Workshop 5 - Time Series

JPS

Introduction

We are going to practice time-series analysis using ARIMA models. In the first exercise we will cover the main steps that should be taken into consideration when describing and modelling time-series. We will learn how to plot and decompose time-series into its main different elements (T, S, and I), and how to build ARIMA models by carefully considering the number of *differences* required, and their AR and MA components. In the second exercise we will follow an unsupervised (*data driven*) approach to build ARIMA models. This follows the steps undertaken in exercise 1, but does so in an unsupervised way, i.e. without having a person making the modelling decisions. The first exercise will be more tedious but it is important so you can see everything that goes behind the estimation of even relatively simple ARIMA models. Once we have learnt how the *black box* works we will employ the faster (unsupervised) approach to explore more substantively interesting research questions.

Exercise 1: This first exercise borrows different examples from R. Dalinina's and S. Sapegina's time-series tutorials, and is based on the same dataset they use. The data comes from a bike sharing company, capturing daily count of bikes rented between 2011 and 2012 (if you want to know more about this dataset click here). This is not a great dataset to make forecasts since the window of observation is not that wide. Still, by analysing this time-series we are going to be able to practice key exploratory and modelling procedures, and see how we can use them to learn key features, such as: Is there a trend? I.e., do more people rent bikes over time? Is there a seasonal effect? Do more people rent bikes certain days of the week? Or different months of the year?

Exercise 2: In this exercise we are going to replicate some of the analyses carried out in Pina-Sánchez et al. (2019) 'Have The England and Wales Guidelines Affected Sentencing Severity? An Empirical Analysis Using a Scale of Severity and Time-Series Analyses'. As the title indicates in this paper we assess whether the new sentencing guidelines can be blamed for having increased sentence severity in England and Wales. To explore this question we will use data from the Ministry of Justice Quarterly Statistics and ARIMA models built using the command *auto.ARIMA*.

Exercise 1. Bike Share

We start by importing the data, which is available in Minerva as a .csv file in Minerva.

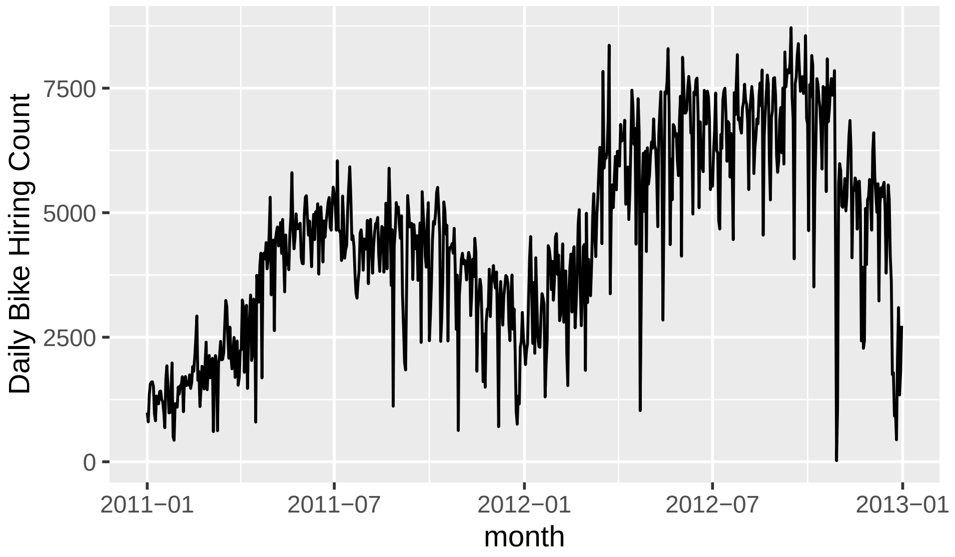
```r
bike = read.csv('day.csv')
```

We can see that every case represents a different day, from the 1st of January of 2011 to the 31st of December of 2012. For each observation we have multiple variables capturing the characteristics of that day, day of the week, whether a working day, and weather conditions such as temperature, windspeed, etc.

```r
head(bike)
#We have the specific date
bike$dteday[731]  #731 is the last observation in the dataset.
#For some reason day of the week starts at 0 rather than 1.
table(bike$weekday)
#So we correct that here.
bike$weekday = bike$weekday + 1
```

The two most important variables in the dataset are ‘Date’ and count (‘cnt’). Putting these two variables together we will be able to generate our time-series describing the number of bikes that were hired across the window of observation. But before doing that we need to tell R that ‘dteday’ needs to be considered a variable of class date, instead of a character type variable.

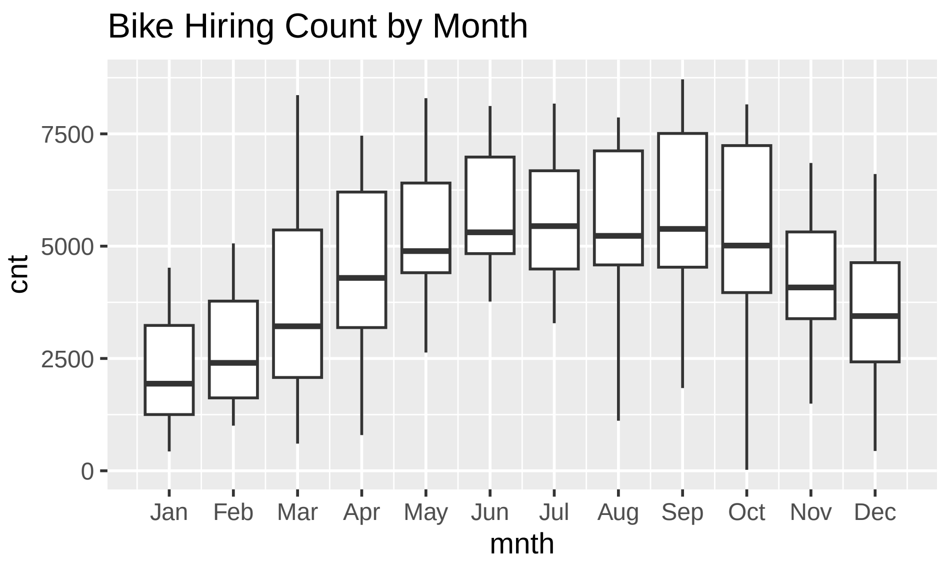
```
#Setting the variable 'Date' as a date class variable in R.
bike$Date = as.Date(bike$dteday)
library(ggplot2)
#We can now plot the time series using a line plot.
ggplot(bike, aes(Date, cnt)) + geom_line() + scale_x_date('month') +
                               ylab("Daily Bike Hiring Count")
```



