DSO 545: HW 1

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1/27/2019

Load the data:

```
baggage = read.csv(here("HW1", "Baggage.csv"), header=T,stringsAsFactors = F)
indus_med = read.csv(here("HW1","IndustryMedians.csv"),header=T)
head(baggage)
```

```
##          Airline    Date Month Year Baggage Scheduled Cancelled Enplaned
## 1 American Eagle 01/2004     1 2004   12502     38276      2481   992360
## 2 American Eagle 02/2004     2 2004    8977     35762       886  1060618
## 3 American Eagle 03/2004     3 2004   10289     39445      1346  1227469
## 4 American Eagle 04/2004     4 2004    8095     38982       755  1234451
## 5 American Eagle 05/2004     5 2004   10618     40422      2206  1267581
## 6 American Eagle 06/2004     6 2004   13684     39879      1580  1347303
```

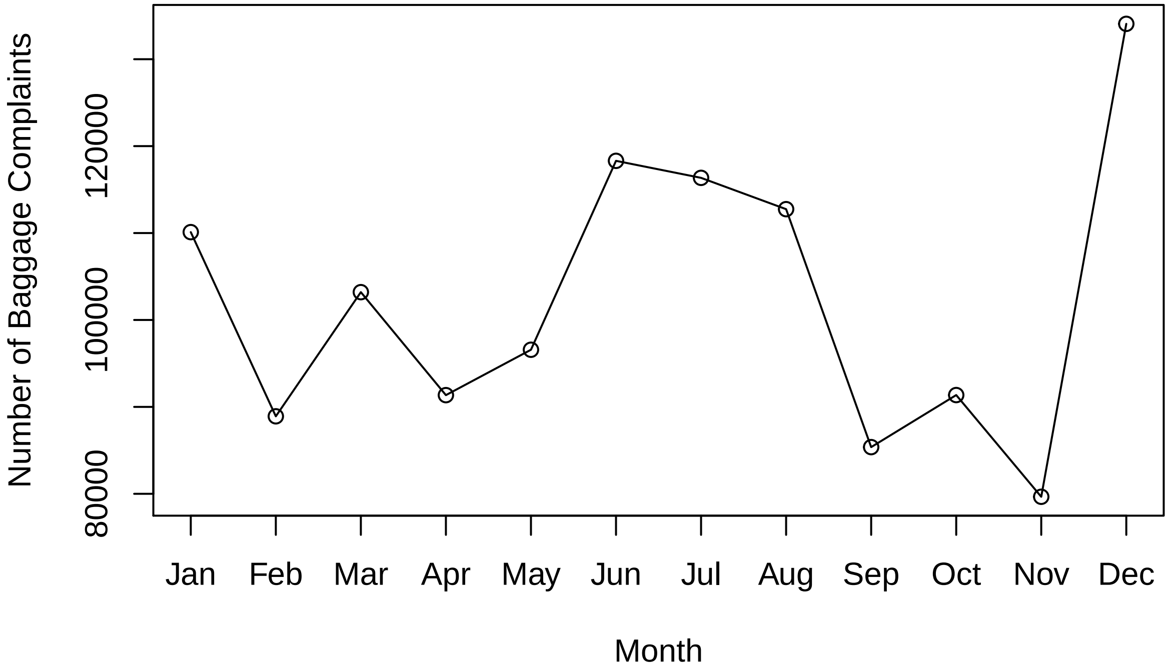
Process data:

```
baggage$Date = as.Date(paste0("02/",baggage$Date),"%d/%m/%Y")
baggage$Month = factor(baggage$Month,labels=c("Jan","Feb","Mar","Apr","May","Jun","Jul","Aug","Sep","Oc
baggage$Airline = as.character(baggage$Airline)
```

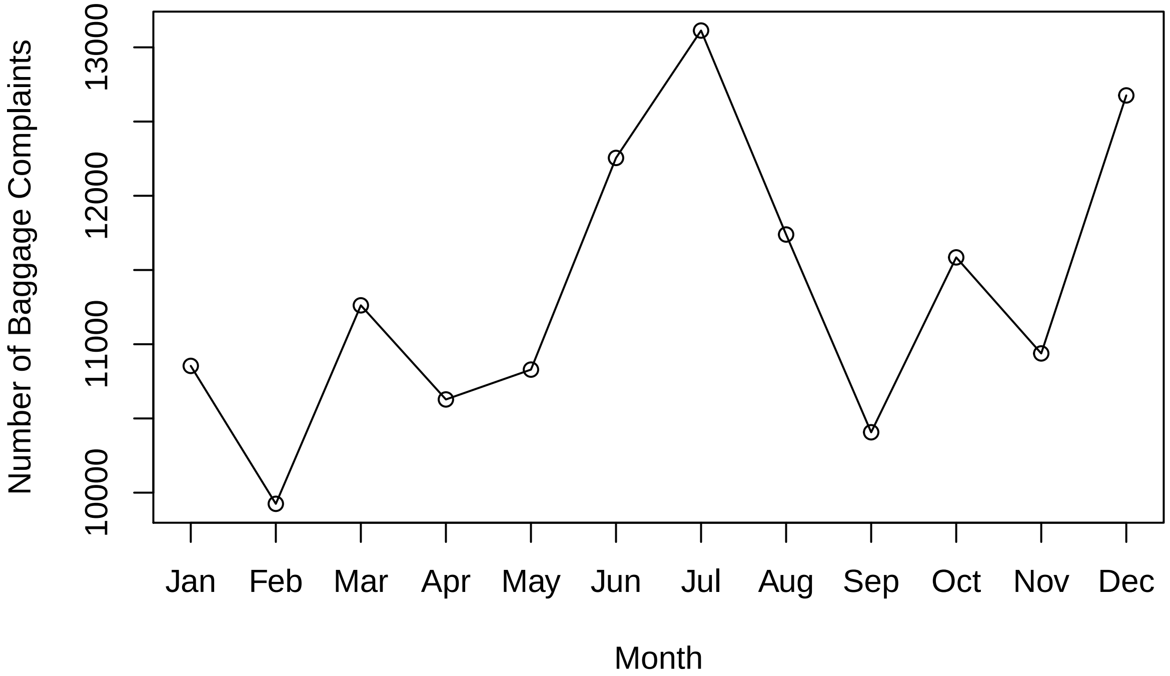
1. Explore baggage complaints over time: create 3 time series plots for the variable *Baggage* by Date for each of the airlines separately.

