

Розрахункова робота №2

Завантажимо необхідні бібліотеки та дані.

```
library(ggplot2)
library(scales)
library(dplyr)
library(lubridate)
library(openair)
library(pastecs)
library(psych)
library(Mcomp)
library(xts)
library(zoo)
library(TTR)
library(timeDate)
library(tseries)
library(rlist)
library(knitr)
library(skimr)
library(readr)
library(magrittr)
library(tidyr)
library(corrplot)
library(circlize)
library(ggpubr)
library(forecast)
library(h2o)
```

```
movie_weekend <- read.delim("C:/Users/danie/Downloads/movieweekend-dat.txt", TRUE)
movie_daily <- read.delim("C:/Users/danie/Downloads/moviedaily-dat.txt", TRUE)
movie_total <- read.delim("C:/Users/danie/Downloads/movietotal-dat.txt", TRUE)
```

```
head(movie_weekend, 7)
```

##	NUMBER	MOVIE	WEEK_NUM	WEEKEND_PER_THEATER	WEEKEND_DATE
## 1	1	A Beautiful Mind	1	701	12/21/2001
## 2	1	A Beautiful Mind	2	14820	12/28/2001
## 3	1	A Beautiful Mind	3	8940	1/4/2002
## 4	1	A Beautiful Mind	4	6850	1/11/2002
## 5	1	A Beautiful Mind	5	5280	1/18/2002
## 6	1	A Beautiful Mind	6	5155	1/25/2002
## 7	1	A Beautiful Mind	7	3735	2/1/2002

```
head(movie_daily, 7)
```

##	NUMBER	MOVIE	DAY_NUM	DAILY_PER_THEATER	DATE
## 1	1	A Beautiful Mind	1	8909	12/24/2001
## 2	1	A Beautiful Mind	2	3885	12/25/2001
## 3	1	A Beautiful Mind	3	3365	12/26/2001
## 4	1	A Beautiful Mind	4	3324	12/27/2001
## 5	1	A Beautiful Mind	5	4403	12/28/2001
## 6	1	A Beautiful Mind	6	5475	12/29/2001
## 7	1	A Beautiful Mind	7	4964	12/30/2001

```
head(movie_total, 7)
```

##	NUMBER	MOVIE	TYPE	TOTAL
## 1	1	A Beautiful Mind	Best Picture	170.71
## 2	2	American Beauty	Best Picture	130.06
## 3	3	Batman	Biggest Gross	251.19
## 4	4	Beverly Hills Cop	Biggest Gross	234.76
## 5	5	Chicago	Best Picture	170.69
## 6	6	Crash	Best Picture	55.33
## 7	7	Departed, The	Best Picture	133.31

```
summary(movie_weekend)
```

##	NUMBER	MOVIE	WEEK_NUM	WEEKEND_PER_THEATER	WEEKEND_DATE
##	Min. : 1.00	Length:1292	Min. : 1.00	Min. : 128	Length:1292
##	1st Qu.:11.00	Class :character	1st Qu.: 7.00	1st Qu.: 1034	Class :character
##	Median :25.00	Mode :character	Median :13.00	Median : 1922	Mode :character
##	Mean :24.24		Mean :14.92	Mean : 3635	
##	3rd Qu.:36.00		3rd Qu.:21.00	3rd Qu.: 3733	
##	Max. :49.00		Max. :52.00	Max. :53846	
##	NA's :38		NA's :38	NA's :38	

```
summary(movie_daily)
```

##	NUMBER	MOVIE	DAY_NUM	DAILY_PER_THEATER	DATE
##	Length:2501	Length:2501	Min. : 1.00	Length:2501	Length:2501
##	Class :character	Class :character	1st Qu.: 19.00	Class :character	Class :character
##	Mode :character	Mode :character	Median : 42.00	Mode :character	Mode :character
##			Mean : 53.17		
##			3rd Qu.: 75.00		

```
##                               Max.    :186.00
##                               NA's     :47
```

```
summary(movie_total)
```

```
##      NUMBER      MOVIE      TYPE      TOTAL
## Min.   : 1  Length:49  Length:49  Min.   : 1.28
## 1st Qu.:13  Class :character  Class :character  1st Qu.:100.32
## Median :25  Mode  :character  Mode  :character  Median :261.99
## Mean   :25                                     Mean   :228.55
## 3rd Qu.:37                                     3rd Qu.:321.01
## Max.   :49                                     Max.   :600.79
```

Перетворення та очищення даних:

