FORECASTING PRODUCT DEMAND IN R

Residuals from regression model

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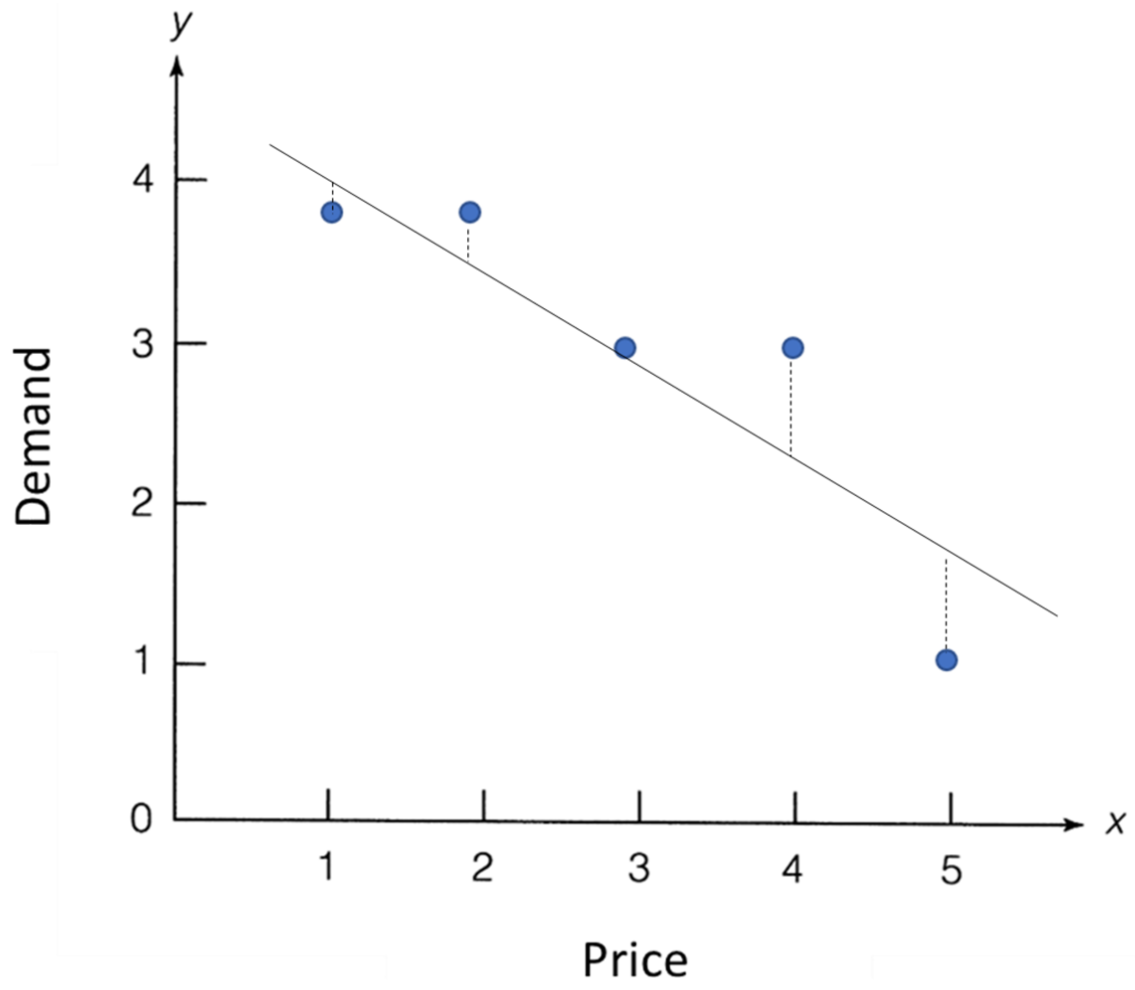
Linear Regression



Regression Residuals

- Ways to reduce residuals further:
    1. Add more important variables to the model
    2. Use time series if your residuals are related over time