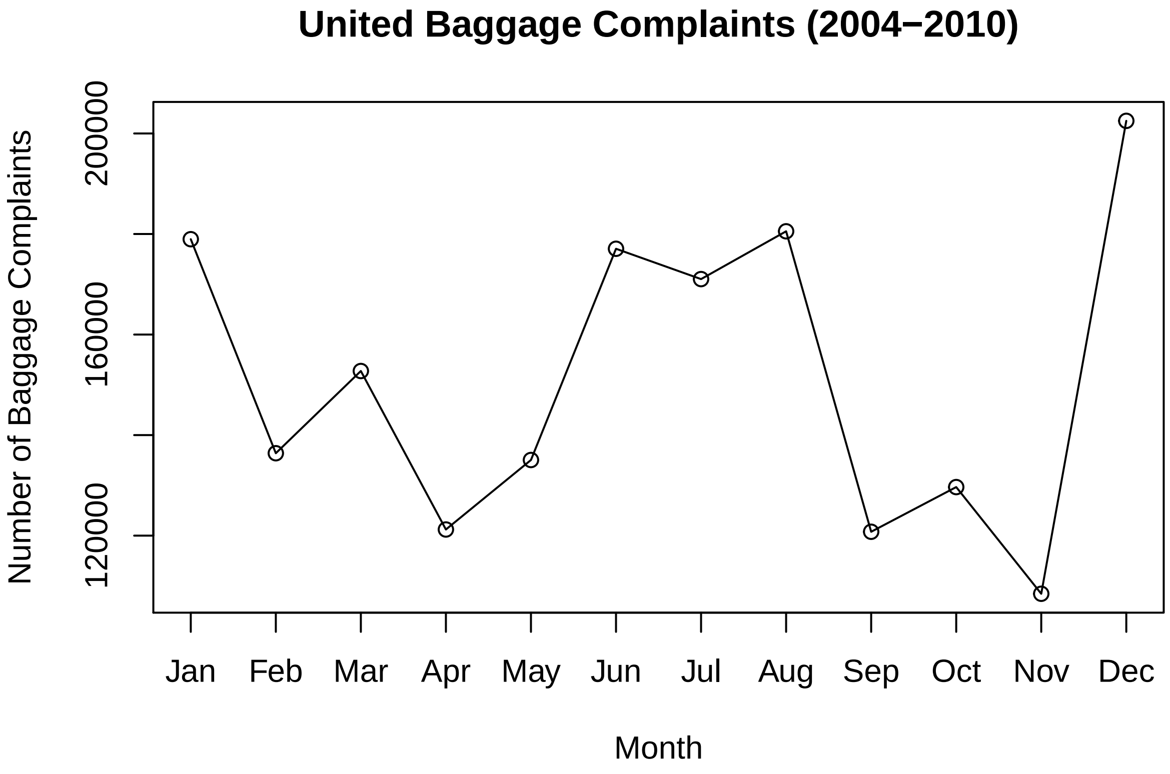
```
airlines = unique(baggage$Airline)
for(i in 1:length(airlines)){
    airline = airlines[i]
    data = baggage[baggage$Airline == airline,]
    res = aggregate(data["Baggage"], by=list(Month = data$Month), sum)
    plot(x=as.integer(res$Month),y=res$Baggage,type="o",xaxt="n",xlab="Month", ylab="Number of Baggage 
    axis(1,at = seq(1,12),labels = levels(res$Month))
    title(paste(airline,"Baggage Complaints (2004-2010)"))

}
```

American Eagle Baggage Complaints (2004−2010)



Hawaiian Baggage Complaints (2004−2010)





2. Briefly describe what patterns you see in the plots

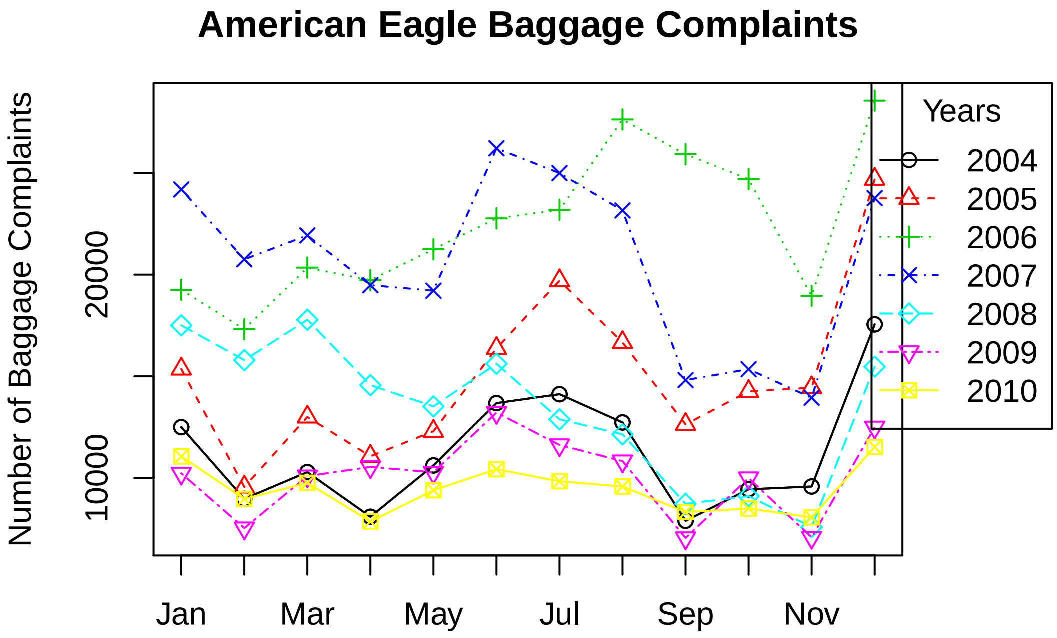
In some of the plots we see a cyclical pattern with the number of baggage complaints increasing during the winter holiday travel season (November-January). There is often another spike in baggage complaints in the summer likely when families are going on summer vacations.

