

ISYE 6051 : Homework 4
2/17/2021

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7.1 Current Situations where exponential smoothing is relevant

Scheduling the administration of vaccines to protect the population against series illness and death related to COVID-19 has proven to be a challenge for larger municipalities. The raw numbers of eligible recipients, the fluctuating availability in the allocation per states and the ability of individuals to schedule vaccines at multiple locations makes exponential smoothing a viable model to determine the percentage of shot 1 versus shot 2 recipients to schedule.

States request allocations of shots on different days of the week – Thursdays for shot 1 and Sundays for shot 2. The obvious method to scheduling would be to schedule the number of participants based on the allocation requested and approved for each phase of the shot.

However, widely publicized issues with vaccine sites either not having enough recipients (and having to beg people to come take shots who may not be in the eligibility group so that the vaccine doesn't go to waste) or having to turn away eligible recipients due to overscheduling proves that the obvious method isn't a strong model. Two of the most challenging issues are:

- 1) Eligible recipients don't show up for the shot 1 appointment for any number of reasons and*
- 2) Shot 2 eligible recipients don't show up due to the fact that in larger municipalities they can register in more than one county*

and will go to the first one that has an available appointment after having signed up in multiple locations.

The vaccine is date and temperature sensitive; waste is of paramount concern and both shots are exactly the same in formulation. This is where exponential smoothing utilizing forecasting and trends would be of benefit. These are short term models where the most recent data would be of value in determining the potentially best allocation of vaccines on a given day. In this case the α value would be closer to 1 based on the high possibility of randomness based on several factors such as location, day of the week, weather conditions and any other number of variances.

7.2 Using Exponential Smoothing

Using the temps.txt data, the assignment is to develop a model to determine the unofficial end of summer with exponential smoothing. Exponential smoothing is valuable when there is “noise” or variations in the pattern of data. In order to determine if the temps.txt contains variations, I started with creation of a data vector that was plotted for visualization.

```
# Set the working directory
rm(list = ls())
setwd("~/Documents/ISYE6501 Intro to Analytics
Modeling/FA_SP_hw4")
# Read the data in
matrix1 <- read.table("temps.txt", header = TRUE)
head(matrix1)
tail(matrix1)

temps_vec <- as.vector(unlist(matrix1[,2:21]))
temps_vec
plot(temps_vec)
```

Viewing the head and tail of ingested temps.txt data

```
> head(matrix1)
```

```
DAY X1996 X1997 X1998 X1999 X2000 X2001 X2002 X2003  
X2004 X2005 X2006 X2007
```

```
1 1-Jul 98 86 91 84 89 84 90 73 82 91 93 95  
2 2-Jul 97 90 88 82 91 87 90 81 81 89 93 85  
3 3-Jul 97 93 91 87 93 87 87 87 86 86 93 82  
4 4-Jul 90 91 91 88 95 84 89 86 88 86 91 86  
5 5-Jul 89 84 91 90 96 86 93 80 90 89 90 88  
6 6-Jul 93 84 89 91 96 87 93 84 90 82 81 87
```

```
X2008 X2009 X2010 X2011 X2012 X2013 X2014 X2015
```

```
1 85 95 87 92 105 82 90 85  
2 87 90 84 94 93 85 93 87  
3 91 89 83 95 99 76 87 79  
4 90 91 85 92 98 77 84 85  
5 88 80 88 90 100 83 86 84
```

```
tail(matrix1)
```