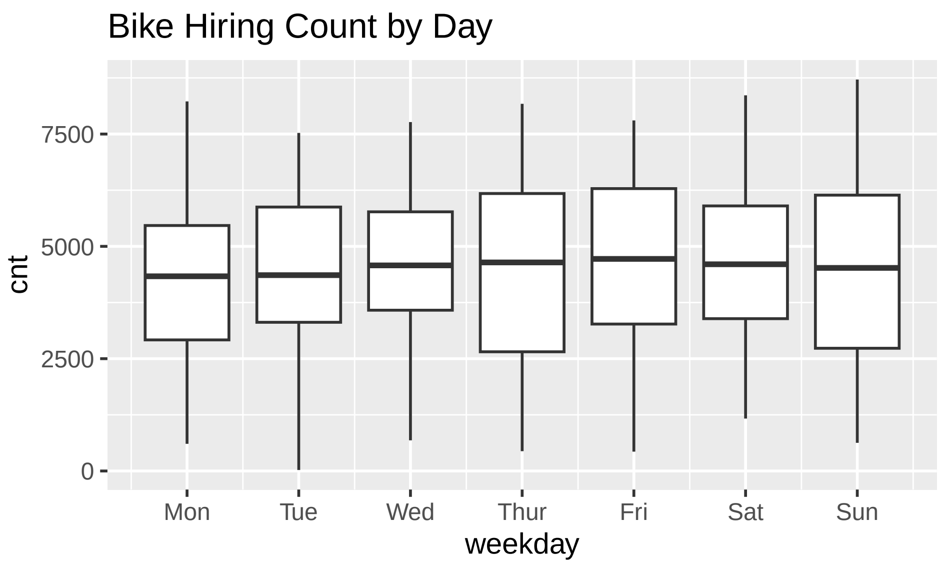
Visualising the time-series in a plot should always be the first step in the analysis of time-series. This will provide us with some initial insights about the patterns and trends in the data, which will help us guide our modelling strategy. From the above plot we can see lots of volatility, with some strong fluctuations from one day to another. However, even with this volatility present, we can already see some patterns emerge. For example, it seems that the use of bicycles decreases in the winter months and increases in the summer months. There also seems to be a trend roughly growing until October 2012 but then it declines rapidly from then. It is not clear whether fluctuations are also due to day of the week since we do not have enough resolution in the graph to identify the specific days of the week, but from a theoretical point of view one might expect that if bike sharing is a recreational service we should see higher usage during the weekend.

In order to assess these potential seasonal effects (*seasonal* understood loosely as any kind of fluctuations observable in the dataset over a regular time period) across the months of the year, and the days of the week, more clearly, we can use boxplots.

```
#A boxplot capturing bike counts per month
ggplot(bike, aes(y=cnt, x=mnth)) +
  geom_boxplot(aes(group=mnth)) +
  scale_x_continuous(breaks=seq(1,12,1),
  labels=c("Jan","Feb","Mar","Apr","May","Jun","Jul","Aug","Sep","Oct","Nov","Dec")) +
  ggtitle("Bike Hiring Count by Month")
```

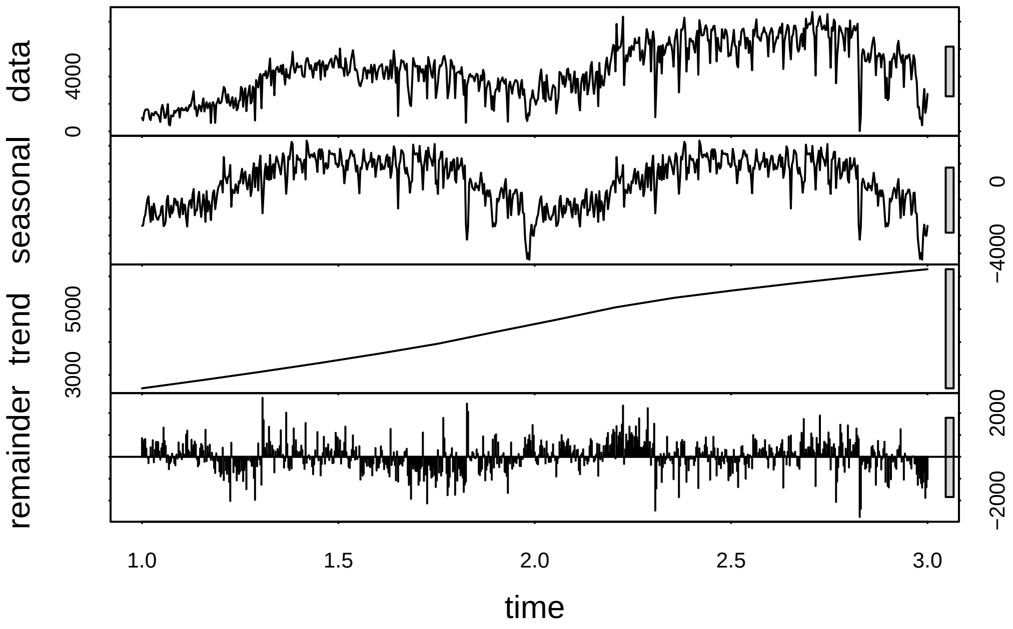


```
#Another one for the day of the week.
ggplot(bike, aes(y=cnt, x=weekday)) +
  geom_boxplot(aes(group=weekday)) +
  scale_x_continuous(breaks=seq(1,7,1),
  labels=c("Mon","Tue","Wed","Thur","Fri","Sat","Sun")) +
  ggtitle("Bike Hiring Count by Day")
```



As suspected we can see some clear seasonal effects across months. However, the day of the week does not seem to influence bike usage at all. This is an important insight, it will help us identify the S component when modelling the time-serie. To visualise all the other components defining the time-series we can use the really useful command *stl*, for which we first need to define the time-series itself using *ts*. Notice that in defining our time-series, and in the presence of a seasonal effect, we also need to include the number of observations that need to be contemplated within each *season*. Since we have observations at the day level, and we have identified seasonal effects at the month level that seem to be repeated each year, we can use a frequency of 365 for *ts*. This indicates that the seasonal cycle is repeated every 365 time periods (in our case days).

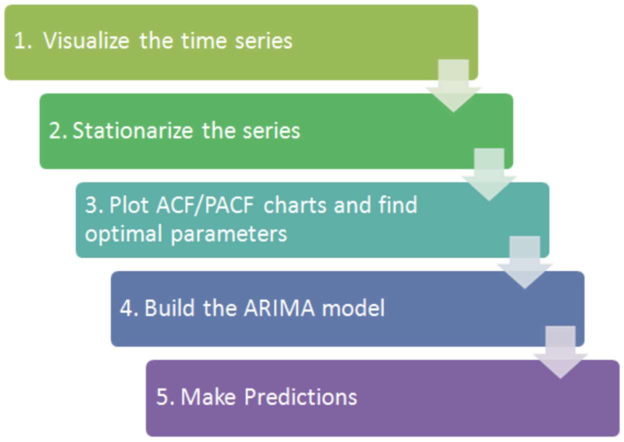
```
count_ts = ts(bike$cnt, frequency=365)
decomp = stl(count_ts, s.window="periodic")
plot(decomp)
```



The first plot (*data*) represents the time-series as it is. The second (*seasonal*) depicts the seasonal effect that we have noticed previously, bike usage goes up in the summer and down in the winter. The third plot is the *trend*, which is obtained after subtracting *seasonal* and *remainder* from *data*. The fourth plot (*remainder*) represents the irregularity component, i.e. what remains unexplained after controlling for the *trend* and *seasonal* effect.

Notice as well that the seasonal effect is only repeated twice since the window of observation used in this dataset only covers two years, this will make any meaningful forecasts very unreliable. To be able to do so we would need probably at least 10 years worth of data.

We are now going to move from the descriptive part of the analysis into the modelling part. It is important to understand how when building ARIMA models we will need to follow a specific sequence of steps. These are nicely represented in the following flowchart (source: Tavish Srivastava)


1. Visualize the time series
2. Stationarize the series
3. Plot ACF/PACF charts and find optimal parameters
4. Build the ARIMA model
5. Make Predictions

We have just completed step 1. Step 2 involves checking that the time-series is stationary, and if it is not, proceed to differentiate it until it becomes stationary. In the lecture we saw that the main condition for a time-series to be considered stationary is that its properties remain constant across time. Just from the look of the upward trend in our time-series we can see that it does not seem stationary. However, if we want to test this more formally we can use an Augmented Dickey Fuller test, which can be called using the command *adf.test* from the package *tseries*.