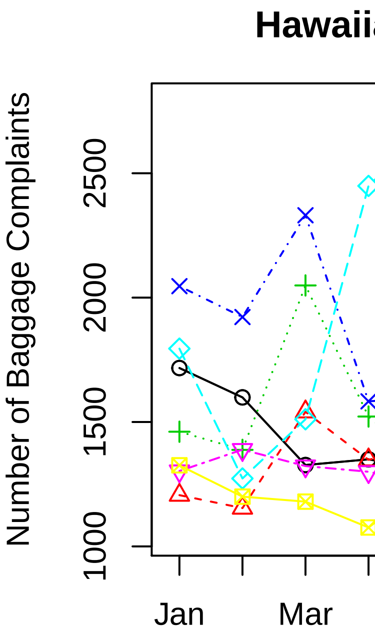
- American Eagle
  - We see that the cyclical yearly trend described above holds for American Eagle. Furthermore we see that there is an increase in the total number of complaints in 2006-2008 and then the number of complaints drops back down from 2009 onward.
- Hawaiian Airlines
  - Compared to American Eagle, Hawaiian Airlines has a smaller number of complaints each month. This is expected because Hawaiian Airlines is a smaller airline compared to American Eagle. Whereas American Eagle had a spike in baggage complaints during the winter holiday travel season, Hawaiian Airlines seems to have spikes in baggage complaints during the Spring and Summer. This perhaps could be because they see an influx of passengers wishing to travel to Hawaii during the Spring and Summer months.
  - The most concerning trend for Hawaiian Airlines is the trend of larger spikes in each of the successive years, culminating with a large spike in baggage complaints during the 2010 holiday season.
- United Airlines
  - Unsurprisingly United Airlines has a larger number of baggage complaints overall which can be explained by its much larger size compared to the other two companies.
  - Like American Eagle we see that United Airlines also experiences a surge in baggage claims during the holiday season. Additionally, it is interesting that both American Eagle and United Airlines have a spike in baggage complaints during 2006. Perhaps there was some external event that caused this for both airlines?
  - Since both American Eagle and United Airlines provide a variety of flights to domestic destinations it is not surprising to see that they have similar baggage complaint patterns in the summer and

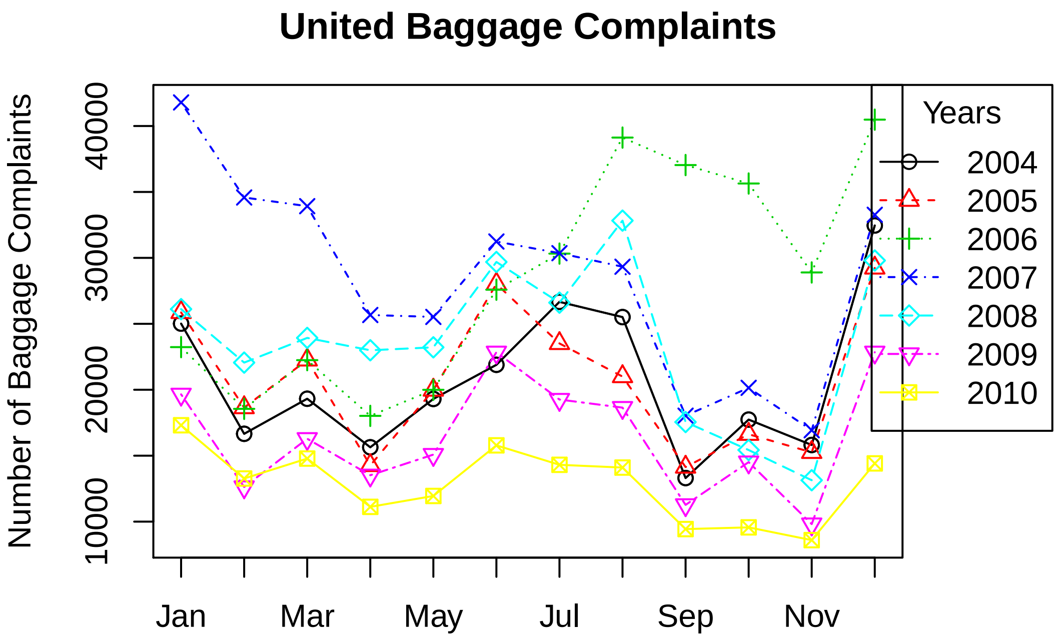
winter months.

3.

```
airlines = unique(baggage$Airline)
for(i in 1:length(airlines)){
    airline = airlines[i]
    data = baggage[baggage$Airline == airline,]
    res = aggregate(data["Baggage"], by=list(Month = data$Month, Year = data$Year), sum)
    years = unique(data$Year)
    plot_dat = res[res$Year == years[1],]

    #bottom,left,top,right margin
    par(mar=c(7.1, 4.1, 3.1, 8.9), xpd=TRUE)

    plot(x=as.integer(plot_dat$Month),y=plot_dat$Baggage,type="o",xaxt="n",xlab="", ylab="Number of Bagg
    axis(1,at = seq(1,12),labels = levels(res$Month))
    title(paste(airline,"Baggage Complaints"))
    for(j in 1:length(years)){
        plot_dat = res[res$Year == years[j],]
        lines(x=as.integer(plot_dat$Month),y=plot_dat$Baggage,type="o",lty=j, col=j,pch=j)

    }
    legend("topright", inset=c(-0.2,0), legend=years, pch=1:length(years),lty=1:length(years),col=1:leng


}
```







