

5_Nile_HoltWinters.R

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```
# Course: Time series analysis
# Exercise: 5th / Nile Holt-Winters
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```

```
require(astsa)
```

```
## Loading required package: astsa
```

```
require(tseries)
```

```
## Loading required package: tseries
```

```
## Registered S3 method overwritten by 'quantmod':
##   method      from
##   as.zoo.data.frame zoo
```

```
require(Metrics)
```

```
## Loading required package: Metrics
```

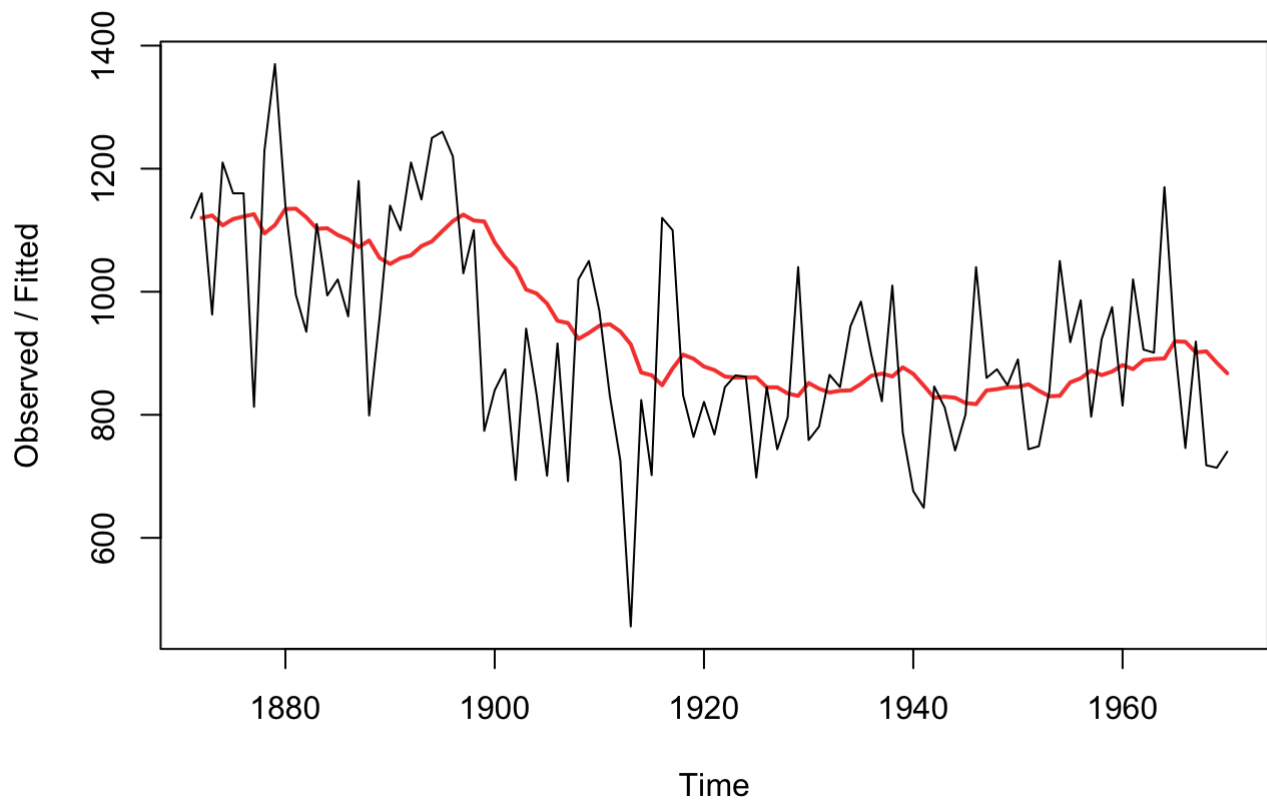
```
# 1.)
alpha_1 = 0.1
Nile_exp_1 = HoltWinters(Nile, alpha = alpha_1, beta = FALSE, gamma = FALSE)

alpha_2 = 0.3
Nile_exp_2 = HoltWinters(Nile, alpha = alpha_2, beta = FALSE, gamma = FALSE)