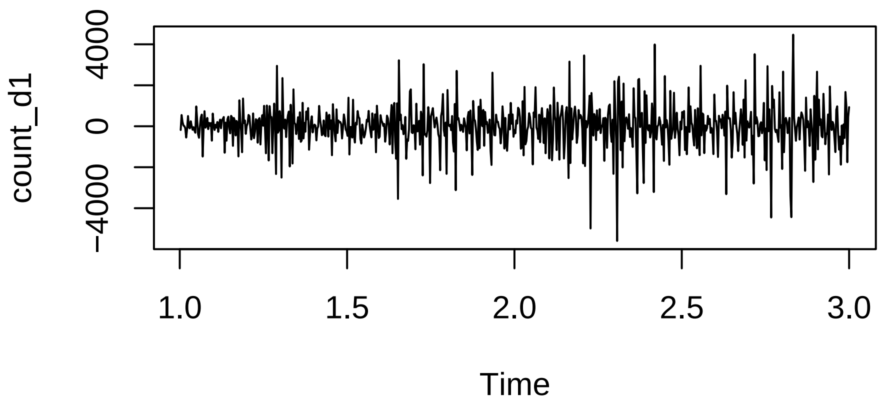
```
library(tseries)
adf.test(count_ts)
```

```
##
##  Augmented Dickey-Fuller Test
##
## data:  count_ts
## Dickey-Fuller = -1.6351, Lag order = 9, p-value = 0.7327
## alternative hypothesis: stationary
```

We can see that the p-value obtained for 'H_0: time-series not stationary' is too high, so we cannot reject H_0, which means we accept the alternative hypothesis pointing at the time-series being non-stationary.

What we need to do now is proceed to differentiate the time-series until it becomes stationary. We can start with a difference of one time period, $Y_t^d = Y_t - Y_{t-1}$. Then, check the Dicky Fuller test and do this again if it is still non-significant.

```
library(forecast)
count_d1 = diff(count_ts, differences=1) #The differentiation process
plot(count_d1)  #To assess stationarity visually
```



```
adf.test(count_d1)
```

```
##
##  Augmented Dickey-Fuller Test
##
## data:  count_d1
## Dickey-Fuller = -13.798, Lag order = 8, p-value = 0.01
## alternative hypothesis: stationary
```

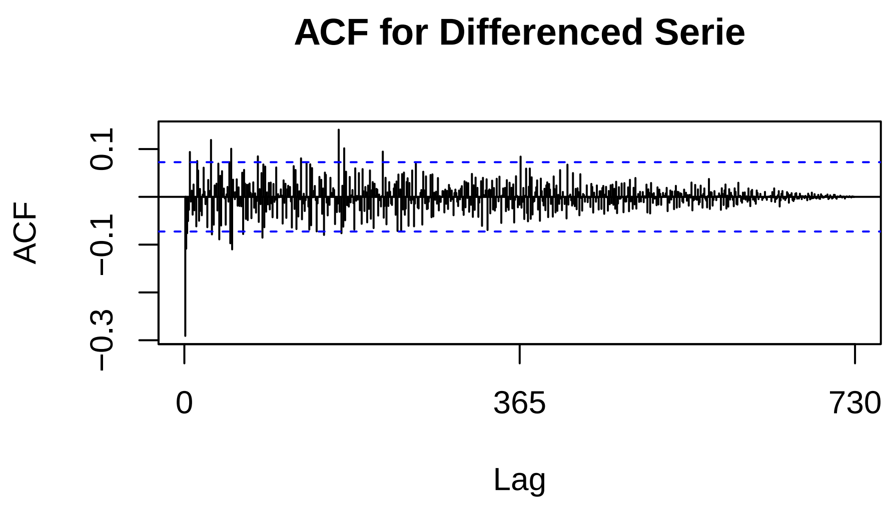
One difference was enough to turn the time-series stationary. This could be determined visually by plotting the differentiated serie, as we did above, where we cannot detect any trend or seasonality, which is confirmed by the subsequent ADF test.

Ok, so we have now completed step 2 of the modelling process. Let's now move to step 3, plotting auto-correlation (ACF) and partial auto-correlation functions (PACF) to help us decide on the number of parameters to be included in our ARIMA model.

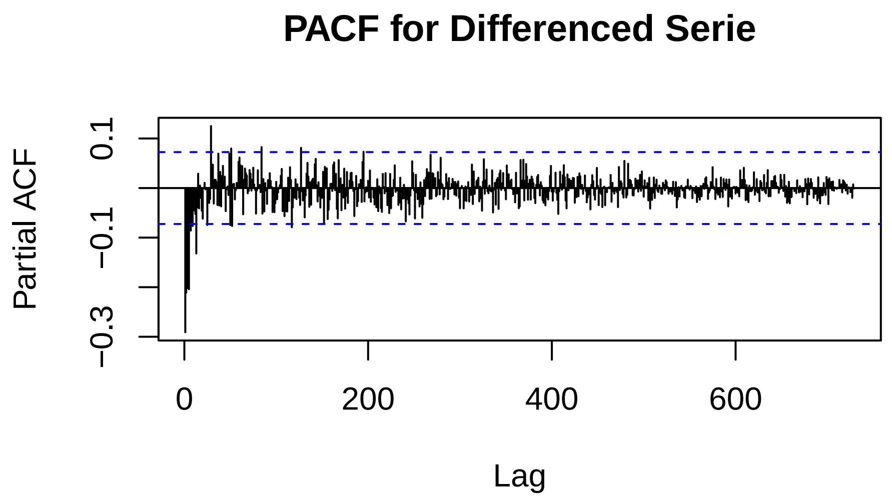
The rule of thumb is to define the AR order by looking at how many auto-correlations appear to be significant, starting from the left-hand side of the plot, that is, starting from the auto-correlation of the time-series with its previous lag, then looking at the second lag, third, etc. To define the order of the MA component we will follow the same approach but looking at the PACF.

This process, however, is not deterministic, it involves a bit of comparing and tweaking. This is because, by definition, the more auto-regressive components you include in your model the less unexplained variance there will be, therefore the smaller the partial auto-correlation components and the less of a need for moving averages. And vice versa. Remember as well that we should penalise overfitted models, or put differently, we should aim for simple models. So, we need to use our judgement, consider two or more model specifications and then compare their goodness of fit, for which we will use the Akaike Information Criteria (AIC, which we also used to compare models in stepwise regression in Week 2).

```
Acf(count_d1, main='ACF for Differenced Serie')
```



```r
Pacf(count_d1, main='PACF for Differenced Serie')
```



There is one clear autoregressive correlation that we should definitely incorporate in our model. For the case of partial autocorrelation the picture is less clear, we could consider one or more of those. Based on the ACF and PACF plots I would suggest considering two models, one relatively simple, and another one a bit more complex:

1. Model 1, defined as AR(1) and MA(1). This is because the first lags are by far the more prominent in both ACF and PACF plots, so I suspect after controlling for these, the other lags that appear significant in the ACF and PACF plots might become less relevant.
2. Model 2, defined as AR(1) and MA(3). Here I seek to investigate the potential recurrent MA lag for the first five lags. These are all significant in the PACF, and the fact that they do not decay across that interval of time makes me think that those components might be relevant in specifying our time-serie.