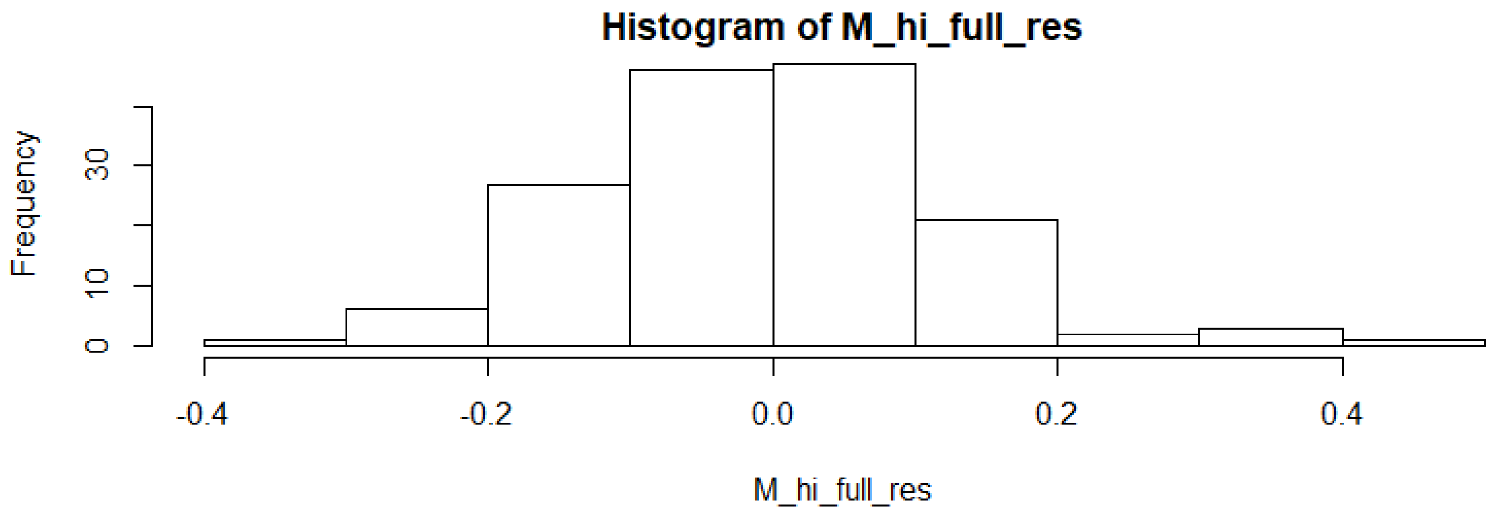
Examine Residuals

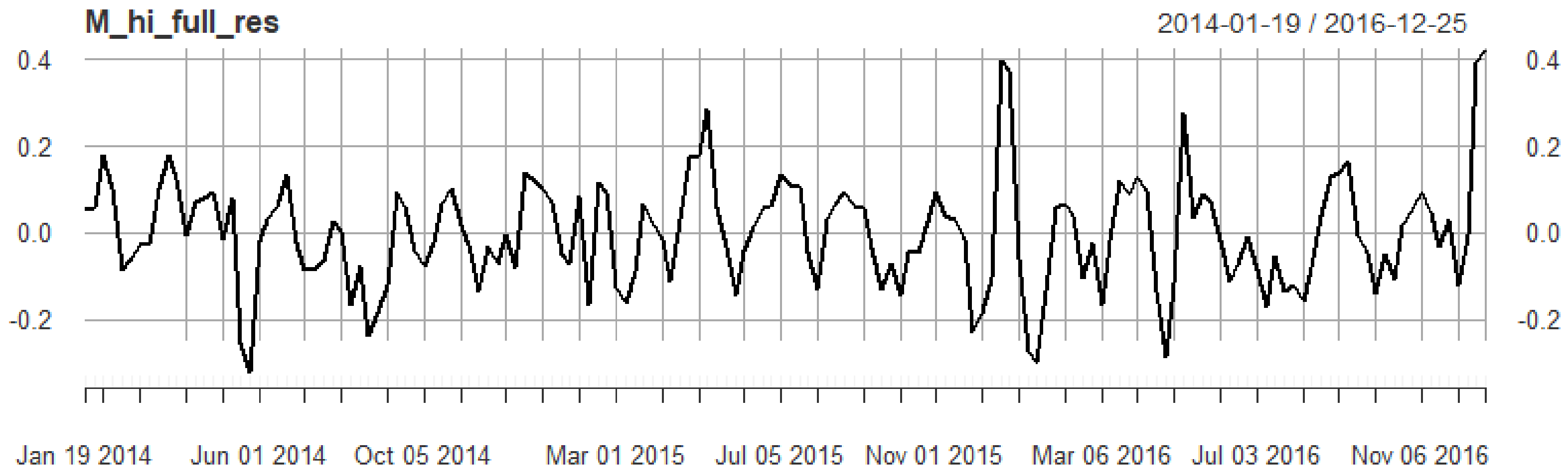
```
M_hi_full_res <- residuals(model_M_hi_full)

M_hi_full_res <- xts(M_hi_full_res, order.by = dates_train)

hist(M_hi_full_res)
plot(M_hi_full_res)
```

Residual Plots





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Let's practice!