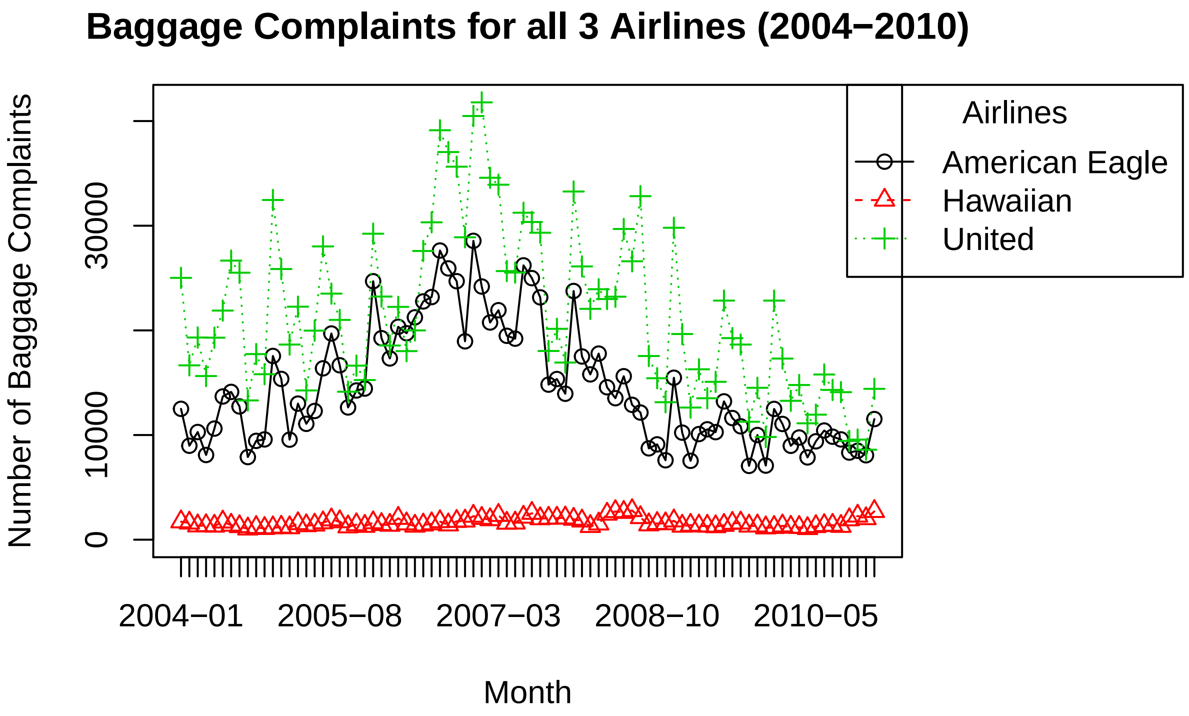
4. Describe the patterns in the plot

5. Plot all three airline Baggage data by Date on one graph.

```
# Maybe do this on the log scale?
airlines = unique(baggage$Airline)
airline = airlines[1]

total_aggregated = aggregate(baggage["Baggage"], by=list(Date = baggage$Date,Airline=baggage$Airline), 

res = total_aggregated[baggage$Airline == airline,]
res_ts = ts(res$Baggage, frequency = 12, start = 2004)
tsp = attributes(res_ts)$tsp
dates = seq(as.Date("2004-01-02"), by = "month", along = res_ts)


par(mar=c(7.1, 4.1, 3.1, 8.9), xpd=TRUE)

#plot(x=res$Date,y=res$Baggage,type="o",xaxt="n",xlab="Month", ylab="Number of Baggage Complaints",lty=
plot(res_ts,type="o",xaxt="n",xlab="Month", ylab="Number of Baggage Complaints",lty=1, col=1, pch = 1,y
```

```
## numeric(0)
```

```
title("Baggage Complaints for all 3 Airlines (2004-2010)")
for(i in 2:length(airlines)){
    airline = airlines[i]
    res = total_aggregated[baggage$Airline == airline,]
    res_ts = ts(res$Baggage, frequency = 12, start = 2004)
    lines(res_ts,type="o",lty=i, col=i,pch=i)
}
legend("topright", inset=c(-0.375,0), legend=airlines, pch=1:length(airlines),lty=1:length(airlines),co
```



6. Based on the graph in question 5., do some airlines have better baggage handling practices?

According to the plot, Hawaiian line seems to have much smaller baggage complaints throughout 2004-2010, which has been below 50000. Other two lines, however, are above 50000.

7. Based on the graph in question 5., which airline has the best record? The worst?

Based on the graph, Hawaiian has the best record, United has the worst record.

8. Based on the graph in question 5., are complaints getting better or worse over time?

There is no clear pattern that the curves are going up or down, in fact they all once increase and fluctuate back to the level where they started with. So based on the graph the complaints are not getting better nor wose.

9. Are the conclusions, you have drawn based on the graphs of the raw data you created, accurate? Are there any potential factors that may distort your conclusions and should be taken into consideration?

The conclusions are not necessarily accurate since we only looked at the number of baggage complains of the three airlines. Chances are that Hawaiian is a smaller airline and have way fewer passengers than United or American Eagle. So we look at the ratio of (# of complaints)/(# of boarded passengers), i.e., “baggage”/“enplaned” in our dataset.

10. Report the average of scheduled flights and the average of enplaned passengers by airline.

```
mean_scheduled = rep(0, length(unique(airlines)))
names(mean_scheduled) = unique(airlines)
for(i in 1:length(unique(airlines)))
{
  mean_scheduled[i] = mean(baggage[baggage$Airline == airlines[i],6])
}
```

```
mean_enplaned = rep(0, length(unique(airlines)))
names(mean_enplaned) = unique(airlines)
for(i in 1:length(unique(airlines)))
{
  mean_enplaned[i] = mean(baggage[baggage$Airline == airlines[i],8])
}
```

The average of scheduled flights are:

```
mean_scheduled
```

```
## American Eagle       Hawaiian         United
##      41314.048       4844.679      38225.298
```

The average of enplaned passengers are:

```
mean_enplaned
```

```
## American Eagle       Hawaiian         United
##      1396725.5       594174.2      4620712.3
```

11. What insights, ideas, and concerns does the data in the table in 10. provide you with?

The number of scheduled planes and enplaned passengers of United and Hawaiian are not on the same scale. Again this confirms our concern in problem 9 that simply looking at the number of complains is not fair for assessing the baggage handling practices of these companies.