To estimate these two models we are going to use the command *ARIMA*. We can feed the time-series that we have already differentiated, which is what the code below does, or we could simply specify the required difference in the command by changing 'order=c(1,0,1)' to 'order=c(1,1,1)' in the specification of model 1 and 'order=c(1,0,3)' to 'order=c(1,1,3)' in model 2. Notice that we have now entered step 4 in the flowchart "Build the ARIMA model".

```
model1 = arima(count_ts, order=c(1,1,1))
model2 = arima(count_ts, order=c(1,1,3))
```

One way to assess the goodness of fit of the model is to plot the model's residuals and any potential remaining auto-correlation and partial auto-correlation. To do so we can use the command *tsdisplay*.

```
tsdisplay(residuals(model1), lag.max=15, main='(1,1,1) Model Residuals')
```

```
tsdisplay(residuals(model2), lag.max=15, main='(1,1,3) Model Residuals')
```

Notice how the residuals from the two models look kind of similar. To assess more clearly which is the better model we can also compare their AICs, which are recorded in the objects that we have created for each model. So we can simply call those and see.

```
model1
```

```
##
## Call:
## arima(x = count_ts, order = c(1, 1, 1))
##
## Coefficients:
##          ar1      ma1
##       0.3584  -0.8896
## s.e.  0.0423   0.0192
##
## sigma^2 estimated as 855419:  log likelihood = -6021.96,  aic = 12049.91
```

```
model2
```

```
##
## Call:
## arima(x = count_ts, order = c(1, 1, 3))
##
## Coefficients:
##          ar1      ma1      ma2      ma3
##       0.0365  -0.5581  -0.1854  -0.0880
## s.e.  0.2663   0.2641   0.1526   0.0745
##
## sigma^2 estimated as 853145:  log likelihood = -6020.99,  aic = 12051.98
```

Model 1 shows a lower AIC and can therefore be considered the better model. We could keep estimating different combinations of AR and MA to see if another model performs better. But this could take some time, in the next exercise we will see how we can automatise this process using the function *auto.arima*.

Exercise 2. Sentence Severity

In this exercise we will use time-series analysis to assess the causal effect of specific interventions. The idea is to learn from the time-series by modelling it up to the point when a given intervention took place, and forecast from that point on. Then, look at the time-series after the intervention took place and assess whether it falls within our forecast region (within the 95% confidence interval) or not. If it moves away from the forecast region then we can take that as evidence that the intervention might have had a causal effect on the outcome variable, by either shifting the time-series up or down, or changing its slope.

We are going to practice this type of analysis by looking at whether the sentencing guidelines have had an effect on sentence severity. The research question to be explored is, in my view, quite important. Just to provide some context, crime has been declining for decades, yet, prisons are becoming ever more overcrowded.

This paradox is explained by sentencing becoming more punitive over time. This is a real problem that has led different researchers to investigate the causes that could be behind such sentence inflation. A number of researchers (Allen, 2016; Padfield, 2016) have pointed at the new sentencing guidelines (imposed in England and Wales from 2011 to 2020), as a factor contributing to the increase in severity. However, the evidence used is mostly qualitative or based on simple descriptive statistics. Here, we will use time-series to look into this question more proficiently.

Before we get into the analysis of the impact of the sentencing guidelines using ARIMA models, it is important to visualise the phenomenon of sentence inflation experienced in England and Wales. To do so, we are going to access two datasets capturing the different types of sentences that have been imposed in this jurisdictions over the last couple of decades. The first dataset captures all offences imposed in the jurisdiction, the second is restricted to indictable offences, which represent the most serious offences.

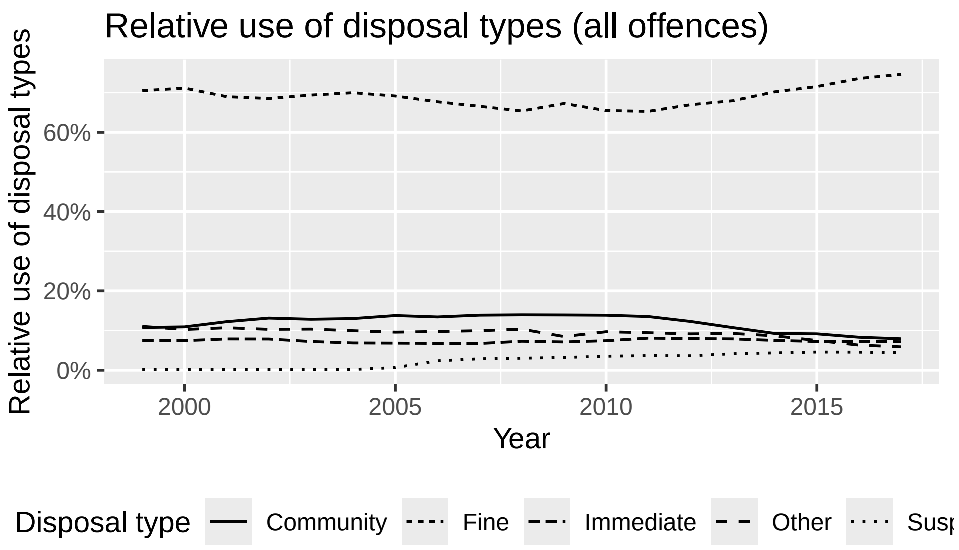
```
MoJ = read.csv("Tables_Final.csv")
Indict = read.csv("Indictable.csv")
```

We have one observation per year, and variables capturing the total of cases imposed aggregated and broken down by sentence type. In order of severity (from high to low), these can be ranked as: immediate custodial sentences (for which we also have their length), suspended custodial sentences, community orders, fines, and others (mainly conditional and absolute discharges).

```
summary(MoJ)
summary(Indict)
```

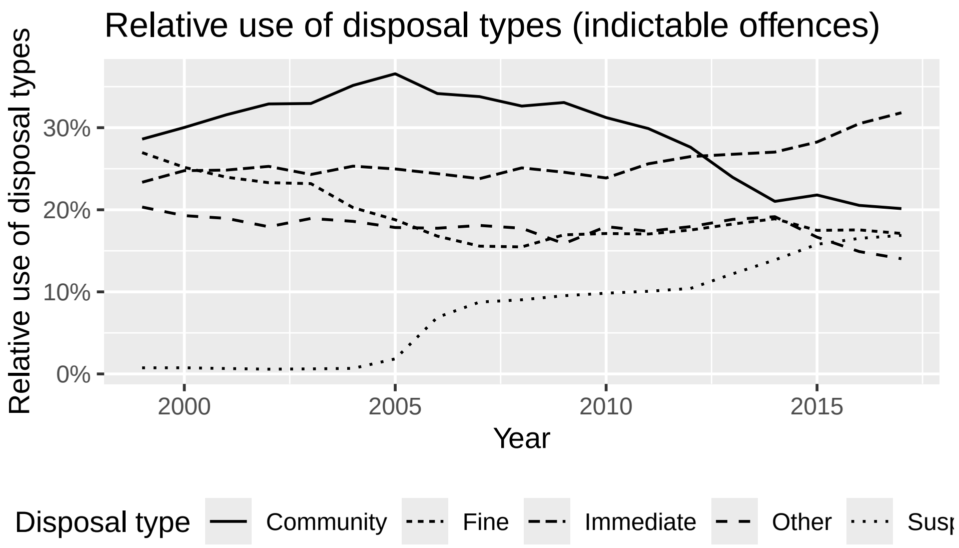
Looking at specific sentence types divided by the total number of sentences imposed that same year we can plot the relative frequency of each sentence type. We can do this first using ‘MoJ’, the dataset that captures all the offences imposed in England and Wales.

```
ggplot(MoJ, aes(x=Year, y=Other/Total)) + geom_line(aes(linetype="Other")) +
  geom_line(aes(x=Year, y=Fine/Total, linetype="Fine")) +
  geom_line(aes(x=Year, y=Community/Total, linetype="Community")) +
  geom_line(aes(x=Year, y=Suspended/Total, linetype="Suspended")) +
  geom_line(aes(x=Year, y=Immediate/Total, linetype="Immediate")) +
  ylab("Relative use of disposal types") +
  ggtitle("Relative use of disposal types (all offences)") +
  labs(linetype="Disposal type") +
  scale_y_continuous(labels = scales::percent) + theme(legend.position="bottom")
```