alpha_3 = 0.8
Nile_exp_3 = HoltWinters(Nile, alpha = alpha_3, beta = FALSE, gamma = FALSE)

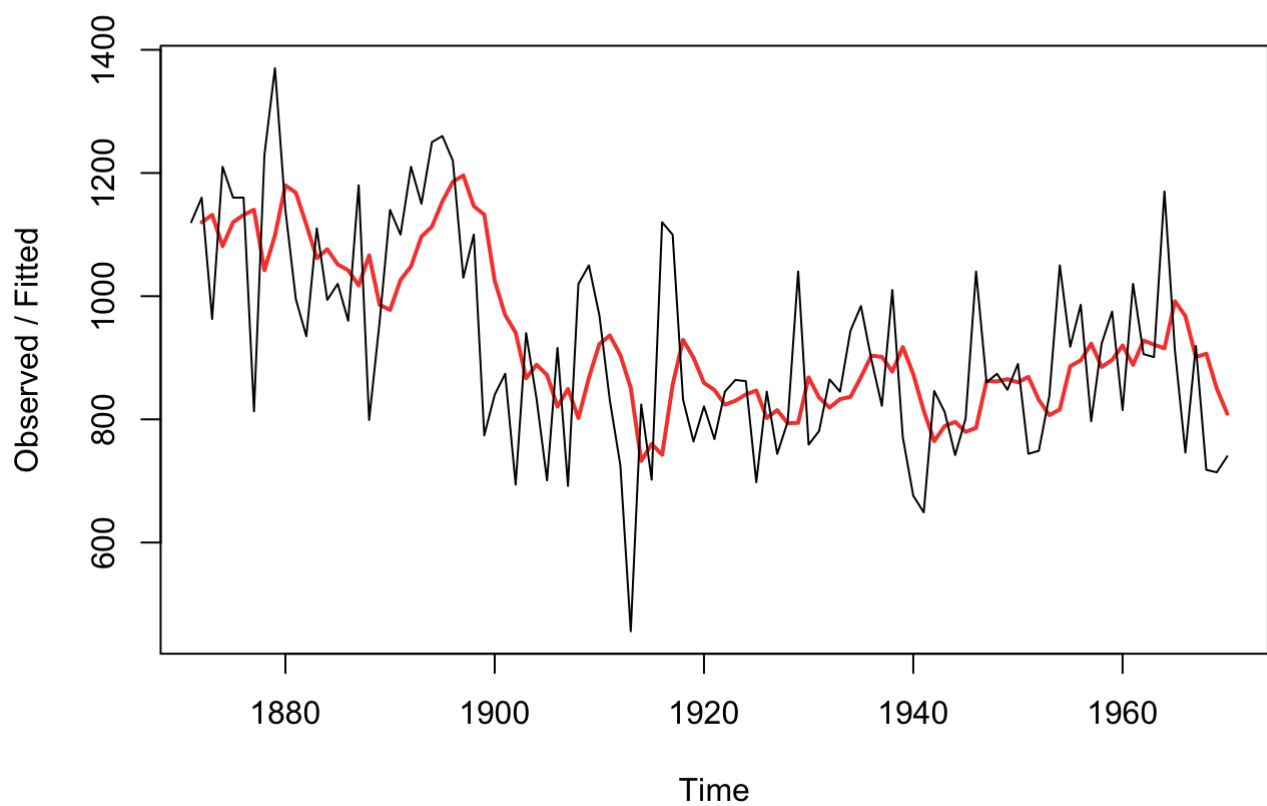
plot(Nile_exp_1, lwd = 2)
```

Holt-Winters filtering



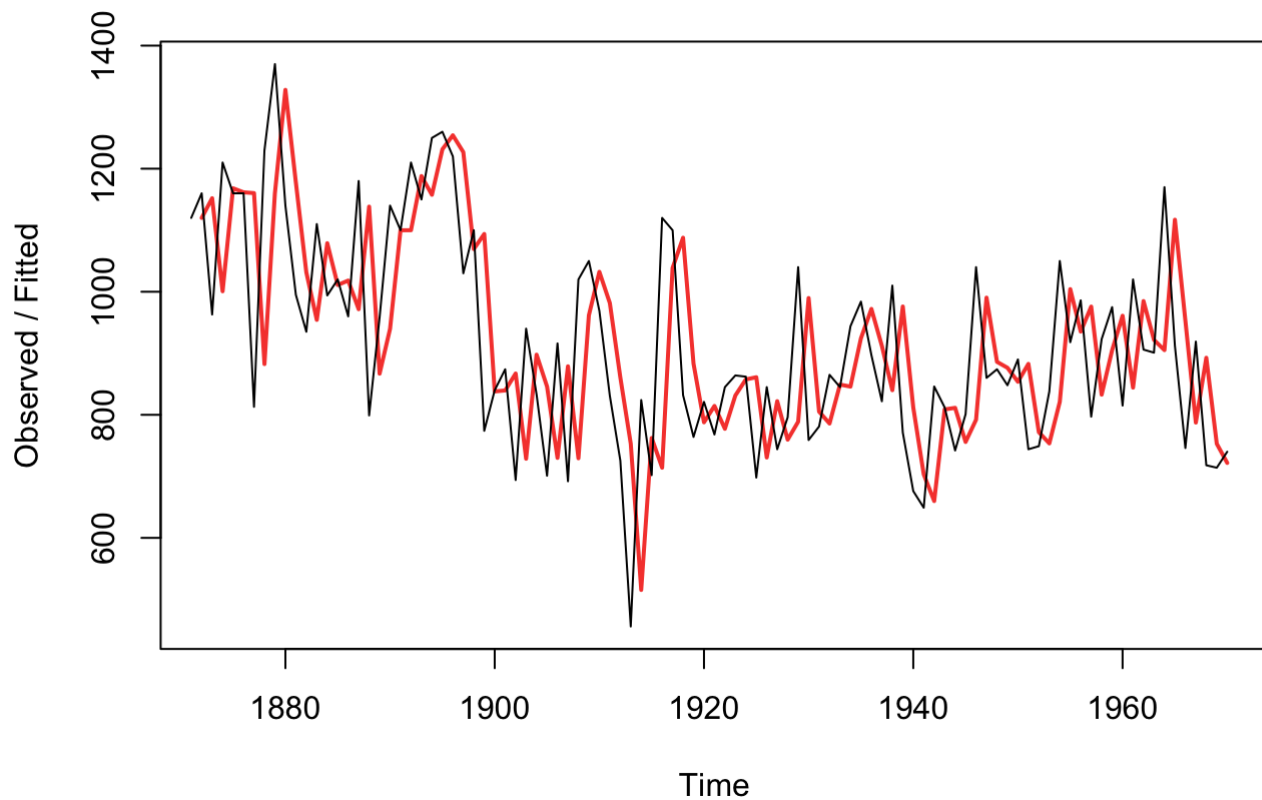
```
plot(Nile_exp_2, lwd = 2)
```

Holt-Winters filtering



```
plot(Nile_exp_3, lwd = 2)
```

Holt-Winters filtering



