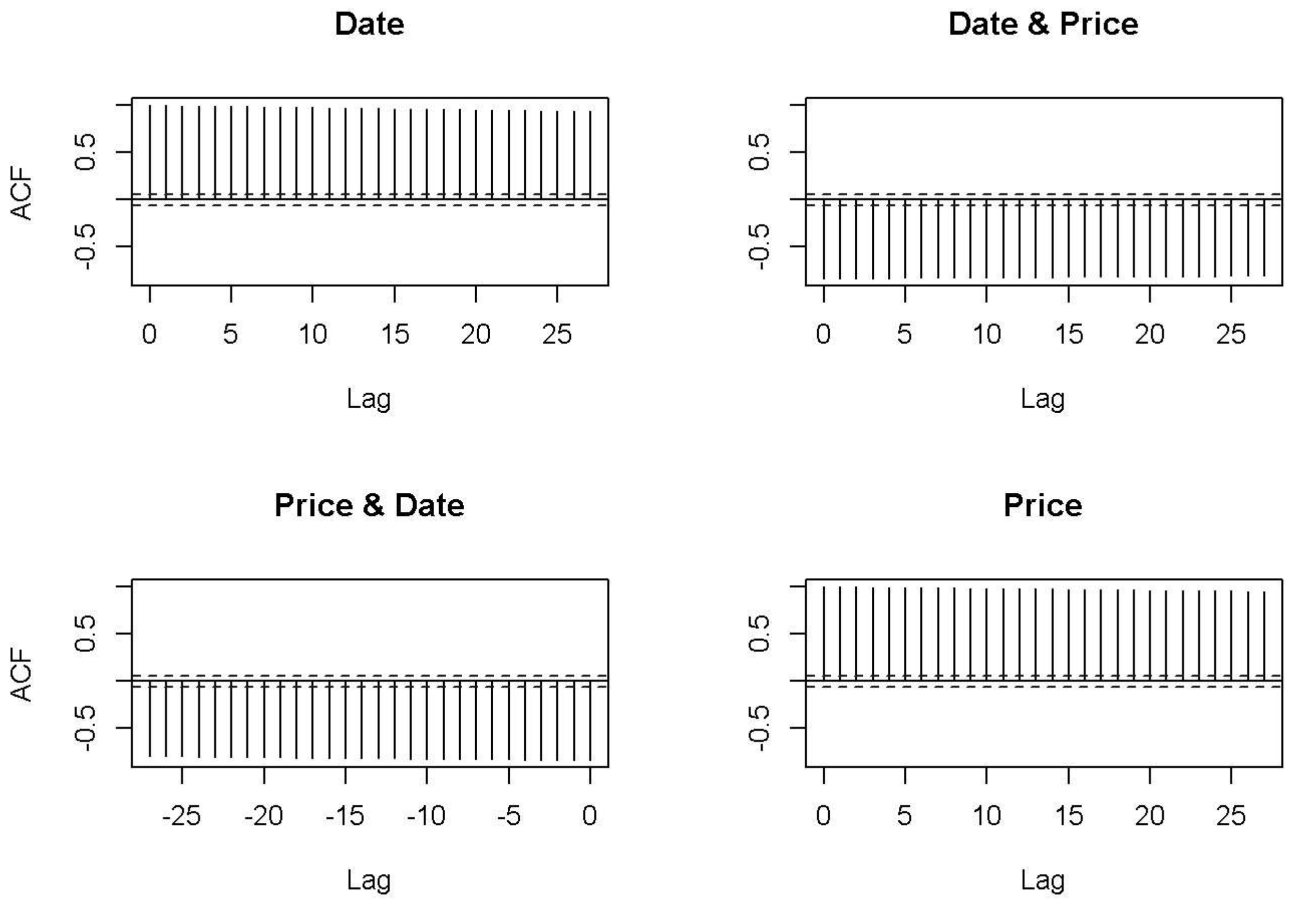
```
## Warning: Removed 4 rows containing missing values (`geom_line()`).
```



All imputation methods except backward fill are unable to fill in all missing values, thus we pick backward fill imputed data.

Now Checking for seasonality in the time series data

```
# ACF plot
acf(data_bfill)
```



Here all the bars for our ACF plots are of same height. We can not see any spike in the graph for any lags which suggest that there is no strong seasonality in the data.