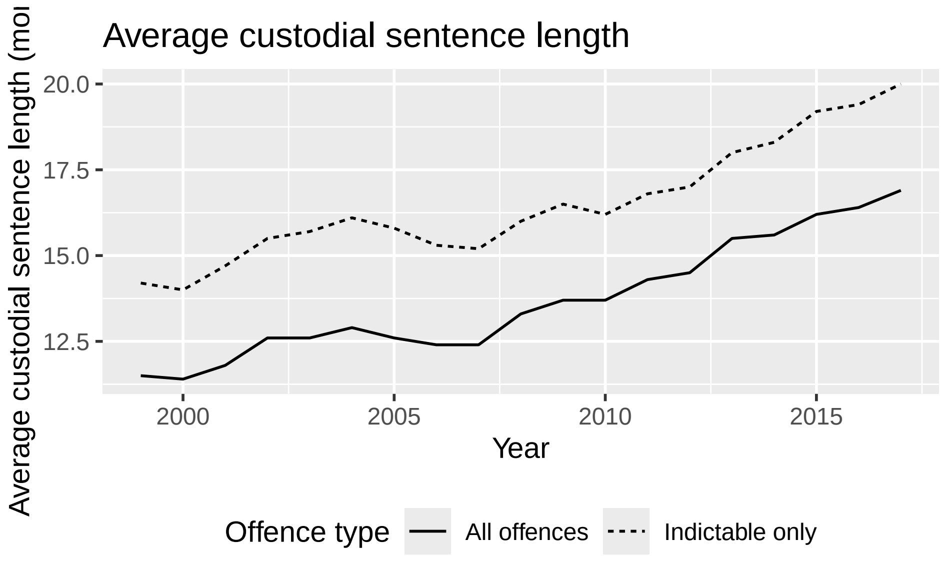
Looking at all offences it is hard to spot a specific pattern. Community orders seem to be on the decline from 2010 while fines are going up. The change in sentence severity is much clearer once we focus on indictable offences.

```r
ggplot(Indict, aes(x=Year, y=Other/Total)) + geom_line(aes(linetype="Other")) +
  geom_line(aes(x=Year, y=Fine/Total, linetype="Fine")) +
  geom_line(aes(x=Year, y=Community/Total, linetype="Community")) +
  geom_line(aes(x=Year, y=Suspended/Total, linetype="Suspended")) +
  geom_line(aes(x=Year, y=Immediate/Total, linetype="Immediate")) +
  ylab("Relative use of disposal types") +
  ggtitle("Relative use of disposal types (indictable offences)") +
  labs( linetype="Disposal type") +
  scale_y_continuous(labels = scales::percent) + theme(legend.position="bottom")
```



Suspended sentences (which are very close to prison time in terms of severity) are clearly on the way up while community orders are in decline. Immediate custodial sentences also seem to be on the way up from 2010, but more worryingly is not just the increase in how often those sentences they are employed, but the longer duration imposed, which can be observed in the following plot.

```r
ggplot(MoJ, aes(x=Year, y=Length, linetype="All offences")) + geom_line() +
       ylab("Average custodial sentence length (months)") +
       ggtitle("Average custodial sentence length") +
       geom_line(data=Indict, aes(x=Year, y=Length, linetype="Indictable only")) +
       labs(linetype="Offence type") + theme(legend.position="bottom")
```



Putting all of that together, it seems that the problem of increasing sentence severity is definitely real, in particular for the case of indictable offences. It makes sense then to question whether the sentencing guidelines that were introduced over the last decade have contributed to this process. To explore that research question we are going to look at three offence-specific guidelines, the sex, robbery and theft guidelines. We can explore together the analysis of sex offences, then you can try exploring the other two on your own by replicating the following analysis.

The data to be used for each of the offence-specific is available on Minerva. Let's start by opening the dataset capturing sex offences.

```
sex = read.csv("MoJ_sex.csv")
```

The first thing to notice is that the time periods used are now quarters, which generally means four observations per year.

```
head(sex)
```

```
##   quarter avgleng cust susp  com fine absdis condis
## 1  Sep-17   60.60 4206 1104 1318   83     25     79
## 2  Jun-17   59.39 4318 1137 1423   76     23     86
## 3  Mar-17   60.10 4447 1093 1430   80     19     93
## 4  Dec-16   60.02 4423 1127 1486   81     16     88
## 5  Sep-16   60.55 4365 1046 1553   83      9     83
## 6  Jun-16   61.55 4257  977 1601   98      9     84
```

```
sex$quarter
```

```
##  [1] "Sep-17" "Jun-17" "Mar-17" "Dec-16" "Sep-16" "Jun-16" "Mar-16" "Dec-15"
##  [9] "Sep-15" "Jun-15" "Mar-15" "Dec-14" "Sep-14" "Jun-14" "Mar-14" "Dec-13"
## [17] "Sep-13" "Jun-13" "Mar-13" "Dec-12" "Sep-12" "Jun-12" "Mar-12" "Dec-11"
## [25] "Sep-11" "Jun-11" "Mar-11" "Dec-10" "Sep-10" "Jun-10" "Mar-10" "Dec-09"
## [33] "Sep-09" "Jun-09" "Mar-09" "Dec-08" "Sep-08" "Jun-08" "Mar-08" "Dec-07"
## [41] "Sep-07" "Jun-07" "Mar-07" "Dec-06"
```

We have a similar set of variables covering sentence types to those we have used in the introduction of the exercise. However, the variable capturing the date for each case ('quarter') needs to be reformatted. We need to turn 'quarter' into a variable that R can recognise as a date. To do so, we can use the command *as.Date*, with specific format "%d-%b-%y", which represents: days expressed as two numbers (%d), months expressed as a three letter word (%b), and years expressed as the last two digits of the year (%y). In order to fully match that particular format we are going to add "15-" to include the day part (%d) in our variable 'quarter' using the command *paste*. The number 15 is an arbitrary choice just to be able to match the format required, but it is a harmless choice since we use the same figure across all our observations, so we are not really modifying the time-series. If you want to know more about what kind of date formats can be used in R this is a good reference from Quick-R. In addition, we will also sort the dataset chronologically using *order*, which will help us write more intuitive commands when we get to the forecast stage.

```
sex$date = as.Date(paste("15-", sex$quarter, sep = ""), format = "%d-%b-%y")
sex = sex[order(sex$date),]
```

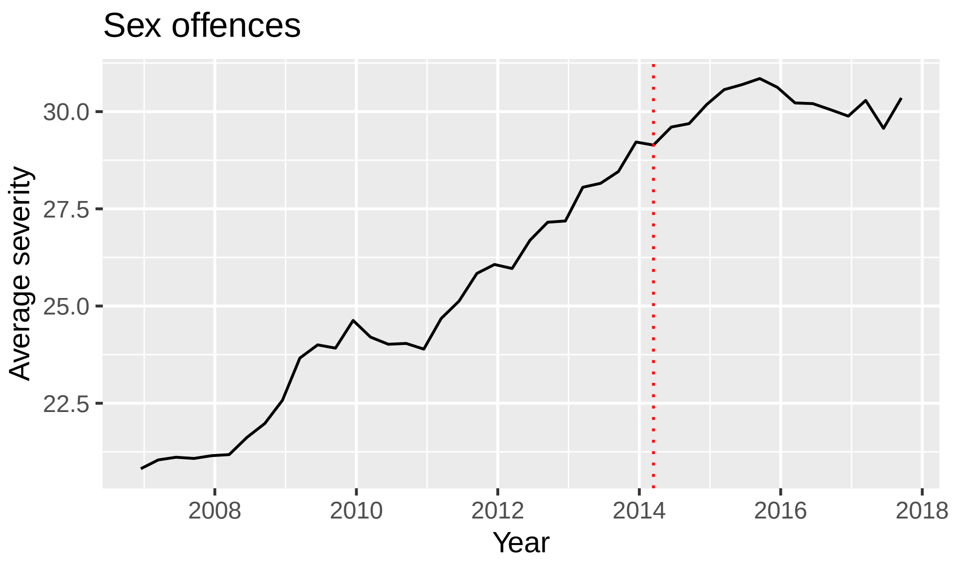
We can now plot the relative frequency for different sentence types and the average sentence length of immediate custodial sentences, as we did before. However, that would give us multiple time-series to monitor and we would not be able to determine exactly whether a decrease in one sentence type is offset by an increase in another. In sum, we need to find a way to aggregate all these different sentence types into a single scale of sentence severity. In Pina-Sánchez et al. (2019)) we did just that, created a ranking of all the main sentence types by their estimated severity based on a survey conducted with magistrates. Here we are going to borrow that scale of severity to aggregate all the different sentence types.