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Forecasting residuals

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Regression Pieces

DEMAND = INPUTS + ERRORS

ARIMA on Residuals

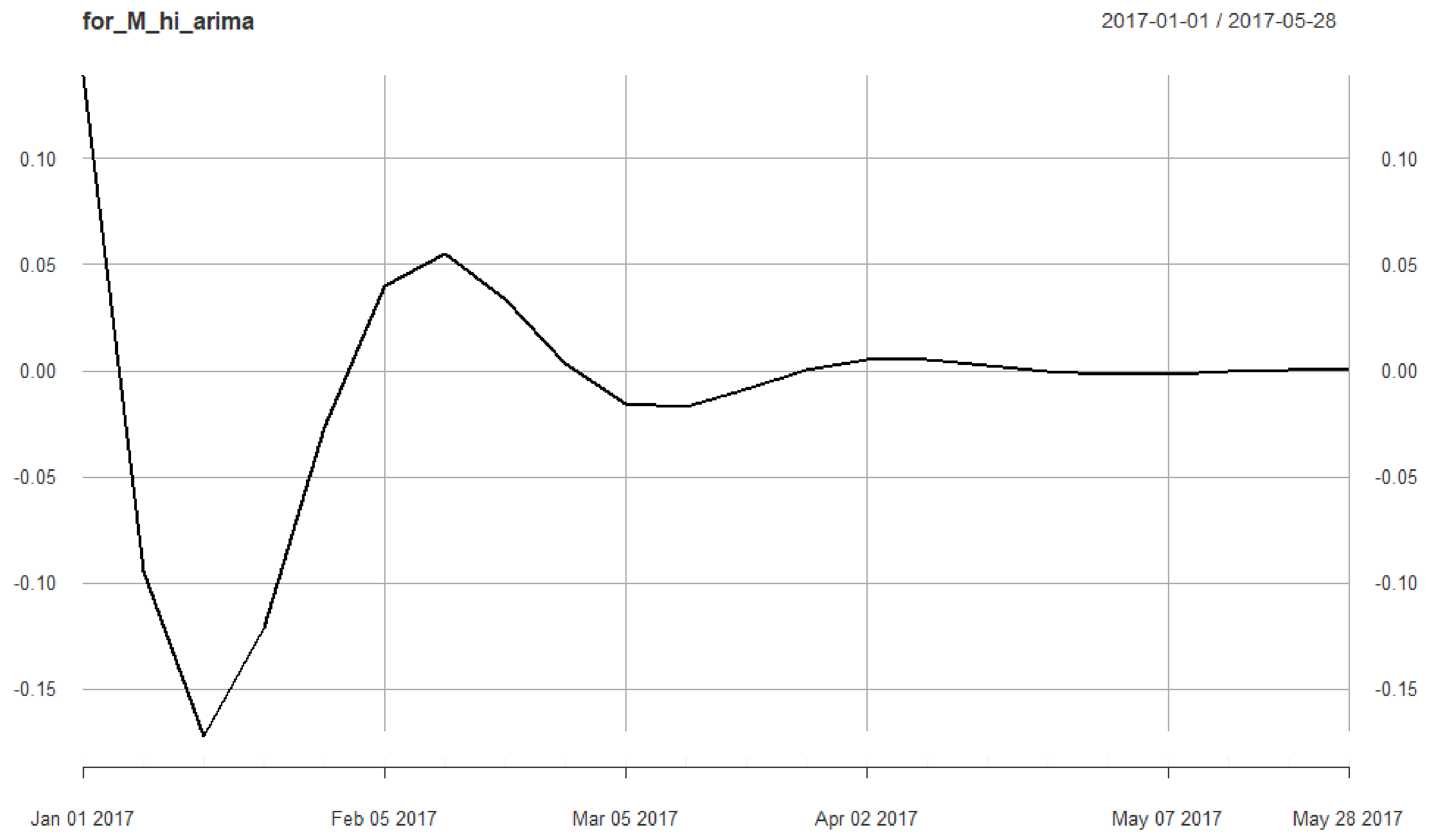
```
M_hi_arima <- auto.arima(M_hi_full_res)

summary(M_hi_arima)

Series: M_hi_full_res
ARIMA(2,0,1) with zero mean

Coefficients:
         ar1      ar2      ma1
      1.0077  -0.5535  -0.4082
s.e.  0.1291   0.0800   0.1412

sigma^2 estimated as 0.01078:  log likelihood=131.45
AIC=-254.9   AICc=-254.63   BIC=-242.75
```