Phase 2: Model Training & Evaluation

```r
data_models <- function(data, eval = TRUE) {
  # 1. Simple Exponential Smoothing (ETS Model: ANN)
  ets_model1 <- ets(data$Price, model="ANN")

  #2. ETS Model with Additive Error and Trend (AAN)
  ets_model2 <- ets(data$Price, model="AAN")

  #3. Auto ARIMA Model
  best_arima_model <- auto.arima(data$Price)

  #4. Simple Exponential Smoothing
  ses_model <- ets(data$Price, model="ZNN")

  #5. Holt’s Linear Trend Method
  holt_model <- ets(data$Price, model="ANN")


  autoplot(ets_model1) + xlab("Time") + ylab("Oil Prices") + ggtitle("ETS Model Fit")
  autoplot(ets_model2) + xlab("Time") + ylab("Oil Prices") + ggtitle("ETS Model Fit")
  autoplot(best_arima_model) + xlab("Time") + ylab("Oil Prices") + ggtitle("Auto ARIMA Model Fit")
  autoplot(ses_model) + xlab("Time") + ylab("Oil Prices") + ggtitle("Simple Exponential Smoothin
g")
  autoplot(holt_model) + xlab("Time") + ylab("Oil Prices") + ggtitle("Holt’s Linear Trend Method")

  if (eval) {
    data_evaluation(ets_model1, ets_model2, best_arima_model, ses_model, holt_model)
  }
}

data_evaluation <- function(ets_model1, ets_model2, best_arima_model, ses_model, holt_model) {
  cat("---- ETS Model 1 (ANN) ----\n")
  print(summary(ets_model1))
  print(accuracy(ets_model1))
  cat("\n--------------------------------\n")

  cat("---- ETS Model 2 (AAN) ----\n")
  print(summary(ets_model2))
  print(accuracy(ets_model2))
  cat("\n--------------------------------\n")

  cat("---- Auto ARIMA Model  ----\n")
  print(summary(best_arima_model))
  print(accuracy(best_arima_model))
  cat("\n--------------------------------\n")

  cat("---- Simple Exponential Smoothing ----\n")
  print(summary(ses_model))
  print(accuracy(ses_model))
  cat("\n--------------------------------\n")

  cat("---- Holt’s Linear Trend Method ----\n")
  print(summary(holt_model))
  print(accuracy(holt_model))
  cat("\n--------------------------------\n")
}
```

```r
data_models(data_bfill)
```

```
## ---- ETS Model 1 (ANN) ----
## ETS(A,N,N)
##
## Call:
##  ets(y = data$Price, model = "ANN")
##
##   Smoothing parameters:
##     alpha = 0.954
##
##   Initial states:
##     l = 93.1356
##
##   sigma:  1.2028
##
##      AIC     AICc      BIC
## 9107.716 9107.735 9123.031
##
## Training set error measures:
##                       ME    RMSE       MAE         MPE     MAPE     MASE
## Training set -0.03953028 1.20184 0.8965985 -0.08424058 1.551493 1.001156
##                       ACF1
## Training set -0.0008160611
##                       ME    RMSE       MAE         MPE     MAPE     MASE
## Training set -0.03953028 1.20184 0.8965985 -0.08424058 1.551493 1.001156
##                       ACF1
## Training set -0.0008160611
##
## --------------------------------
## ---- ETS Model 2 (AAN) ----
## ETS(A,A,N)
##
## Call:
##  ets(y = data$Price, model = "AAN")
##
##   Smoothing parameters:
##     alpha = 0.9436
##     beta  = 1e-04
##
##   Initial states:
##     l = 92.6614
##     b = -0.0363
##
##   sigma:  1.2034
##
##      AIC     AICc      BIC
## 9110.806 9110.855 9136.331
##
## Training set error measures:
##                         ME     RMSE       MAE         MPE     MAPE     MASE
## Training set -0.0007681805 1.201391 0.8974959 -0.01745455 1.551229 1.002158
##                     ACF1
## Training set 0.009481971
##                         ME     RMSE       MAE         MPE     MAPE     MASE
## Training set -0.0007681805 1.201391 0.8974959 -0.01745455 1.551229 1.002158
##                     ACF1
## Training set 0.009481971
## 
## --------------------------------
## ---- Auto ARIMA Model  ----
## Series: data$Price 
## ARIMA(0,1,0) 
## 
## sigma^2 = 1.449:  log likelihood = -1952.37
## AIC=3906.73   AICc=3906.73   BIC=3911.83
## 
## Training set error measures:
##                       ME     RMSE       MAE         MPE     MAPE      MASE
## Training set -0.03759184 1.203095 0.8949041 -0.08030733 1.547907 0.9992644
##                     ACF1
## Training set -0.04614975
##                       ME     RMSE       MAE         MPE     MAPE      MASE
## Training set -0.03759184 1.203095 0.8949041 -0.08030733 1.547907 0.9992644
##                     ACF1
## Training set -0.04614975
## 
## --------------------------------
## ---- Simple Exponential Smoothing ----
## ETS(A,N,N) 
## 
## Call:
##  ets(y = data$Price, model = "ZNN") 
## 
##   Smoothing parameters:
##     alpha = 0.954 
## 
##   Initial states:
##     l = 93.1356 
## 
##   sigma:  1.2028
## 
##      AIC     AICc      BIC 
## 9107.716 9107.735 9123.031 
## 
## Training set error measures:
##                       ME    RMSE       MAE         MPE     MAPE     MASE
## Training set -0.03953028 1.20184 0.8965985 -0.08424058 1.551493 1.001156
##                       ACF1
## Training set -0.0008160611
##                       ME    RMSE       MAE         MPE     MAPE     MASE
## Training set -0.03953028 1.20184 0.8965985 -0.08424058 1.551493 1.001156
##                       ACF1
## Training set -0.0008160611
## 
## --------------------------------
## ---- Holt’s Linear Trend Method ----
## ETS(A,N,N)
##
## Call:
##  ets(y = data$Price, model = "ANN")
##
##   Smoothing parameters:
##     alpha = 0.954
##
##   Initial states:
##     l = 93.1356
##
##   sigma:  1.2028
##
##      AIC     AICc      BIC
## 9107.716 9107.735 9123.031
##
## Training set error measures:
##                       ME    RMSE       MAE         MPE     MAPE     MASE
## Training set -0.03953028 1.20184 0.8965985 -0.08424058 1.551493 1.001156
##                       ACF1
## Training set -0.0008160611
##                       ME    RMSE       MAE         MPE     MAPE     MASE
## Training set -0.03953028 1.20184 0.8965985 -0.08424058 1.551493 1.001156
##                       ACF1
## Training set -0.0008160611
##
## --------------------------------
```