In the following piece of code we provide values of severity for the counts of each sentence type and divide them by the total number of sentences imposed in that period. We will use 1.32 for fines, 2.12 for community orders, 3.88 for suspended sentences, and a range from 5.05 to 120 for custodial sentences depending on their length.

```
sex$severity =
  (sex$fine*1.32+sex$com*2.12+sex$susp*3.88+sex$cust*(5.05+sex$avgleng*(6.45-5.05)/2)) /
  (sex$cust + sex$susp + sex$com + sex$fine + sex$absdis + sex$condis)
```

Now we can plot sentence severity as a single time-serie. This is done below including a vertical line indicating the time when the sex guidelines came into force (more information about the guidelines available here).

```
#First plot
ggplot(sex, aes(x=date, y=severity)) + geom_line() + scale_x_date('Year') +
       ylab("Average severity") + ggtitle("Sex offences") +
       geom_vline(xintercept=as.numeric(sex$date[30]), linetype=3, colour="red")
```



We can see how sentence severity was higher after than before the sex guidelines came into force. However, we can also see that the rate of increase flattened approximately a year after the guidelines were introduced. To assess the effect of the guidelines more proficiently we can model the time-series behaviour up to the point the guidelines were introduce, and compare forecasts based on that model to what we observed in the two years that followed their introduction.

To do so we are first going to use *ts* to tell R that 'sex$severity' should be treated as a time-series with a seasonality of frequency 4 (representing the four quarters within a year), and then, rather than follow the whole model building process that we carried out in the previous exercise, we are going to rely on an unsupervised modelling approach using *auto.arima*. This command basically follows a stepwise process (like the one we saw in Workshop 2) to decide the number of integration (I), auto-regressive (AR), and moving average (MA) components to be used in the model. It does that by estimating different model configurations and comparing them using AIC. If you want to learn more about this process see here.

```
sexsev = ts(sex$severity, frequency = 4)
fitpre = auto.arima(sexsev[-c(30:44)])
#[-c(30:44)] in the above line is used to indicate that we only want to model the
#time-series up to the time the sex guidelines came into force.
fitpre
```

```
## Series: sexsev[-c(30:44)]
## ARIMA(0,1,0) with drift
##
## Coefficients:
##        drift
##       0.3001
## s.e.  0.0699
##
## sigma^2 = 0.1419:  log likelihood = -11.88
## AIC=27.77   AICc=28.25   BIC=30.43
```

The best model selected by *auto.arima* for the sentence severity of sex offences up to the time the guidelines came into force is a simple ARIMA(0,1,0), so no AR or MA components, just one difference to make the time-series stationary (you can see clearly in our last plot the strong trend that makes the time-series non-stationary). In addition, *auto.arima* has estimated a *drift* coefficient. This in essence represents the possibility of modifying the constant of the model. It is a modelling choice that we have not covered in the workshop that is nonetheless available in *auto.arima*. If you want to learn more about drifts in time series see here.

Ok, now that we have our model we can carry out the forecast for the post guidelines period. We can decide for how long we want to extend the forecast using the option *h*. Here we use 'h=15', which covers the whole period since the guidelines came into force up to the end of our window of observation. We have chosen that rather long period to facilitate the integration of our forecast into a dataframe that can be used to plot the forecast together with our observed time-serie. However, to assess the potential causal impact that could be attributed to the guidelines we will focus on the two-year period after the guidelines came into force. The choice of such interval of time can be deemed arbitrary since it is nothing more than an educated guess, but we need to set it at some point, and two years makes sense to us.

```
fcast_fitpre = forecast(fitpre, h=15)
fcast_fitpre
```

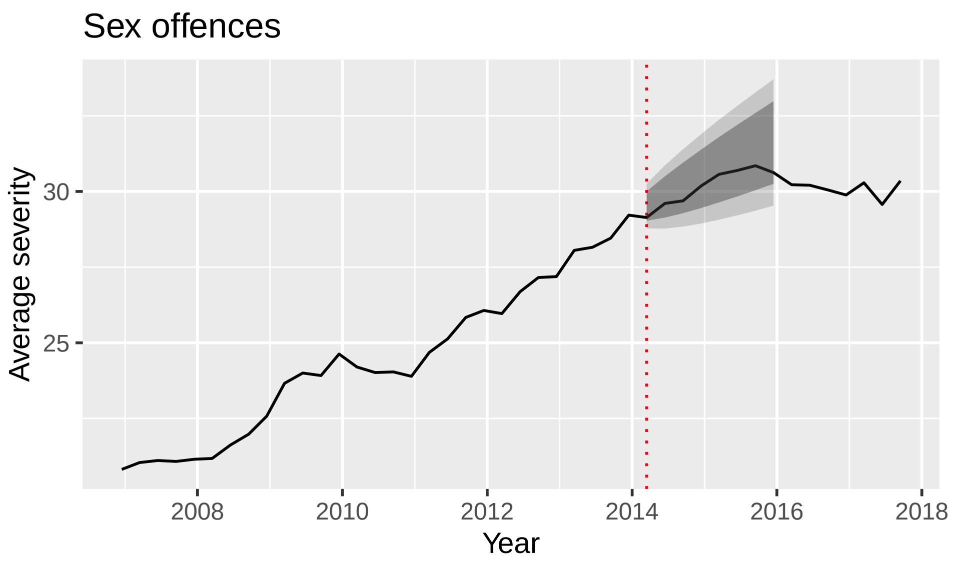
```
##    Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
## 30       29.51813 29.03533 30.00092 28.77976 30.25649
## 31       29.81818 29.13541 30.50095 28.77397 30.86239
## 32       30.11824 29.28202 30.95446 28.83935 31.39712
## 33       30.41829 29.45271 31.38388 28.94156 31.89502
## 34       30.71835 29.63879 31.79790 29.06731 32.36938
## 35       31.01840 29.83581 32.20100 29.20978 32.82702
## 36       31.31846 30.04111 32.59580 29.36492 33.27199
## 37       31.61851 30.25297 32.98405 29.53010 33.70693
## 38       31.91857 30.47019 33.36694 29.70347 34.13367
## 39       32.21862 30.69190 33.74534 29.88370 34.55354
## 40       32.51868 30.91744 34.11992 30.06979 34.96756
## 41       32.81873 31.14629 34.49117 30.26095 35.37651
## 42       33.11879 31.37806 34.85952 30.45657 35.78101
## 43       33.41884 31.61240 35.22528 30.65613 36.18156
## 44       33.71890 31.84905 35.58874 30.85922 36.57858
```

