Marathon Record Progression



Raw Data

	1 2	3 4 5 6 7	9 10 11	12 13 14	15 16	17 enter pag	ge number 27	> >>
Rank	Mark	Competitor	DOB	Nat	Pos	Venue	Date	Results Score
1	2:01:25	Kelvin KIPTUM	02 DEC 1999	KEN	1	London (GBR)	23 APR 2023	1307
2	2:03:47	Bashir ABDI	10 FEB 1989	■■ BEL	1	Rotterdam (NED)	16 APR 2023	1266
3	2:03:50	Timothy KIPLAGAT		KEN	2	Rotterdam (NED)	16 APR 2023	1265
4	2:04:09	Bernard Kiprop KOECH	31 JAN 1988	KEN	1	Hamburg (GER)	23 APR 2023	1259
5	2:04:23	Geoffrey KAMWOROR	22 NOV 1992	KEN	2	London (GBR)	23 APR 2023	1255
6	2:04:33	Joshua BELET	10 FEB 1998	KEN	2	Hamburg (GER)	23 APR 2023	1252
7	2:04:59	Gadisa SHUMIE	15 SEP 1992	ETH	1	Sevilla (ESP)	19 FEB 2023	1245
7	2:04:59	Tamirat TOLA	11 AUG 1991	ETH	3	London (GBR)	23 APR 2023	1245
9	2:05:06	Marius KIMUTAI	10 DEC 1992	BRN	1	Barcelona (ESP)	19 MAR 2023	1243
10	2:05:08	Samwel Nyamai MAILU	07 FEB 1993	KEN	1	Wien (AUT)	23 APR 2023	1242

Data Retrieved from World Athletics Website

General Background Information

- Course > = 42.195 km (26.219 mi).
- WR: Eliud Kipchoge, 2:01:09 = 7269s

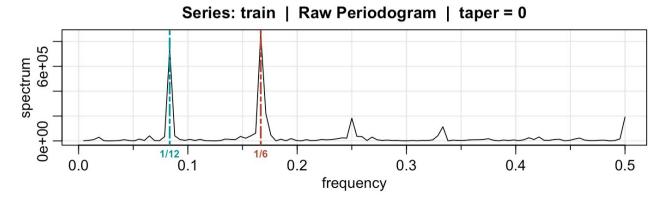
- We can see that due to hot weather, August 2007 and July 2021 has no official race.
- And due to covid, April to September 2020 has no official race

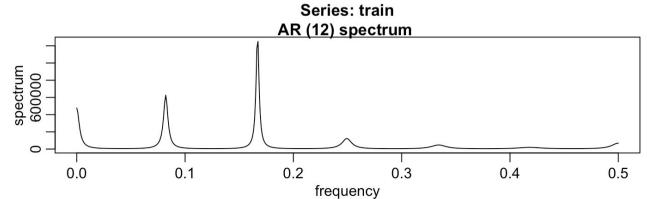
Time: January 2001 - May 2023, with the above exceptions **imputed** Reindex January 2001 as time 1, ..., and May 2023 as 266

Initial Spectral Analysis

 Periodogram with narrow-band peak at around 1/12 and 1/6

 Parametric AR(12) spectrum captures the peak and the harmonic

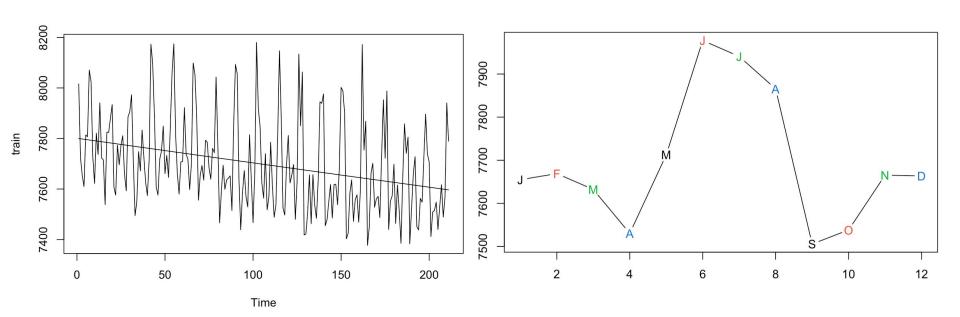




Trend & Cycle Removal

$$y = e^{8.962 - 0.0013* t}$$

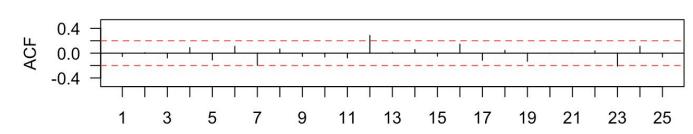
Seasonal Plot (Mean)



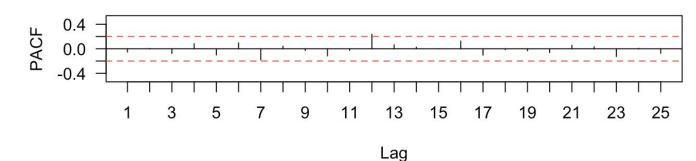
Residual Analysis

- Both ACF & PACF has shrinked after detrending
- Both ACF & PACF tails off.
 - Indication of ARMA model