12. Create Baggage % KPI that adjusts the total number of passenger complaints for size

```
baggage$Baggage_perc = baggage$Baggage / baggage$Enplaned * 100

mean_kpi = rep(0, length(unique(airlines)))
names(mean_kpi) = unique(airlines)
for(i in 1:length(unique(airlines)))
{
  mean_kpi[i] = mean(baggage[baggage$Airline == airlines[i],9])
}
```

The average Baggage % for each airline are:

```
for(i in 1: length(unique(airlines)))
  print(paste(unique(airlines), round(mean_kpi*100,2),"%")[i])
```

```
## [1] "American Eagle 103.3 %"
## [1] "Hawaiian 27.71 %"
## [1] "United 46.41 %"
```

13. Do the results in question 12 support your previous conclusions? Briefly explain.

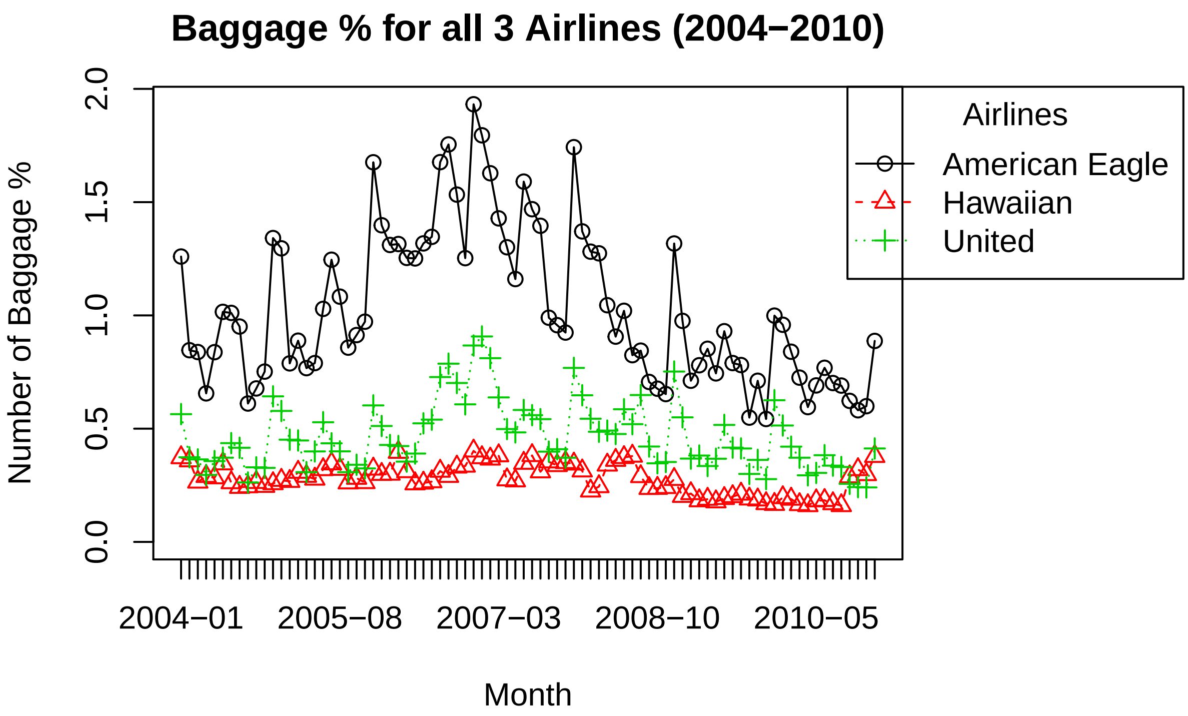
The results in question 12 show that Hawaiian has the lowest **Baggage %**, United is the second; while American Eagle has the highest **Baggage %**. This result contradicts with our previous conclusions in that the worst baggage handling records belongs to American Eagle instead of United.

14. Superimpose all three time series on one graph to display Baggage % by Date.

```
airlines = unique(baggage$Airline)
airline = airlines[1]

perc_aggregated = aggregate(baggage["Baggage_perc"], by=list(Date = baggage$Date,Airline=baggage$Airlin

res = perc_aggregated[perc_aggregated$Airline == airline,]
res_ts = ts(res$Baggage_perc, frequency = 12, start = 2004)
tsp = attributes(res_ts)$tsp
dates = seq(as.Date("2004-01-02"), by = "month", along = res_ts)


par(mar=c(7.1, 4.1, 3.1, 8.9), xpd=TRUE)

plot(res_ts,type="o",xaxt="n",xlab="Month", ylab="Number of Baggage %",lty=1, col=1, pch = 1,ylim= c(0,
```