To plot these forecasted values and their 80% and 95% confidence intervals, on top of the ggplot that we produced before, we can use the following code, which will create a specific dataframe for each of the lower and upper bounds of the 80% and 95% intervals of the forecast separately, and set their values for any period different from the two years following the guidelines coming into force as NAs.

```
x = rep(NA,29)
slo95 = rbind(as.data.frame(x),as.data.frame(fcast_fitpre$lower[,2]))
slo80 = rbind(as.data.frame(x),as.data.frame(fcast_fitpre$lower[,1]))
sup95 = rbind(as.data.frame(x),as.data.frame(fcast_fitpre$upper[,2]))
sup80 = rbind(as.data.frame(x),as.data.frame(fcast_fitpre$upper[,1]))
slo95[38:44,] = NA
slo80[38:44,] = NA
sup95[38:44,] = NA
sup80[38:44,] = NA
```

Below is the code to plot the observed time-series with our forecast region (the space confined within the confidence interval of the forecasted values). Notice that this is identical to the code we used for the previous plot plus an added line indicating the variables to be used to define the confidence intervals.

```
ggplot(sex, aes(x=date, y=severity)) + geom_line() + scale_x_date('Year') +
       ylab("Average severity") + ggtitle("Sex offences") +
       geom_vline(aes(xintercept=as.numeric(sex$date[30])), linetype=3, colour="red") +
       geom_ribbon(aes(ymax=sup95$x, ymin=slo95$x), alpha=0.2) +
       geom_ribbon(aes(ymax=sup80$x, ymin=slo80$x), alpha=0.4)
```



So, we can see that the level of sentence severity used for sex offences following the introduction of the guidelines falls right within the forecast region. Therefore, we cannot really claim that, in this case, the guidelines are to be blamed for the observed increase in severity. In fact, it seems that the trend of increased severity started much earlier, and if something, the guidelines seem to have stabilised that trend.

For the rest of the exercise you are requested to explore the effect of the robbery (which came into force 1st of April of 2016, so you can consider the first quarter of 2016) and theft guidelines (into force since the 1st of February of 2016, also the first quarter of the year). You can do so by replicating the analysis that we have just conducted for the sex guidelines.

-Open the data for one of those offence types.

-Make sure that you set the date variable as a date that R understands (*as.Date*), for which you might need to provide an arbitrary value for days, if you plan to replicate the code we used above.

-Sort the dataset in chronological order.

-Turn the relative frequency of each sentence type into values of severity using the suggested scale of severity.

-Create the first plot for the time-serie, including a vertical line indicating the robbery guidelines coming into force.

-Formatting severity as a time-serie (*ts*)

-Estimate an ARIMA model (*auto.arima*) considering only the period covered before the guideline came into force.

-Forecast the level of severity for the X number of quarters following the time when the guideline came into force.

-Prepare the datasets to be used to include the lower and upper confidence interval bounds.

-Draw the plot and assess whether the severity level stood within or our of the forecast region.

Looking at robbery first.

Opening the data.

```r
rob = read.csv("MoJ_robbery.csv")
```

Setting the date.

```r
rob$date = as.Date(paste("15-", rob$quarter, sep=""), format="%d-%b-%y")
```

Sorting the dataset in increasing chronological order to facilitate making sense of the forecasts, i.e. the further down the value in the dataset the further away in time.

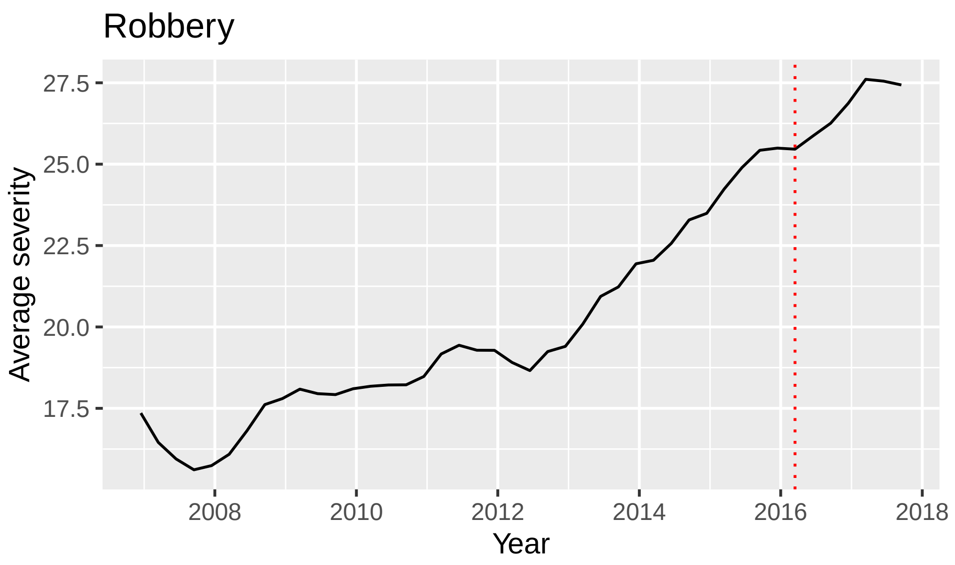
```r
rob = rob[order(rob$date),]
```

We now turn the relative frequency for different sentence types into values of severity.

```r
rob$severity =
(rob$fine*1.32+rob$com*2.12+rob$susp*3.88+rob$cust*(5.05+rob$avgleng*(6.45-5.05)/2)) /
(rob$cust + rob$susp + rob$com + rob$fine + rob$absdis + rob$condis)
```

Create the first plot including a vertical line indicating the robbery guidelines coming into force.

```r
ggplot(rob, aes(x=date, y=severity)) + geom_line() + scale_x_date('Year') +
  ylab("Average severity") + ggtitle("Robbery") +
  geom_vline(aes(xintercept=as.numeric(rob$date[38])), linetype=3, colour="red")
```



Formatting severity as a time-serie.

```
robsev = ts(rob$severity, frequency = 4)
```

Estimating an ARIMA model for the before period.

```
fitpre = auto.arima(robsev[-c(38:44)])
fitpre
```

We will be using an ARIMA(1,2,0).

Undertaking the forecast for the 7 quarters following the robbery guidelines coming into force.

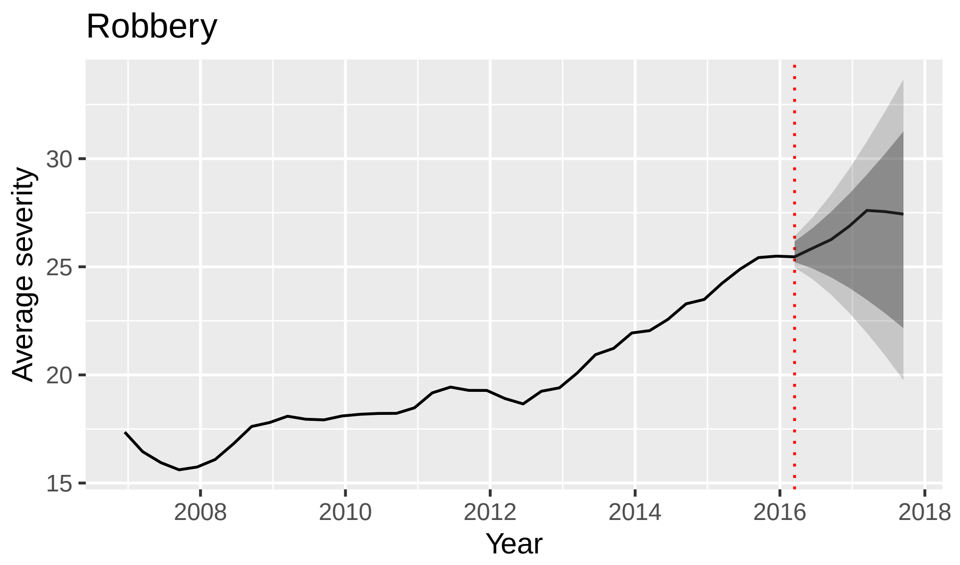
```
fcast_fitpre = forecast(fitpre, h=7)
```