```
# 2.)
actual_values <- c(Nile[2:100])
actual_values
```

```
## [1] 1160 963 1210 1160 1160 813 1230 1370 1140 995 935 1110 994 1020 960
## [16] 1180 799 958 1140 1100 1210 1150 1250 1260 1220 1030 1100 774 840 874
## [31] 694 940 833 701 916 692 1020 1050 969 831 726 456 824 702 1120
## [46] 1100 832 764 821 768 845 864 862 698 845 744 796 1040 759 781
## [61] 865 845 944 984 897 822 1010 771 676 649 846 812 742 801 1040
## [76] 860 874 848 890 744 749 838 1050 918 986 797 923 975 815 1020
## [91] 906 901 1170 912 746 919 718 714 740
```

```
predicted_values_1 <- c(Nile_exp_1$fitted[1:99])
predicted_values_1
```

```
## [1] 1120.0000 1124.0000 1107.9000 1118.1100 1122.2990 1126.0691 1094.7622
## [8] 1108.2860 1134.4574 1135.0116 1121.0105 1102.4094 1103.1685 1092.2516
## [15] 1085.0265 1072.5238 1083.2714 1054.8443 1045.1599 1054.6439 1059.1795
## [22] 1074.2615 1081.8354 1098.6519 1114.7867 1125.3080 1115.7772 1114.1995
## [29] 1080.1795 1056.1616 1037.9454 1003.5509 997.1958 980.7762 952.7986
## [36] 949.1187 923.4069 933.0662 944.7596 947.1836 935.5652 914.6087
## [43] 868.7478 864.2731 848.0458 875.2412 897.7171 891.1454 878.4308
## [50] 872.6877 862.2190 860.4971 860.8474 860.9626 844.6664 844.6997
## [57] 834.6298 830.7668 851.6901 842.4211 836.2790 839.1511 839.7360
## [64] 850.1624 863.5461 866.8915 862.4024 877.1621 866.5459 847.4913
## [71] 827.6422 829.4780 827.7302 819.1572 817.3414 839.6073 841.6466
## [78] 844.8819 845.1937 849.6744 839.1069 830.0962 830.8866 852.7979
## [85] 859.3181 871.9863 864.4877 870.3389 880.8050 874.2245 888.8021
## [92] 890.5219 891.5697 919.4127 918.6714 901.4043 903.1639 884.6475
## [99] 867.5827
```