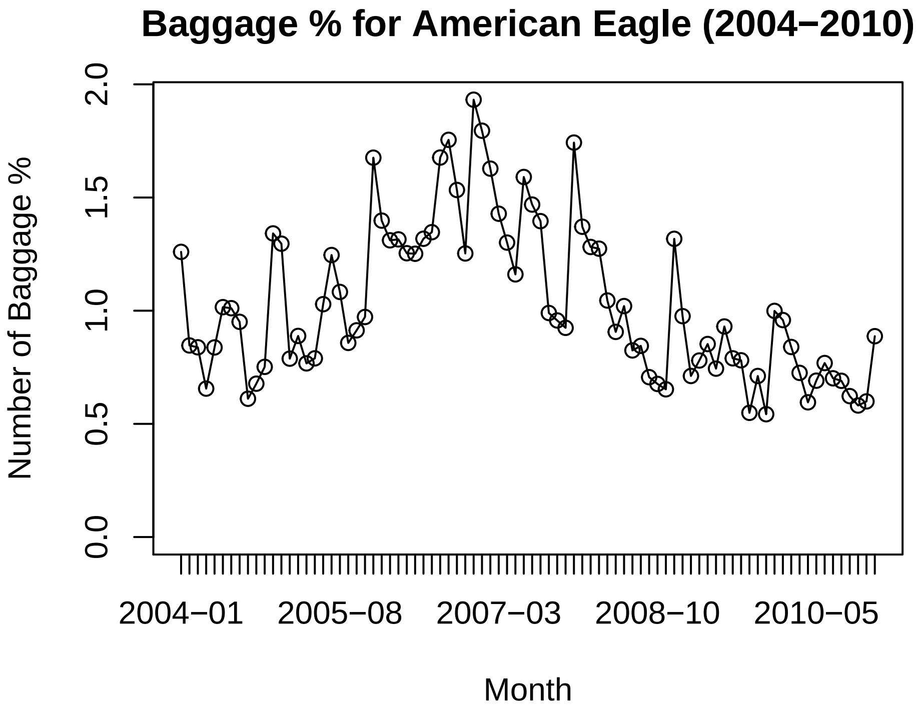
```
## numeric(0)
```

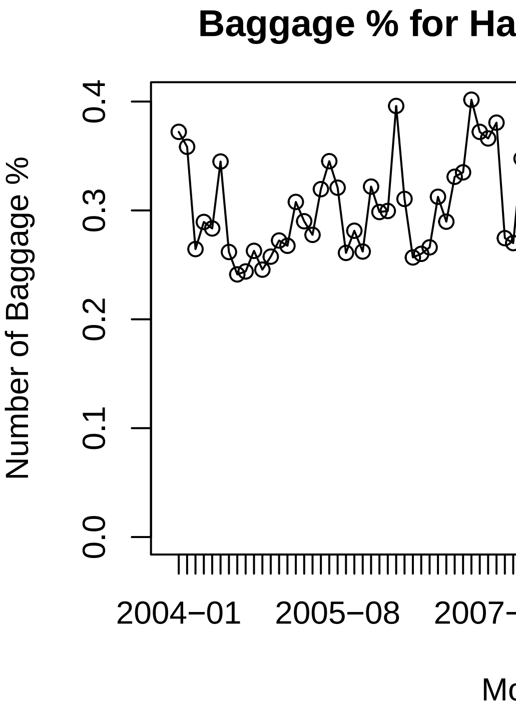
```
title("Baggage % for all 3 Airlines (2004-2010)")
for(i in 2:length(airlines)){
    airline = airlines[i]
    res = perc_aggregated[perc_aggregated$Airline == airline,]
    res_ts = ts(res$Baggage_perc, frequency = 12, start = 2004)
    lines(res_ts,type="o",lty=i, col=i,pch=i)
}
legend("topright", inset=c(-0.375,0), legend=airlines, pch=1:length(airlines),lty=1:length(airlines),col
```

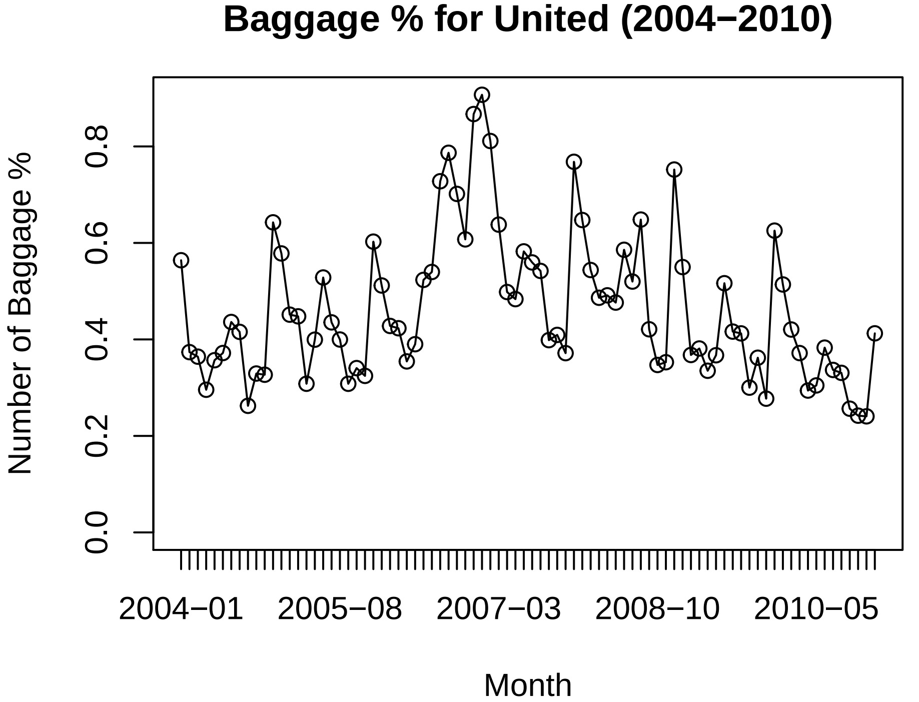


15. In addition to the graph in question 14., would plotting each series on a separate graph be beneficial and why? Create a graph to support your answer.

```
airlines = unique(baggage$Airline)
for(i in 1:length(airlines))
{
  airline = airlines[i]
  perc_aggregated = aggregate(baggage["Baggage_perc"], by=list(Date = baggage$Date,Airline=baggage$Airl
  res = perc_aggregated[perc_aggregated$Airline == airline,]



  res = perc_aggregated[baggage$Airline == airline,]
  res_ts = ts(res$Baggage_perc, frequency = 12, start = 2004)
  tsp = attributes(res_ts)$tsp
  dates = seq(as.Date("2004-01-02"), by = "month", along = res_ts)


  par(mar=c(7.1, 4.1, 3.1, 8.9), xpd=TRUE)

  plot(res_ts,type="o",xaxt="n",xlab="Month", ylab="Number of Baggage %",lty=1, col=1, pch = 1,ylim=c(0
  title(paste0("Baggage % for ", airline,  " (2004-2010)"))
}
```


Baggage % for American Eagle (2004−2010)


Baggage % for Ha


Baggage % for United (2004−2010)

Plotting each series on a separate graph is beneficial because this way we can pay a closer look to how every curve fluctuated. In the previous plot, since the range for American Eagle is too big, it is hard to tell how the curve of Hawaiian changed over time.