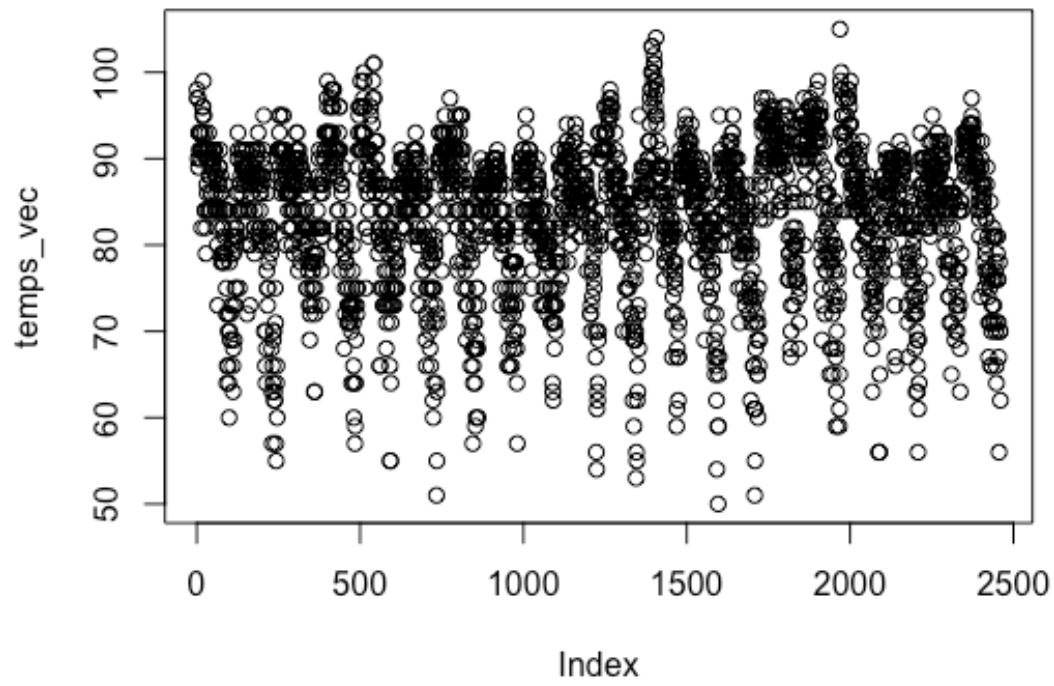
```
DAY X1996 X1997 X1998 X1999 X2000 X2001 X2002 X2003  
X2004 X2005 X2006
```

```
118 26-Oct 75 71 79 69 75 64 68 68 79 61 62  
119 27-Oct 75 57 79 75 78 51 69 64 81 63 66  
120 28-Oct 81 55 79 73 80 55 75 57 78 62 63  
121 29-Oct 82 64 78 72 75 63 75 70 75 64 72  
122 30-Oct 82 66 82 75 77 72 68 77 78 69 73  
123 31-Oct 81 60 79 75 78 71 60 75 82 70 68
```

```
X2007 X2008 X2009 X2010 X2011 X2012 X2013 X2014 X2015
```

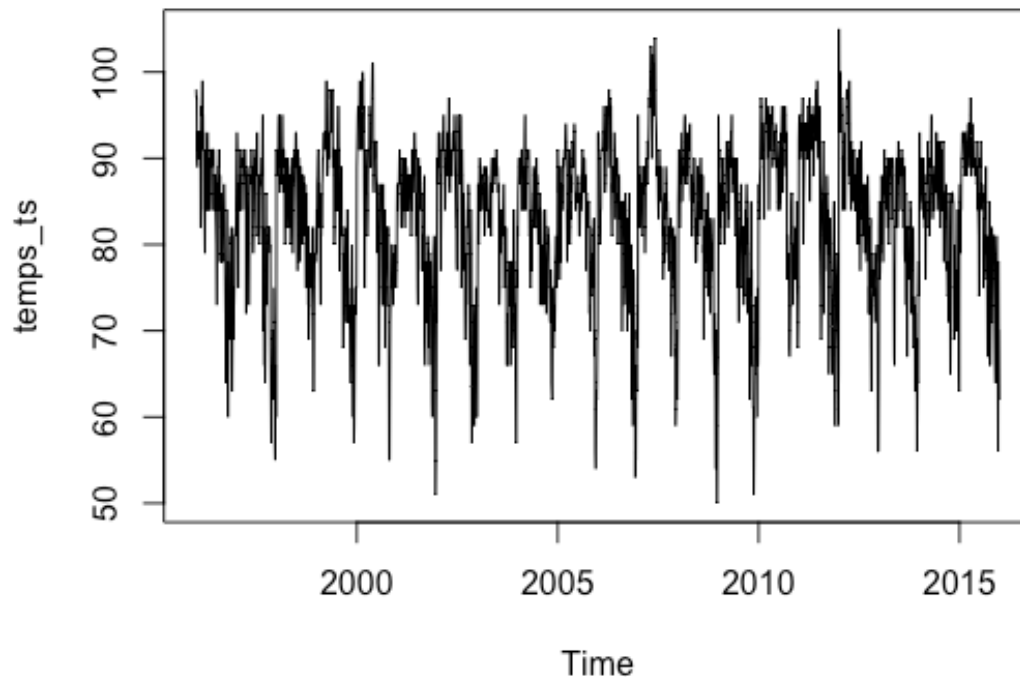
```
118 68 70 65 85 77 80 61 84 67  
119 67 59 60 76 79 70 69 84 56  
120 70 50 71 74 74 56 64 77 78  
121 62 59 75 68 59 56 75 73 70  
122 67 65 66 71 61 56 78 68 70  
123 71 67 69 75 65 65 74 63 62
```

Plot of vector data to visualize noise.