```
mse1 <- mse(actual_values, predicted_values_1)
mse1
```

```
## [1] 21495.81
```

```
mae1 <- mae(actual_values, predicted_values_1)
mae1
```

```
## [1] 114.3894
```

```
mape1 <- mape(actual_values, predicted_values_1)
mape1
```

```
## [1] 0.1348183
```

```
predicted_values_2 <- c(Nile_exp_2$fitted[0:99])
predicted_values_2
```

```
## [1] 1120.0000 1132.0000 1081.3000 1119.9100 1131.9370 1140.3559 1042.1491
## [8] 1098.5044 1179.9531 1167.9672 1116.0770 1061.7539 1076.2277 1051.5594
## [15] 1042.0916 1017.4641 1066.2249 986.0574 977.6402 1026.3481 1048.4437
## [22] 1096.9106 1112.8374 1153.9862 1185.7903 1196.0532 1146.2373 1132.3661
## [29] 1024.8563 969.3994 940.7796 866.7457 888.7220 872.0054 820.7038
## [36] 849.2926 802.1048 867.4734 922.2314 936.2620 904.6834 851.0784
## [43] 732.5549 759.9884 742.5919 855.8143 929.0700 899.9490 859.1643
## [50] 847.7150 823.8005 830.1604 840.3123 846.8186 802.1730 815.0211
## [57] 793.7148 794.4003 868.0802 835.3562 819.0493 832.8345 836.4842
## [64] 868.7389 903.3172 901.4221 877.5954 917.3168 873.4218 814.1952
## [71] 764.6367 789.0457 795.9320 779.7524 786.1267 862.2887 861.6021
## [78] 865.3214 860.1250 869.0875 831.5613 806.7929 816.1550 886.3085
## [85] 895.8160 922.8712 885.1098 896.4769 920.0338 888.5237 927.9666
## [92] 921.3766 915.2636 991.6845 967.7792 901.2454 906.5718 850.0003
## [99] 809.2002
```

```
mse2 <- mse(actual_values, predicted_values_2)
mse2
```

```
## [1] 20637.51
```

```
mae2 <- mae(actual_values, predicted_values_2)
mae2
```

```
## [1] 113.6598
```

```