Forecasting Residuals

```
for_M_hi_arima <- forecast(M_hi_arima, h = 22)

dates_valid <- seq(as.Date("2017-01-01"), length = 22, by = "weeks")

for_M_hi_arima <- xts(for_M_hi_arima$mean, order.by = dates_valid)

head(for_M_hi_arima, n = 5)

                  [,1]
2017-01-01  0.13888498
2017-01-08 -0.09448731
2017-01-15 -0.17209098
2017-01-22 -0.12112306
2017-01-29 -0.02680729
```

Visualizing Forecasted Residuals

```
plot(for_M_hi_arima)
```



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Transfer Functions & Ensembling

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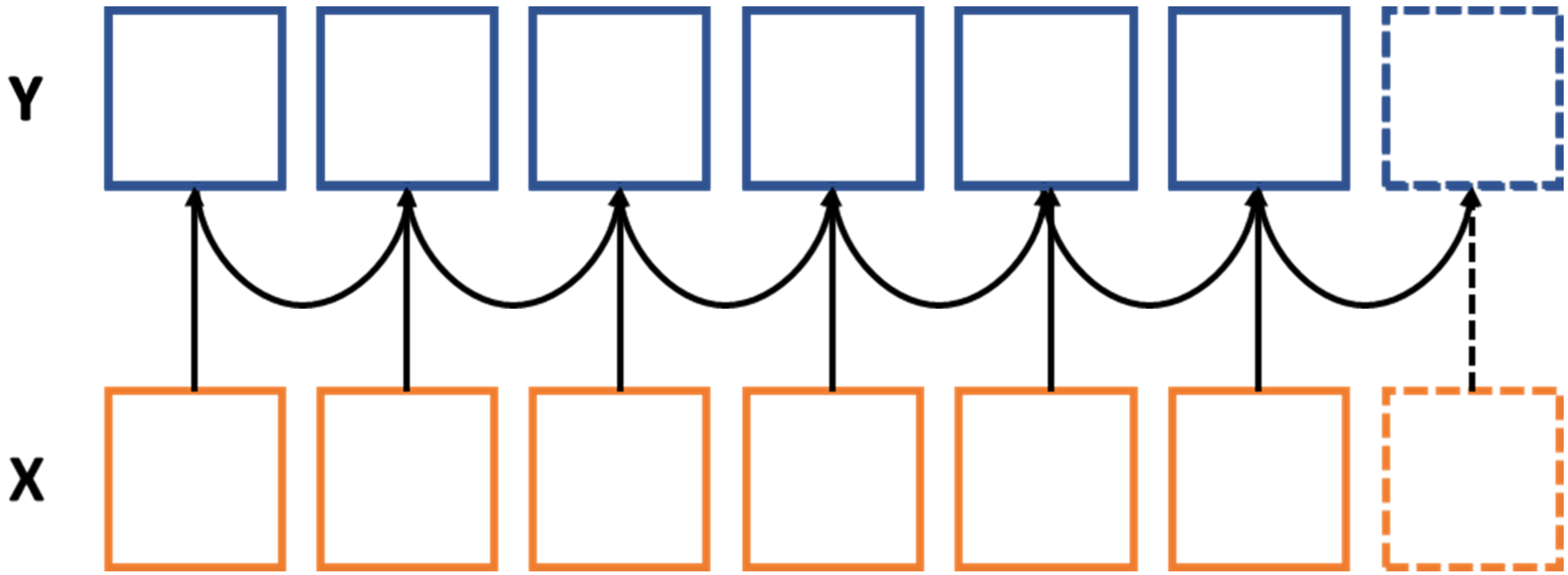
Combining Techniques

- Multiple ways to combine forecasting techniques:
    1. Transfer Functions - everything gets built into one model
    2. Ensembling - "Average" multiple types of model forecasts

Combining Techniques - Transfer Functions

DEMAND = INPUTS (REGRESSION) + ERRORS (TIME SERIES)

Combining Forecasts



Mathematics in the Background

- Combining two different techniques into one mathematically:

$$\log(Y_t) = \beta_0 + \beta_1 \log(X_t) + \beta_2 X_2 + \ldots + \varepsilon_t$$

$$\varepsilon_t = \alpha_0 + \alpha_1 \varepsilon_{t-1} + \alpha_2 \varepsilon_{t-2} + \ldots + \epsilon$$

- Combining the forecasts into one mathematically:

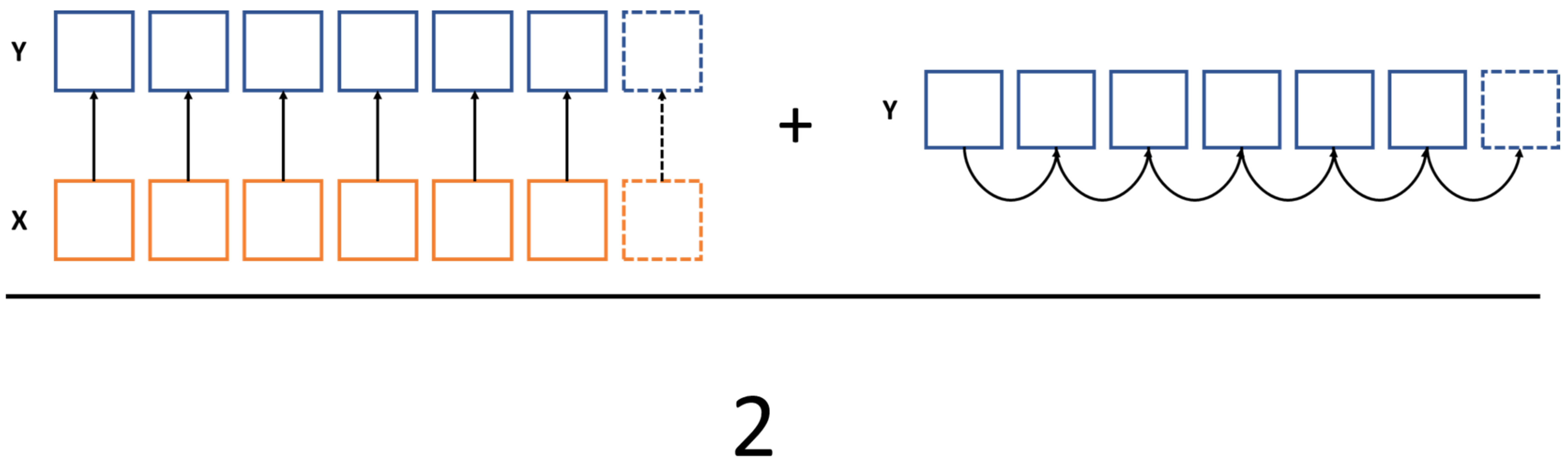
$$\log(Y_t) = \log(\hat{Y}_t) + \hat{\varepsilon}_t$$

$$Y_t = \hat{Y}_t \times \exp(\hat{\varepsilon})$$

Transfer Function Example

```
for_M_hi_arima <- exp(for_M_hi_arima)
for_M_hi_final <- pred_M_hi_xts * for_M_hi_arima

M_hi_v <- bev_xts_valid[,"M.hi"]

MAE <- mean(abs(for_M_hi_final - M_hi_v))
MAPE <- 100*mean(abs((for_M_hi_final - M_hi_v)/M_hi_v))

print(MAE)
[1] 61.46033

print(MAPE)
[1] 13.45189
```

Combining Forecasts - Ensembling



Time Series for Demand

```
M_hi_model_arima <- auto.arima(M_hi)
summary(M_hi_model_arima)

Series: M_hi
ARIMA(4,0,2) with non-zero mean

Coefficients:
          ar1     ar2      ar3      ar4     ma1     ma2      mean
      -0.1332  0.1546  -0.2638  -0.2063  0.7622  0.0492  458.7097
s.e.   0.4729  0.4150   0.2542   0.1399  0.4807  0.3204    5.7040

sigma^2 estimated as 3323:  log likelihood=-839.66
AIC=1695.33   AICc=1696.32   BIC=1719.62
```

Time Series for Demand

```
dates_valid <- seq(as.Date("2017-01-01"), length = 22, by = "weeks")
for_M_hi_xts <- xts(for_M_hi$mean, order.by = dates_valid)

MAE <- mean(abs(for_M_hi_xts - M_hi_v))
MAPE <- 100*mean(abs((for_M_hi_xts - M_hi_v)/M_hi_v))

print(MAE)
[1] 71.43732

print(MAPE)
[1] 16.29178
```

Ensembling Example

```
for_M_hi_en <- 0.5*(for_M_hi_xts + pred_M_hi_xts)

MAE <- mean(abs(for_M_hi_en - M_hi_v))
MAPE <- 100*mean(abs((for_M_hi_en - M_hi_v)/M_hi_v))

print(MAE)
[1] 64.12486

print(MAPE)
[1] 14.38913
```

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