The vector data is converted to time series data and plotted for visualization of noise. Seasonality in temperature changes (both up and down across the years) appear.

```
# Start at the year 1996 and use the frequency equal to 123 which  
represents the number of days Jul 1 - Oct 31  
temps_ts <- ts(temps_vec, start = 1996, frequency = 123)  
temps_ts  
plot(temps_ts)
```



There are 3 types of exponential smoothing models that can be used. However, each one should be used based on data complexity (weighted average, trending and seasonality).

Single exponential smoothing looks at weighted data. It assumes that there is not much variance. Data that is closer to the date of the observation is weighted heavier.

Double exponential smoothing assumes that there are trends in data. In the case of the temps.txt data a possible trend could be longer ends of summer.

Triple exponential smoothing looks at data where there is seasonality and trends can be extracted.

Single Exponential smoothing using the HoltWinters function. HoltWinters can be used for simple, trend and seasonality modeling. I used $\alpha = 0.2$ as the common default.

```
#Single exponential smoothing view. Use of HoltWinters function with
beta and gamme = FALSE
#for weighted average
install.packages("forecast")
library(forecast)

singleexp <- HoltWinters(temps_ts,
                        alpha = 0.2, #common starting point for alpha
                        beta = FALSE,
                        gamma = FALSE)

singleexp
summary(singleexp)
plot(singleexp)
```

Holt-Winters exponential smoothing without trend and without seasonal component.

Call:

```
HoltWinters(x = temps_ts, alpha = 0.2, beta = FALSE, gamma =
FALSE)
```

Smoothing parameters:

```
alpha: 0.2
beta : FALSE
```

```
gamma: FALSE
```

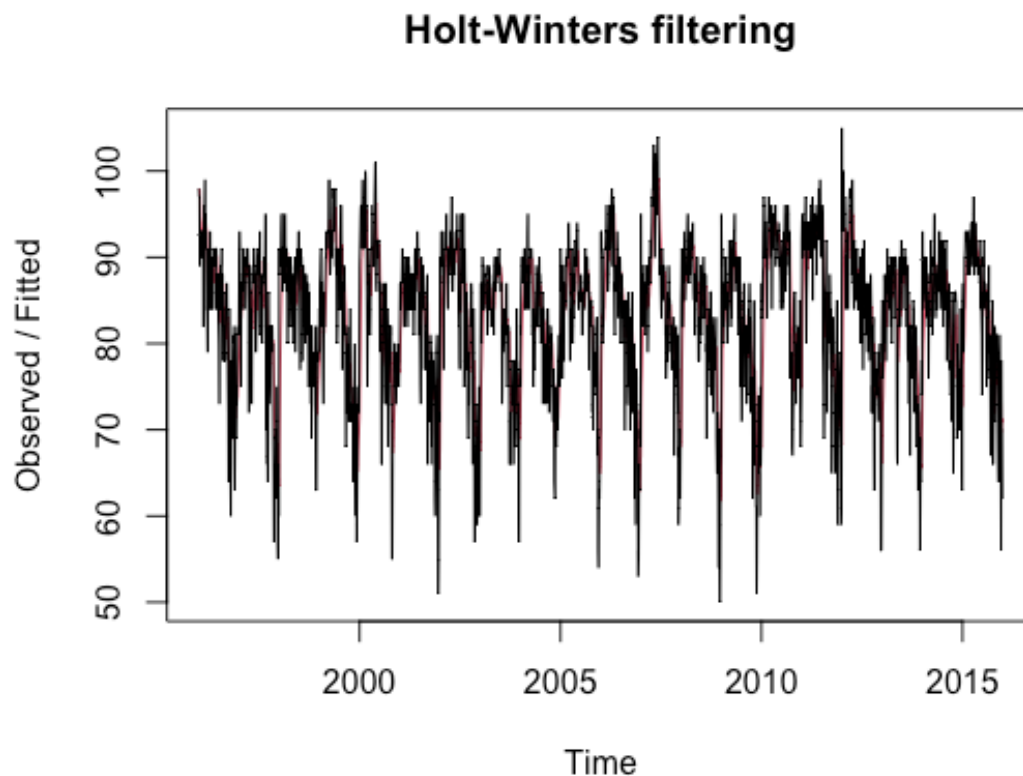
```
Coefficients:
```

```
[,1]
```

```
a 69.0748
```

```
> summary(singleexp)
```