mape2 <- mape(actual_values, predicted_values_2)
mape2
```

```
## [1] 0.1308681
```

```
predicted_values_3 <- c(Nile_exp_3$fitted[0:99])
predicted_values_3
```

```
## [1] 1120.0000 1152.0000 1000.8000 1168.1600 1161.6320 1160.3264 882.4653
## [8] 1160.4931 1328.0986 1177.6197 1031.5239 954.3048 1078.8610 1010.9722
## [15] 1018.1944 971.6389 1138.3278 866.8656 939.7731 1099.9546 1099.9909
## [22] 1187.9982 1157.5996 1231.5199 1254.3040 1226.8608 1069.3722 1093.8744
## [29] 837.9749 839.5950 867.1190 728.6238 897.7248 845.9450 729.9890
## [36] 878.7978 729.3596 961.8719 1032.3744 981.6749 861.1350 753.0270
## [43] 515.4054 762.2811 714.0562 1038.8112 1087.7622 883.1524 787.8305
## [50] 814.3661 777.2732 831.4546 857.4909 861.0982 730.6196 822.1239
## [57] 759.6248 788.7250 989.7450 805.1490 785.8298 849.1660 845.8332
## [64] 924.3666 972.0733 912.0147 840.0029 976.0006 812.0001 703.2000
## [71] 659.8400 808.7680 811.3536 755.8707 791.9741 990.3948 886.0790
## [78] 876.4158 853.6832 882.7366 771.7473 753.5495 821.1099 1004.2220
## [85] 935.2444 975.8489 832.7698 904.9540 960.9908 844.1982 984.8396
## [92] 921.7679 905.1536 1117.0307 953.0061 787.4012 892.6802 752.9360
## [99] 721.7872
```

```
mse3 <- mse(actual_values, predicted_values_3)
mse3
```

```
## [1] 24386.14
```

```
mae3 <- mae(actual_values, predicted_values_3)
mae3
```

```
## [1] 124.0603
```

```
mape3 <- mape(actual_values, predicted_values_3)
mape3
```

```
## [1] 0.1405985
```

```
# in my chosen grid: alpha = 0.3
```

```
# 3.)
```

```
# -> Unknown parameters are determined by minimizing the squared one-step prediction error.
```

