Exponential Smoothing

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Introduction

Blah blah

Simple Exponential

What is exponential smoothing?

Forecasting future observations using weighted averages of past observations, with the weights decaying exponentially as observations recede further into the past

ES_1: Naive model

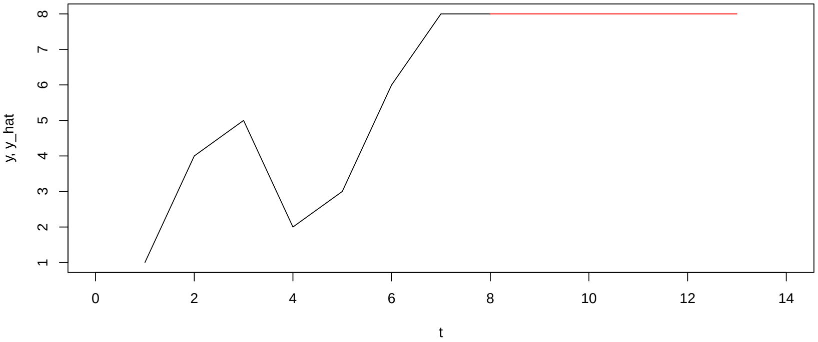
- The naive forecasting model can be thought of us exponential smoothing
- Where 100 percent of weight is given to the last observation:

```
forecast_naive <- function(y, h) {
    n <- length(y)
    y_hat <- rep(y[n], h)
    return( y_hat )
}
```

ES_1: Naive model: Example

```r
y <- c(1, 4, 5, 2, 3, 6, 8)
y_hat <- forecast_naive(y, h=7)

plot_forecast(y, y_hat)
```



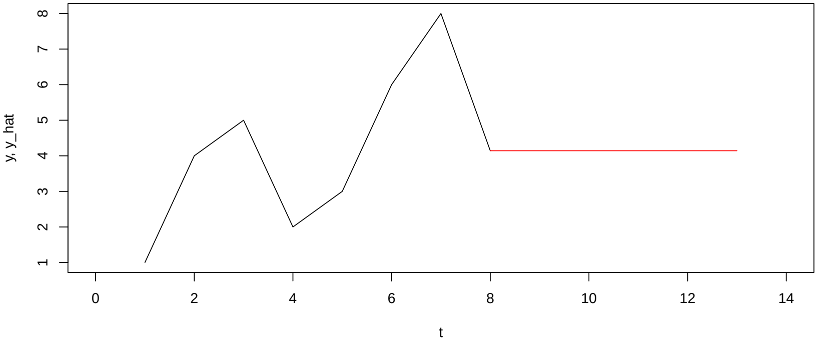
ES_2: Average model

- All future values are forecast as the average of the observed data
- Equivalent to to exponential smoothing where each observation is given equal weight

```
forecast_avg <- function(y, h) {
    y_hat <- rep(mean(y), h)
    return( y_hat )
}
```

ES_2: Average model: Example

```
y_hat <- forecast_avg(y, h=7)
plot_forecast(y, y_hat)
```



ES_3: Weighted average

- More sophisticated model would given recent observations more weight, and decreasing weight for past observations
- Control the pace of decreasing weight with a parameter α between 0 and 1
- Like the previous two models, this is a flat forecast where all forecasts take the same value, equal to the last level component

```
y <- c(1, 2, 3, 4)

alpha <- 0.5

y_5_c <- c()

T <- length(y)
for (i in 1:T-1) {
    a <- alpha * (1 - alpha)^i * y[T - i] + (1 - alpha)^T *
    y_5_c <- append(a, y_5_c)
}
```

ES_3: Weighted average: Optimize $\hat{\alpha}$

ES_3: Weighted average: Example

Holt's linear trend + damped

Holt-Winters method + multiplicative + taxonomy

ETS modeling (Innovations state space models)

Conclusion

Blah blah