	Length	Class	Mode
fitted	4918	mts	numeric
x	2460	ts	numeric
alpha	1	-none-	numeric
beta	1	-none-	logical
gamma	1	-none-	logical
coefficients	1	-none-	numeric
seasonal	1	-none-	character
SSE	1	-none-	numeric
call	5	-none-	call



In order to determine if this visual seasonality and possibly by extracting trends that it can be demonstrated that summers are unofficially becoming longer, HoltWinters using trend and seasonality will be used (triple exponential smoothing). Multiplicative or additive modeling can be done in the triple exponential smoothing. Since seasonality is consistent across all of the years (in other words there are seasonal changes each year that is being measured), the additive form will most likely be the best to use.

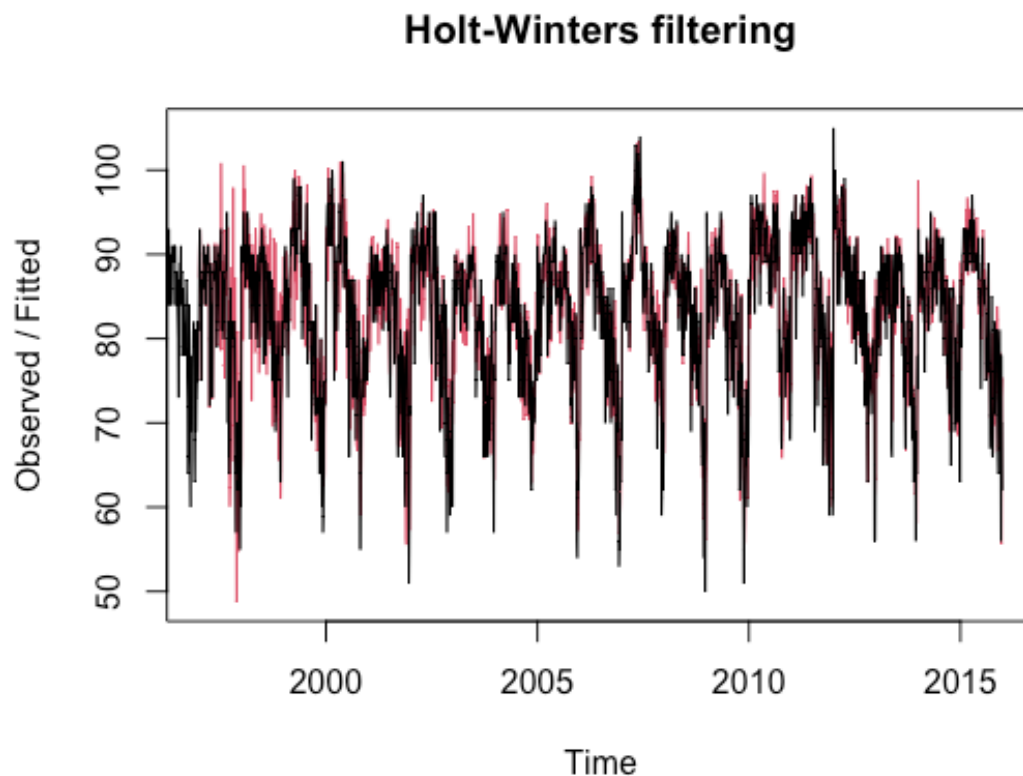
```
set.seed(1)
tripleexp <- HoltWinters(temps_ts,
                        seasonal = 'additive')
tripleexp
summary(tripleexp)

plot(tripleexp)
```