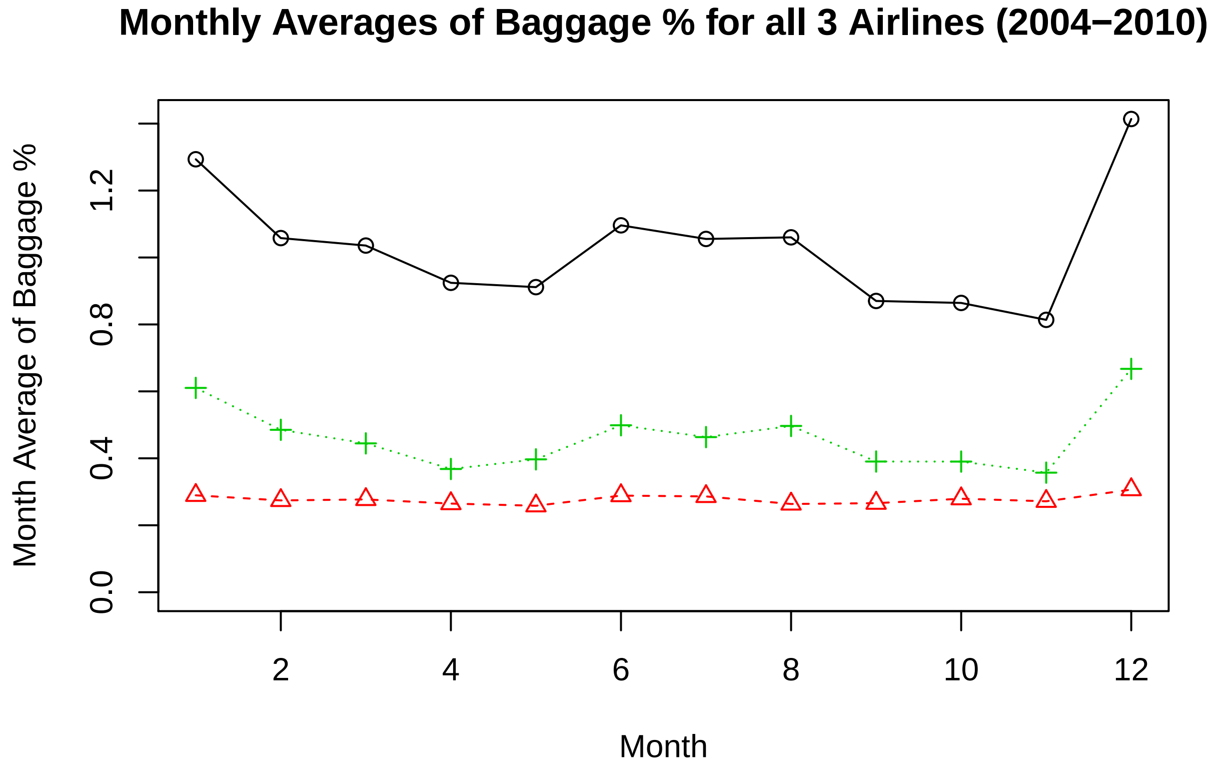
16. Based on the analysis of KPI Baggage %, have any of your conclusions drawn in questions 6. - 8. changed? Briefly discuss.

The conclusion for the best service and worst service has been changed. If we look at the KPI Baggage %, we would find that Hawaiian still has the best service, whilst American Eagle has the worst service.

How complaints are changing over time remains non-significant. For United the Baggage % level seems pretty stable; For American Eagle Baggage % seems to rise up and fall back to the begining level; for Hawaiian it seems that the Baggage % once seems to drop but at the end of 2010 it increases rapid to the highest level. Therefore, by the current data we cannot tell whether the complaints level are becoming better or worse.

17. Superimpose time series plots of monthly averages of Baggage % by time for the three airlines

```
airlines = unique(baggage$Airline)
airline = airlines[1]

perc_averaged= aggregate(baggage["Baggage_perc"], by=list(Date = baggage$Month,Airline=baggage$Airline)
res = perc_averaged[perc_averaged$Airline == airline,]
plot(x=1:12, y=res$Baggage_perc, type="o",xlab="Month", ylab="Month Average of Baggage %",lty=1, col=1,

title("Monthly Averages of Baggage % for all 3 Airlines (2004-2010)")
for(i in 2:length(airlines)){
    airline = airlines[i]
    res = perc_averaged[perc_averaged$Airline == airline,]
    lines(res$Baggage_perc,type="o",lty=i, col=i,pch=i)
}
legend("topright", inset=c(-0.375,0), legend=airlines, pch=1:length(airlines),lty=1:length(airlines),co
```

