**Homework 3: Exponential Smoothing in Time Series**

Georgia Institute of Technology, Business Analytics

Introduction to Analytics Modeling

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Files submitted: homework4\_answers.pdf (this doc), homework4.R

**Question 7.1**

**Describe a situation or problem from your job, everyday life, current events, etc., for which exponential smoothing would be appropriate. What data would you need? Would you expect the value of α(the first smoothing parameter) to be closer to 0 or 1, and why?**

**Situation**

At my job as a software engineer, our team monitors the **number of daily user logins** to our platform. The login counts fluctuate from day to day; weekdays tend to be higher, weekends lower, but there’s also random noise due to marketing campaigns, outages, or holidays.

**Data Needed**

We would need **time-series data** of daily user login counts over several weeks or months. This dataset would allow us to see both the underlying pattern and the random variation.

**Use of Exponential Smoothing**

Exponential smoothing could help us **smooth out random spikes** (like an unusual jump from a single promotion) while still tracking the general baseline level of logins. This makes it easier to monitor trends and detect unusual changes in user engagement.

**Choice of α (Smoothing Parameter)**

* I would expect **α to be closer to 0** because login activity has a fair amount of randomness (e.g., sudden spikes from promotions, dips on holidays).
* A lower α puts more weight on past smoothed values, making the baseline less sensitive to one-off fluctuations.
* If α were closer to 1, the model would overreact to every daily jump or dip, which would not be useful for identifying the stable underlying trend.

**Question 7.2**

**Using the 20 years of daily high temperature data for Atlanta (July through October) from Question 6.2 (file temps.txt), build and use an exponential smoothing model to help make a judgment of whether the unofficial end of summer has gotten later over the 20 years. (Part of the point of this assignment is for you to think about how you might use exponential smoothing to answer this question. Feel free to combine it with other models if you’d like to. There’s certainly more than one reasonable approach.)**

**Note: in R, you can use either HoltWinters (simpler to use) or the smooth package’s es function (harder to use, but more general). If you use es, the Holt-Winters model uses model=”AAM” in the function call (the first and second constants are used “A”dditively, and the third (seasonality) is used “M”ultiplicatively; the documentation doesn’t make that clear).**

**Methodology**

* I used **single exponential smoothing** (SES) on each year’s July–October daily high temperatures (1996-2015) using the smooth::es function in R with model = "ANN".
* For each year, I defined a **July baseline** (median of July highs). The “end of summer” was the first day after August 1 where the smoothed highs fell at least **2°F below** the July baseline, with persistence (≥5 of the next 7 days also below).
* Converted the date to **day-of-year (DOY)** and regressed DOY on calendar year. Also ran a **Kendall trend test.**

**Results**

* The extracted end-of-summer dates ranged from early August (~DOY 213) to late September (~DOY 268).

**Table of results (ends tibble with year, end\_date, doy)**  
A screenshot of a computer

AI-generated content may be incorrect.

**Second part of table (2006–2015)**  
A screenshot of a computer

AI-generated content may be incorrect.

* Linear regression gave a slope of **+1.15 days/year (≈ +11.5 days/decade)** with p ≈ 0.015.
* Kendall’s τ = 0.34, p ≈ 0.045, confirming a positive monotonic trend.

**Regression output (summary of lm\_fit)**

A screenshot of a computer

AI-generated content may be incorrect.

* Plotting DOY vs year shows an upward slope: **the unofficial end of summer has been getting later.**

**Scatterplot with regression line (ggplot)**

A graph with a line and numbers

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**Discussion of Results**

* The exponential smoother reduced day-to-day noise and revealed a consistent cooling-off signal across years.
* The results suggest summers are extending ~11 days later per decade.
* Some year-to-year variation remains (e.g., 1999 late drop vs 2003 earlier drop).
* Limitations: choice of δ = 2°F and persistence threshold affects sensitivity. Using δ = 1°F or 3°F produced qualitatively similar trends.
* Potential improvements: Holt-Winters with seasonal adjustment; change-point detection.
* Broader implication: later ends of summer are consistent with climate warming trends, with possible consequences for energy demand and health.

**REFERENCES**

https://www.linkedin.com/pulse/arima-vs-garch-time-series-forecasting-mahdi-navaei/