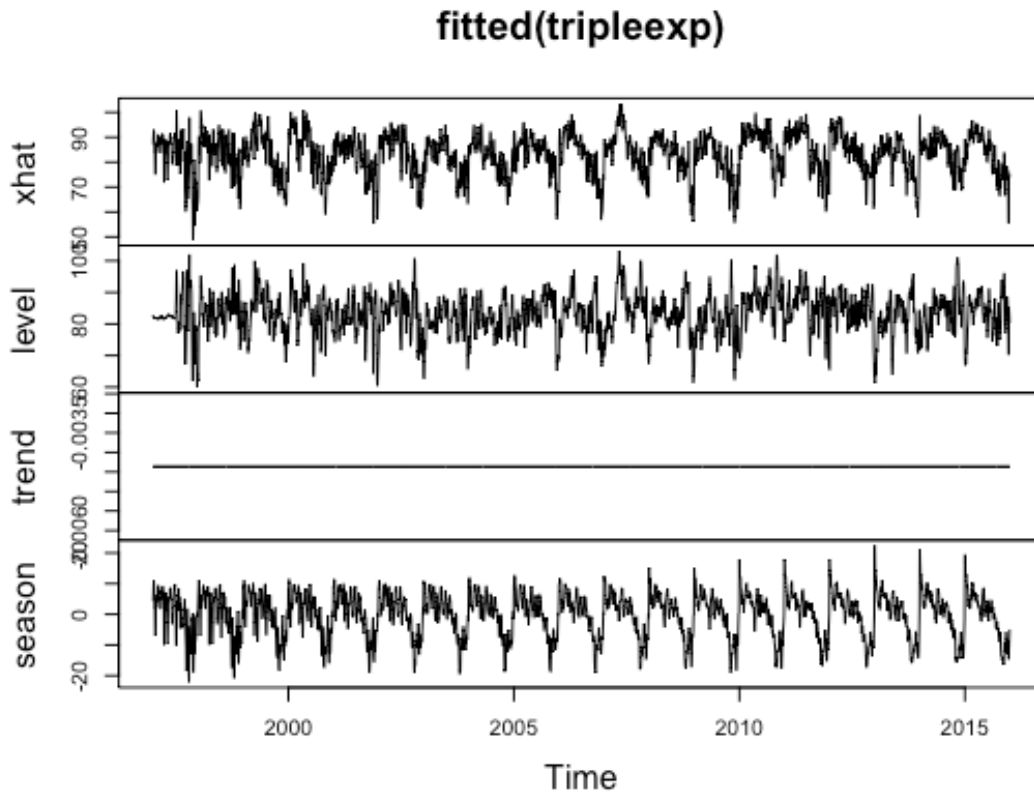
```
cat('\tThe Alpha for the single exponential method is', tripleexp$alpha,
'\n')
cat('\tThe Trend for the single exponential method is', tripleexp$beta,
'\n')
cat('\tThe Seasonality for the single exponential method is',
tripleexp$gamma, '\n')
```

```
summary(tripleexp)
      Length Class Mode
fitted   9348 mts  numeric
x        2460 ts   numeric
alpha     1 -none- numeric
beta      1 -none- numeric
gamma     1 -none- numeric
coefficients 125 -none- numeric
seasonal   1 -none- character
SSE        1 -none- numeric
call       3 -none- call
> plot(tripleexp)
> cat('\tThe Alpha for the triple exponential method is', tripleexp$alpha,
'\n')
      The Alpha for the triple exponential method is 0.6610618
> cat('\tThe Trend for the triple exponential method is', tripleexp$beta,
'\n')
      The Trend for the triple exponential method is 0
> cat('\tThe Seasonality for the triple exponential method is',
tripleexp$gamma, '\n')
      The Seasonality for the triple exponential method is 0.6248076
```



The fitted data is in red. Note that the Trend metric is 0. This would indicate that there are no trends detected in this dataset. The alpha, level, trend and seasonality views are plotted below for visualization. Xhat represents the raw fitted data with the decompositions of level, trend and seasonality visualized below.

```
par(mfrow=c(1,2))  
> plot(fitted(tripleexp))
```



Again, trend is visually 0 therefore the fitted data is not showing trends that can easily proven that summers are lasting longer thru the 20 years evaluated.

Row	Xhat	Level	Trend	Seasonality
[1,]	87.17619	82.87739	-0.004362918	4.303159
[2,]	90.32925	82.09550	-0.004362918	8.238119
[3,]	92.96089	81.87348	-0.004362918	11.091777
[4,]	90.93360	81.89497	-0.004362918	9.042997
[5,]	83.99752	81.93450	-0.004362918	2.067387
[6,]	84.04358	81.93177	-0.004362918	2.116168
[7,]	75.06732	81.89860	-0.004362918	-6.826922
[8,]	87.04284	81.84974	-0.004362918	5.197468
[9,]	84.01829	81.81705	-0.004362918	2.205599
[10,]	87.05875	81.80060	-0.004362918	5.262509
[11,]	84.04807	81.75740	-0.004362918	2.295029

[12,]	88.04445	81.72126	-0.004362918	6.327550
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*No change in the length of seasons is seen across the visual data.
Using the triple exponential smoothing model there does not appear to be data to support a statement the unofficial summer is getting longer over the 20 year data sample used.*