```
Nile_exp_opt = HoltWinters(Nile, beta = FALSE, gamma = FALSE)
```

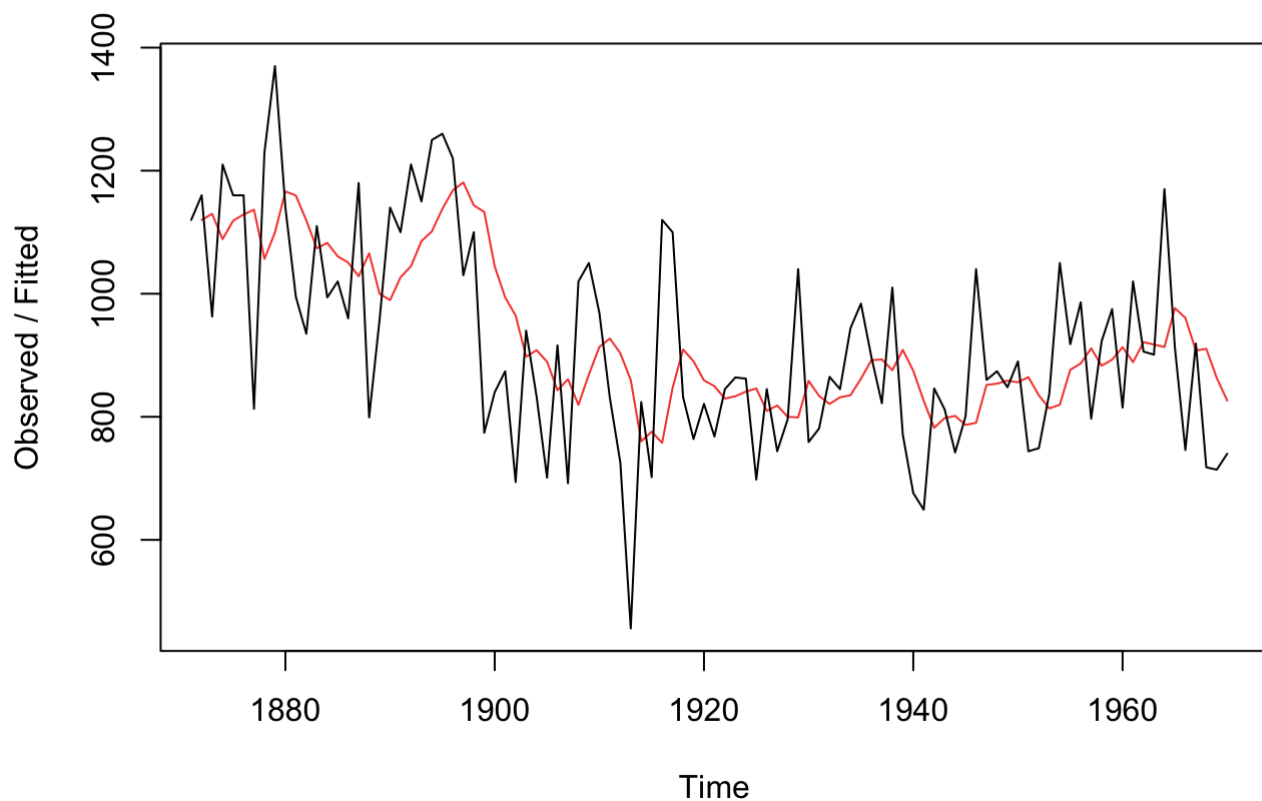
```
alpha_opt <- Nile_exp_opt$alpha
```

```
alpha_opt
```

```
## [1] 0.2465579
```

```
plot(Nile_exp_opt)
```

Holt-Winters filtering



```
predicted_values_opt <- c(Nile_exp_opt$fitted[0:99])
```

```
predicted_values_opt
```

```
## [1] 1120.0000 1129.8623 1088.7211 1118.6234 1128.8251 1136.5115 1056.7472
## [8] 1099.4640 1166.1668 1159.7152 1119.1034 1073.7112 1082.6585 1060.7991
## [15] 1050.7397 1028.3671 1065.7534 999.9833 989.6320 1026.7064 1044.7775
## [22] 1085.5144 1101.4138 1138.0489 1168.1169 1180.9091 1143.7013 1132.9264
## [29] 1044.4303 994.0264 964.4329 897.7556 908.1713 889.6372 843.1272
## [36] 861.0946 819.4030 868.8617 913.5228 927.2011 903.4820 859.7224
## [43] 760.1815 775.9164 757.6918 847.0217 909.3955 890.3130 859.1696
## [50] 849.7586 829.6003 833.3972 840.9426 846.1345 809.6107 818.3362
## [57] 800.0081 799.0198 858.4354 833.9188 820.8713 831.7516 835.0181
## [64] 861.8884 891.9960 893.2298 875.6675 908.7882 874.8155 825.7959
## [71] 782.2055 797.9345 801.4025 786.7563 790.2682 851.8416 853.8531
## [78] 858.8205 856.1526 864.4979 834.7882 813.6365 819.6435 876.4397
## [85] 886.6867 911.1732 883.0229 892.8796 913.1270 888.9330 921.2486
## [92] 917.4889 913.4235 976.6844 960.7360 907.7911 910.5548 863.0789
## [99] 826.3223
```

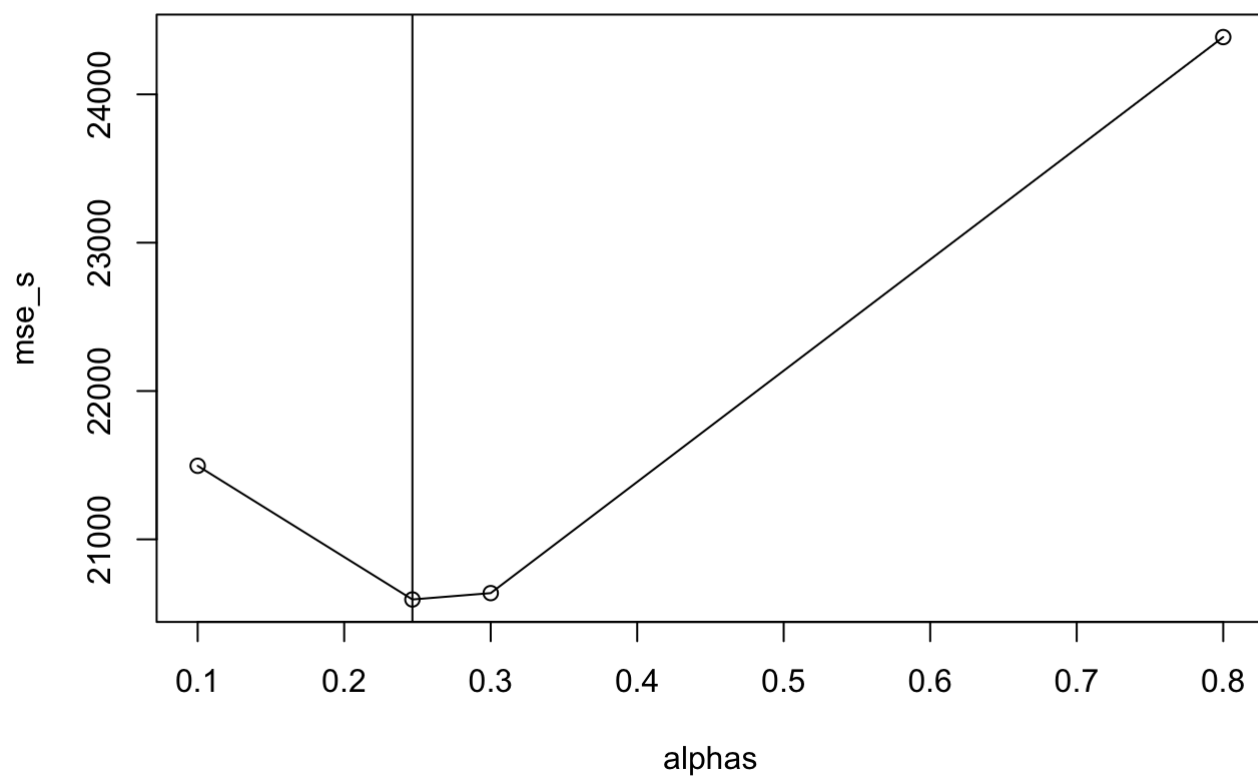
```
mse4 <- mse(actual_values, predicted_values_opt)
mae4 <- mae(actual_values, predicted_values_opt)
mape4 <- mape(actual_values, predicted_values_opt)
mape4 # ~ 13.07% mean abs. perc. err.