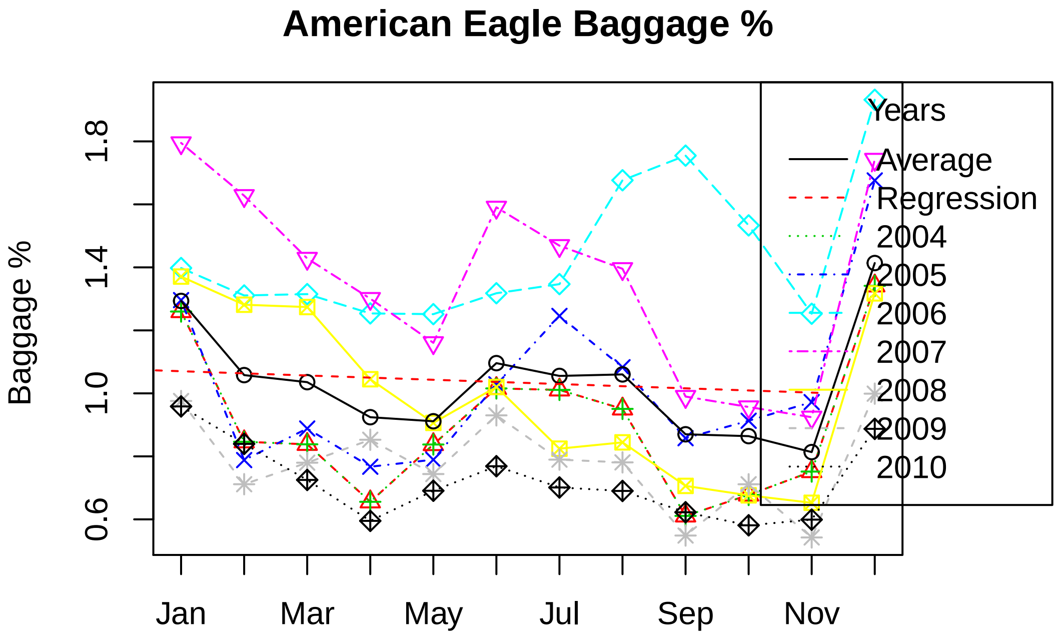


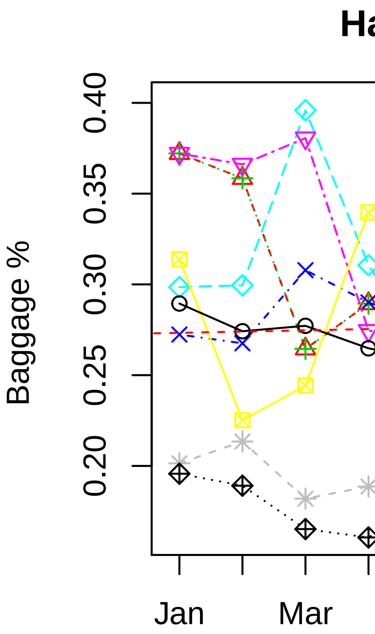
18. Discuss common patterns all three time series exhibit in question 17.

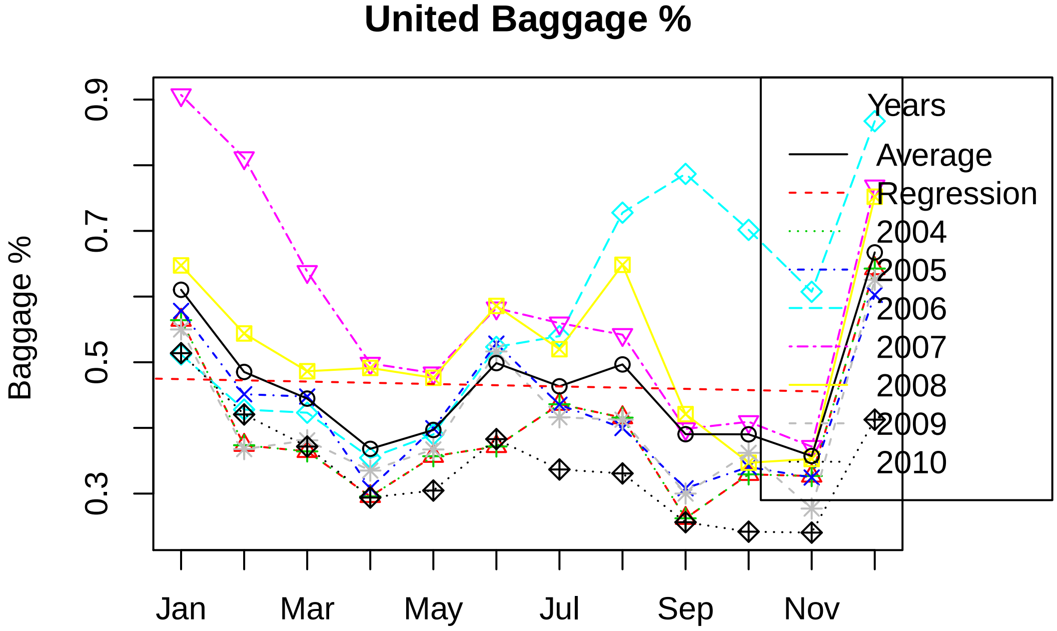
The common patterns that all three series share are as follows: The Baggage % begins to drop during the first 4-5 months, then it will hit the highest point in June, and stay at a high level till August, then it will continue dropping before it soars in Nov.-Dec.

19. Create a timeplot of Baggage %, add average line for Baggage % and a trendline of monthly average Baggage % for each airline.

```
airlines = unique(baggage$Airline)
for(i in 1:length(airlines))
{
  airline = airlines[i]
  data = baggage[baggage$Airline == airline,]
  res = aggregate(data["Baggage_perc"], by=list(Month = data$Month, Year = data$Year), sum)
  years = unique(data$Year)
  plot_dat = res[res$Year == years[1],]

  #bottom,left,top,right margin
  par(mar=c(7.1, 4.1, 3.1, 8.9), xpd=TRUE)

  plot(x=as.integer(plot_dat$Month),y=plot_dat$Baggage_perc,type="o",xaxt="n",xlab="", ylab="Baggage %
  axis(1,at = seq(1,12),labels = levels(res$Month))
  title(paste(airline,"Baggage %"))
  for(j in 1:length(years)){
      plot_dat = res[res$Year == years[j],]
      lines(x=as.integer(plot_dat$Month),y=plot_dat$Baggage_perc,type="o",lty=j+2, col=j+2,pch=j+2)

  }
  # add average line
  perc_averaged= aggregate(res["Baggage_perc"], by=list(Date = res$Month), mean)
  lines(x=as.integer(plot_dat$Month),y=perc_averaged$Baggage_perc, type="o",lty=1, col=1,pch=1)


  legend("topright", inset=c(-0.2,0), legend=c("Average", "Regression", years), lty=1:(length(years)+2)

  # add regression line
  lm_perc = lm(perc_averaged$Baggage_perc~as.integer(plot_dat$Month))
  clip(min(as.integer(plot_dat$Month))-0.48, max(as.integer(plot_dat$Month))-0.9, min(res$Baggage),max(
  abline(lm_perc, lty = 2, col=2)


}
```







For each airline, I superimposed the follow curves: * “Average”: The average monthly Baggage % among the 7 years (black solid curve) * “Regression”: The linear regression of the average monthly Baggage % (red curve), using *lm()* function * 7 years of monthly Baggage %

20. Prepare a brief (one paragraph) executive summary of your findings.

Case 2: CEO Compensation

Load CEO compensation data

```
#ceo_comp = read.table(here("HW1","CEOcompensation.txt"),header=T,sep = "\t")
```

1. **What is the number of female CEOs?**