Preparing the data for the next plot including the forecast region.

```
x = rep(NA,37)
rlo95 = rbind(as.data.frame(x),as.data.frame(fcast_fitpre$lower[,2]))
rlo80 = rbind(as.data.frame(x),as.data.frame(fcast_fitpre$lower[,1]))
rup95 = rbind(as.data.frame(x),as.data.frame(fcast_fitpre$upper[,2]))
rup80 = rbind(as.data.frame(x),as.data.frame(fcast_fitpre$upper[,1]))
```

The final plot including the forecast region.

```
ggplot(rob, aes(x=date, y=severity)) + geom_line() + scale_x_date('Year')  +
  ylab("Average severity") +  ggtitle("Robbery") +
  geom_vline(aes(xintercept=as.numeric(rob$date[38])), linetype=3, colour="red") +
  geom_ribbon(aes(ymax=rup95$x, ymin=rlo95$x), alpha=0.2) +
  geom_ribbon(aes(ymax=rup80$x, ymin=rlo80$x), alpha=0.4)
```



As for the case of sex offences, the sentence severity applied to robbery offences is higher after the guidelines came into force. However, the trend started before the guidelines were introduced, and their behaviour in the post guidelines period falls within the expected forecast region. Hence, again, we cannot conclude that the guidelines have contributed to the increase in sentence severity.

Let's look now into the theft guidelines.

Opening the data.

```
theft = read.csv("MoJ_theft.csv")
```

Setting the date.

```
theft$date = as.Date(paste("15-", theft$quarter, sep=""), format="%d-%b-%y")
```

Sorting the dataset in increasing chronological order

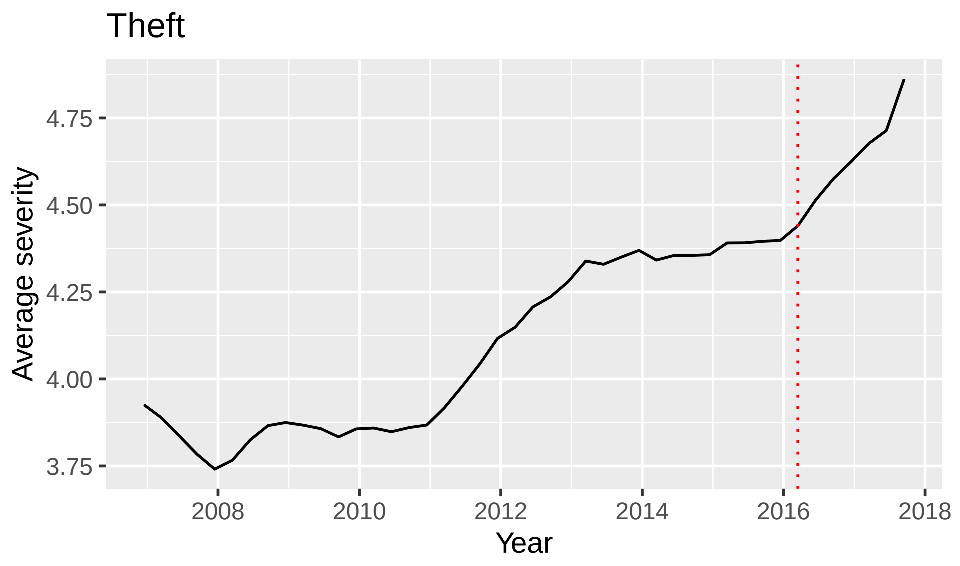
```
theft = theft[order(theft$date),]
```

Turning sentences into values of severity

```
theft$severity =
(theft$fine*1.32+theft$com*2.12+theft$susp*3.88+theft$cust*(5.05+theft$avgleng*(6.45-5.05)/2)) /
(theft$cust + theft$susp + theft$com + theft$fine + theft$absdis + theft$condis)
```

Plot including the vertical line at the time the theft guidelines came into force.

```
ggplot(theft, aes(x=date, y=severity)) + geom_line() + scale_x_date('Year') +
ylab("Average severity") + ggtitle("Theft") +
geom_vline(aes(xintercept=as.numeric(theft$date[38])), linetype=3, colour="red")
```



Formatting severity as a time-serie.

```
theftsev = ts(theft$severity, frequency = 4)
```

The model.

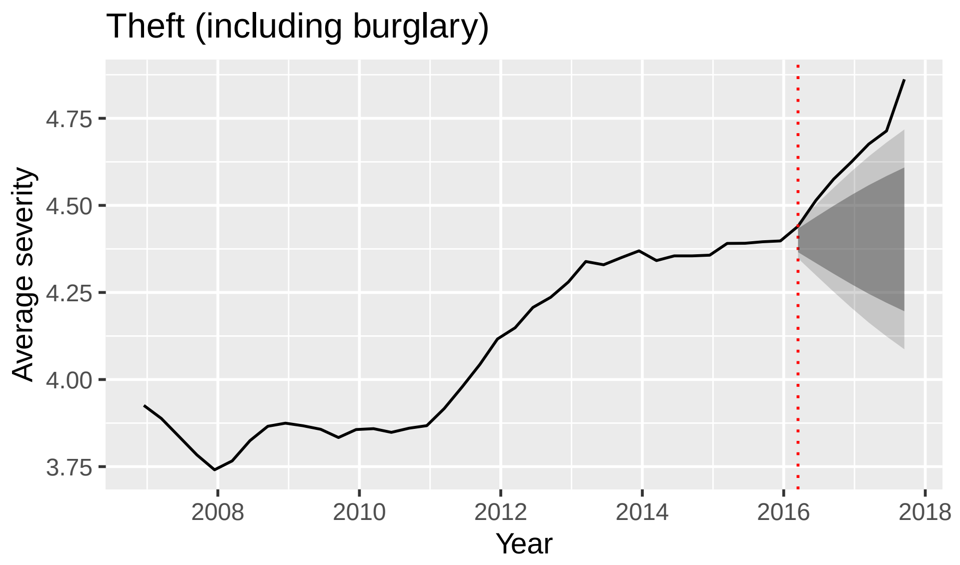
```
fitpre = auto.arima(theftsev[-c(38:44)])
fitpre
```

The forecast.

```
fcast_fitpre = forecast(fitpre, h=7)
x = rep(NA,37)
tlo95 = rbind(as.data.frame(x),as.data.frame(fcast_fitpre$lower[,2]))
tlo80 = rbind(as.data.frame(x),as.data.frame(fcast_fitpre$lower[,1]))
tup95 = rbind(as.data.frame(x),as.data.frame(fcast_fitpre$upper[,2]))
tup80 = rbind(as.data.frame(x),as.data.frame(fcast_fitpre$upper[,1]))
```

The second plot including the forecast region.

```
ggplot(theft, aes(x=date, y=severity)) + geom_line() + scale_x_date('Year') +
  ylab("Average severity") + ggtitle("Theft (including burglary)") +
  geom_vline(aes(xintercept=as.numeric(theft$date[38])), linetype=3, colour="red") +
  geom_ribbon(aes(ymax=tup95$x, ymin=tlo95$x), alpha=0.2) +
  geom_ribbon(aes(ymax=tup80$x, ymin=tlo80$x), alpha=0.4)
```



Here we have a very different situation. The increase in severity following the introduction of the theft guidelines is much sharper than what could have been anticipated, which points at a likely causal effect of the guidelines. The reassuring part of this analysis is that the Sentencing Council is already working on modifying those guidelines that have been identified to have had an effect on sentence severity.

Preparation for next week's workshop

Next week you will see techniques for data reduction, e.g. how to aggregate a group of similar variables into an index, or how to classify cases according to common features. This workshop will be led by Toby.