Model Performance Evaluation

In our analysis, we evaluated several models to forecast oil prices, using key statistical metrics to assess their performance. These metrics include Mean Error (ME), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Percentage Error (MPE), Mean Absolute Percentage Error (MAPE), Mean Absolute Scaled Error (MASE), and the Autocorrelation of the first lag (ACF1). Each metric provides a different perspective on the accuracy and reliability of the forecasting models.

Best Performing Model

The **Auto ARIMA Model** emerged as the best performing model in our analysis. It demonstrated the lowest RMSE (1.203095), MAE (0.8949041), and MASE (0.9992644), which are critical indicators of a model’s accuracy and consistency. Furthermore, the ME (-0.03759184) and MPE (-0.08030733) values are among the lowest, suggesting a lower bias in the model’s predictions. This model’s superior performance across these metrics indicates its robustness in forecasting oil prices.

Specific details of the **Auto ARIMA Model** are as follows: - Model Type: ARIMA(0,1,0) - sigma^2 = 1.449 - Log Likelihood = -1952.37 - AIC = 3906.73 - AICc = 3906.73 - BIC = 3911.83

This information indicates a simple model without AR or MA components but with a differencing order of 1, suggesting that the model primarily focuses on capturing the changes rather than absolute levels in the oil price series.

Poorest Performing Models

The **Simple Exponential Smoothing and Holt’s Linear Trend Method** showed identical metrics and were identified as the poorest performing models in our dataset. They recorded higher RMSE (1.20184), MAE (0.8965985), and MASE (1.001156) compared to the Auto ARIMA Model. Their ME (-0.03953028) and MPE (-0.08424058) were also higher, indicating a greater degree of bias in forecasts. These models, while still providing reasonable forecasts, were outperformed by other models in our evaluation.

Other Models

The **ETS Model 2 (AAN)** displayed competitive performance with a slightly higher RMSE (1.201391), MAE (0.8974959), and MASE (1.002158) than the Auto ARIMA Model. It also showed the lowest MPE (-0.01745455), suggesting minimal bias in its predictions. The **ETS Model 1 (ANN)**, while competitive, slightly underperformed in comparison to the Auto ARIMA and ETS Model 2, as indicated by its RMSE, MAE, and MASE values.

Conclusion

It’s important to note that the differences in performance among the models are relatively minor. However, Based on our analysis, we recommend the **Auto ARIMA Model** for forecasting oil prices, due to its superior performance across various statistical metrics.