Partial Autocorrelation Function



Model Fitting

Γ1.7 92.39901 95.68758 95.65219 94.36388 93.31652 91.05821 88.34669 87.61045 86.04724 [2,] 90.64180 100.88067 87.42562 92.22620 86.91695 87.41688 101.47109 85.78565 85.44019 [3,] 90.58195 115.88636 179.37185 107.17336 102.26921 87.35414 98.31313 89.43111 87.02495 Grid Search w/ RMSE 89.21444 99.51944 89.36075 93.04617 135.90803 106.04821 115.99287 86.79325 86.48071 86.79697 87.68128 87.71589 129.02656 125.04273 as metric \rightarrow ARMA(7,6) [6,] 89.93517 87.34736 86.92376 90.50506 87.44833 131.39315 104.47757 126.31991 88.10991 147.18374 132.40931 146.17898 139.42975 94.66051 89.71582 93.76902 137.54698 85.43159 86.67199 137.22468 162.73005 83.48060 83.08321 96.98145 100.19755 109.47116 [8,] 85.53173 [9,] 85.14055 85.23019 84.84785 86.45289 103.20927 85.04579 105.24499 91.52096 135.45307 87.24750 [10,] 84.78767 84.63329 120.04583 84.23023 134.66566 83.38553 85.75732 105.06556 105.19466 173.28177 [,1][,2] [,3][,4][,5] [,6] [,8] [,10][1,] 2519.517 2524.238 2529.590 2534.047 2538.581 2540.968 2544.472 2543.126 2548.449 2553.570 [2,] 2524.234 2516.400 2521.115 2523.900 2529.100 2534.445 2539.602 2548.456 2553.566 2558.316 Grid Search w/ BIC [3,] 2529.580 2531.561 2531.782 2536.116 2541.095 2539.787 2544.961 2545.299 2550.430 2555.662 [4,] 2533.663 2524.230 2529.066 2533.153 2533.162 2538.183 2544.886 2550.413 2548.035 2560.268 as metric \rightarrow ARMA(1,1) Γ5.7 2537.504 2529.193 2534.407 2539.711 2541.870 2547.143 2542.597 2547.253 2558.058 2554.970 [6,] 2540.601 2534.320 2539.406 2541.744 2547.077 2545.167 2542.738 2546.628 2549.045 2557.589 [7,] 2543.827 2539.663 2544.758 2542.359 2541.381 2543.654 2545.392 2549.936 2554.396 2556.844 [8,] 2541.606 2546.578 2542.473 2543.822 2546.521 2547.779 2552.931 2547.675 2553.735 2555.191 [9,] 2546.589 2552.093 2557.281 2550.356 2550.785 2552.761 2557.423 2560.070 2555.718 2561.898

Γ,47

[,5]

[10,] 2551.764 2556.576 2546.473 2557.151 2552.624 2557.805 2562.953 2556.908 2562.161 2565.597

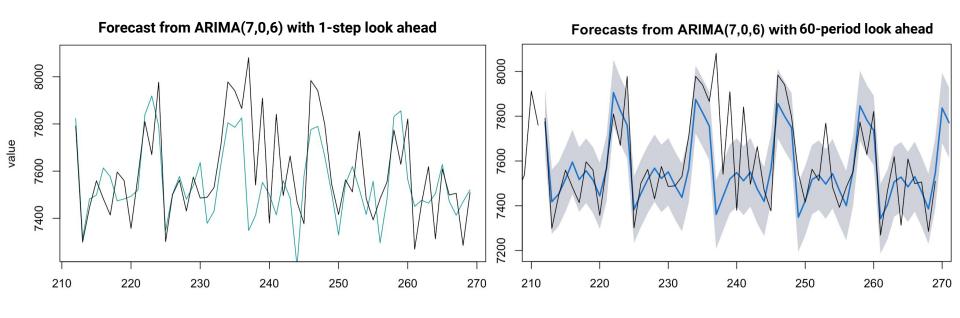
[,6]

[,8]

Γ,107

Γ,17

Prediction



RMSE: 177.4566 RMSE: 84.28

Conclusion

- ARIMA(7,0,6) seems to be a good fit of our training data
- However, for a different dataset (even using a fraction of our training) may lead to different model result.

- Future Work
 - 1. Deep dive into covariates (weather,)
 - 2. Dealing with missing data is key in this model
 - 3. Apply on other race events

Work Cited

- Data Source: <u>Marathon men senior outdoor 2023</u>
- Missing Value Handling Techniques: <u>4 Techniques to Handle Missing</u>
 <u>values in Time Series Data | by Satyam Kumar</u>
- Forecast Package in R: <u>forecast function RDocumentation</u>
- Shumway, Robert H., and David S. Stoffer. Time Series Analysis and Its Applications: With R Examples. Springer, 2017.