```

```
## [1] 0.1307089
```

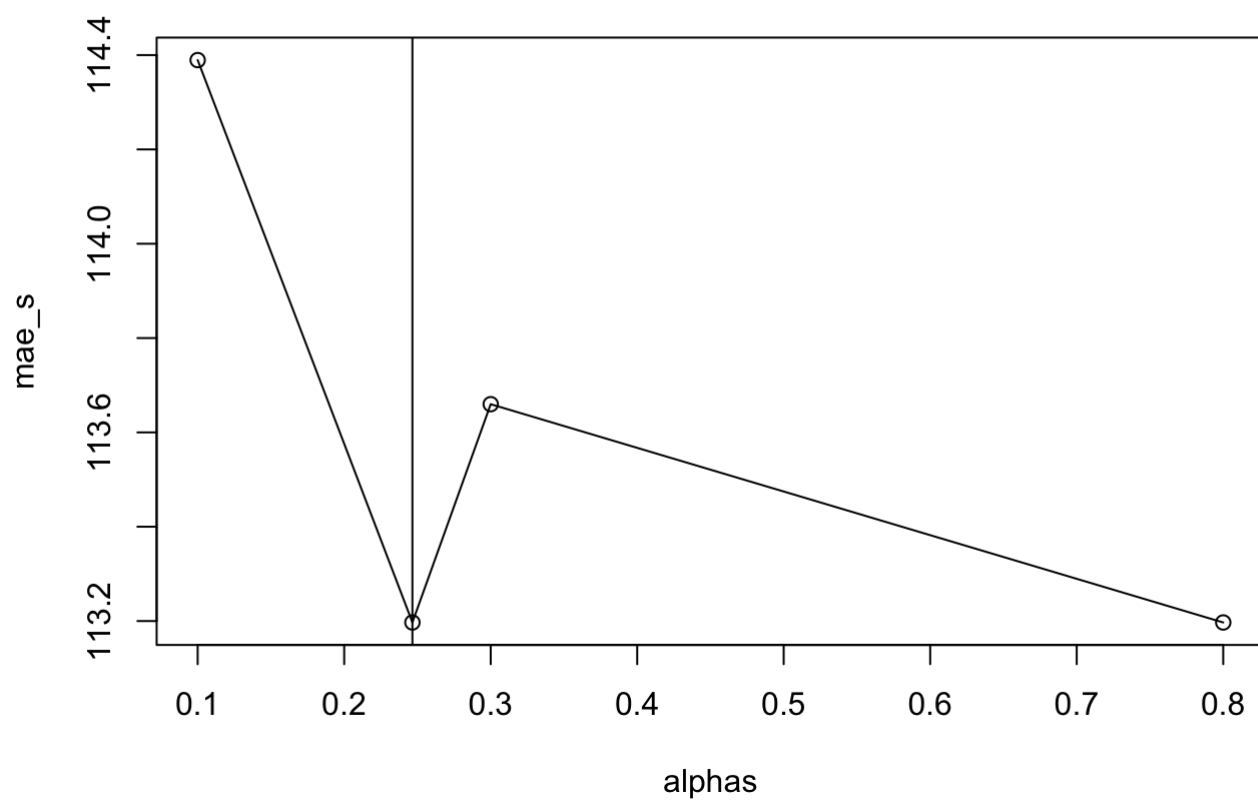
```
# 4.)
alphas <- c(alpha_1, alpha_opt, alpha_2, alpha_3)

mse_s <- c(mse1, mse4, mse2, mse3)
mae_s <- c(mae1, mae4, mae2, mae4)
mape_s <- c(mape1, mape4, mape2, mape3)

# MSE
df_mse <- data.frame(alphas, mse_s)
# could fit a function using a linear model
plot(df_mse)
lines(df_mse)
abline(v = alpha_opt)
```



```
# MAE
df_mae <- data.frame(alphas, mae_s)
plot(df_mae)
lines(df_mae)
abline(v = alpha_opt)
```

```
# MAPE
df_mape <- data.frame(alphas, mape_s)
plot(df_mape)
lines(df_mape)
abline(v = alpha_opt)
```