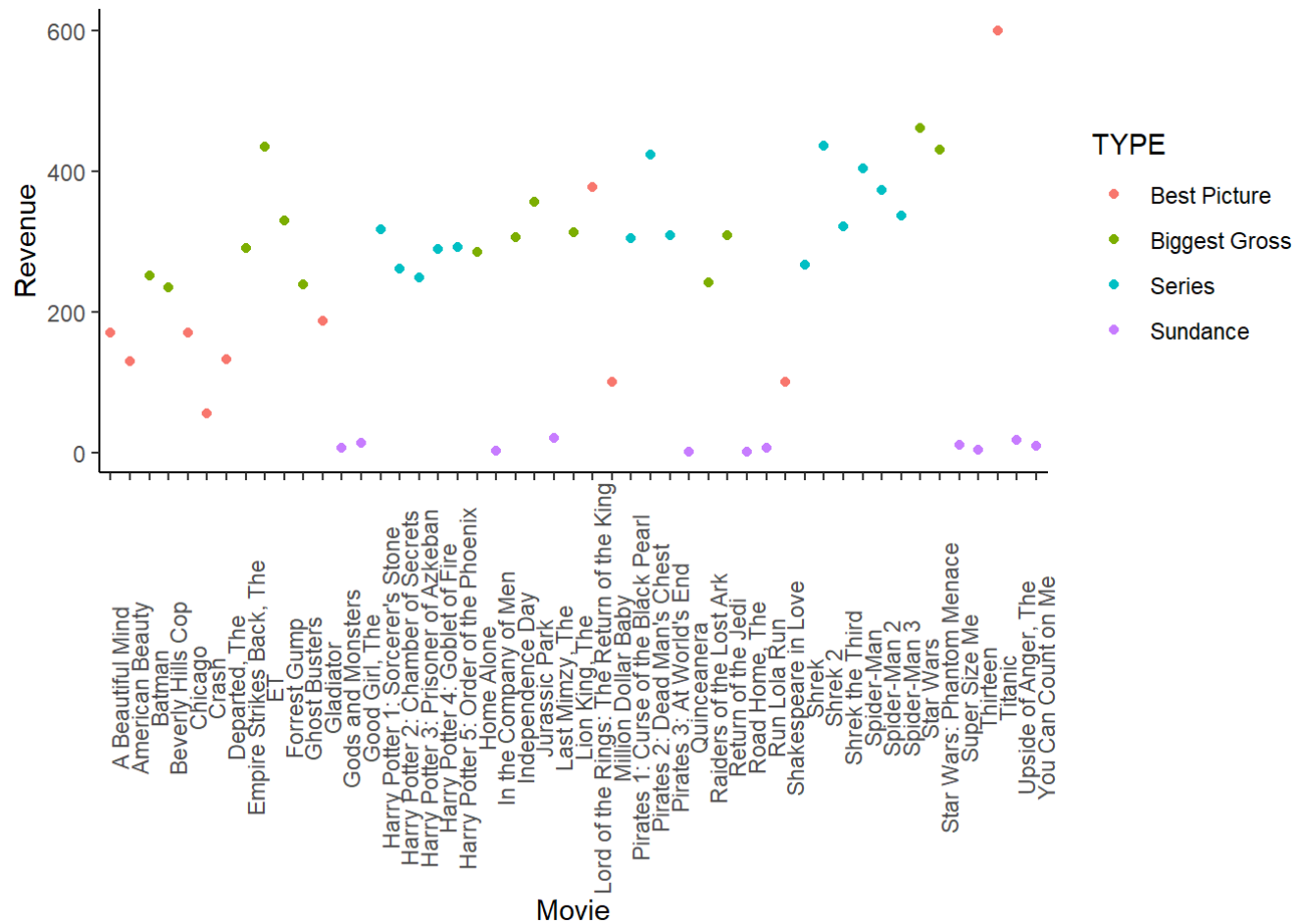
```
movie_weekend$WEEKEND_DATE <- as.Date.character(movie_weekend$WEEKEND_DATE, "%m/%d/%Y")
movie_weekend <- na.exclude(movie_weekend)
```

```
movie_daily[,c(1,4)] <- movie_daily[,c(1,4)] %>% apply(as.integer)
movie_daily$DATE <- as.Date.character(movie_daily$DATE, "%m/%d/%Y")
movie_daily <- na.exclude(movie_daily)
head(movie_daily, 10)
```

##	NUMBER	MOVIE	DAY_NUM	DAILY_PER_THEATER	DATE
## 1	1	A Beautiful Mind	1	8909	2001-12-24
## 2	1	A Beautiful Mind	2	3885	2001-12-25
## 3	1	A Beautiful Mind	3	3365	2001-12-26
## 4	1	A Beautiful Mind	4	3324	2001-12-27
## 5	1	A Beautiful Mind	5	4403	2001-12-28
## 6	1	A Beautiful Mind	6	5475	2001-12-29
## 7	1	A Beautiful Mind	7	4964	2001-12-30
## 8	1	A Beautiful Mind	8	4126	2001-12-31
## 9	1	A Beautiful Mind	9	5110	2002-01-01
## 10	1	A Beautiful Mind	10	2606	2002-01-02

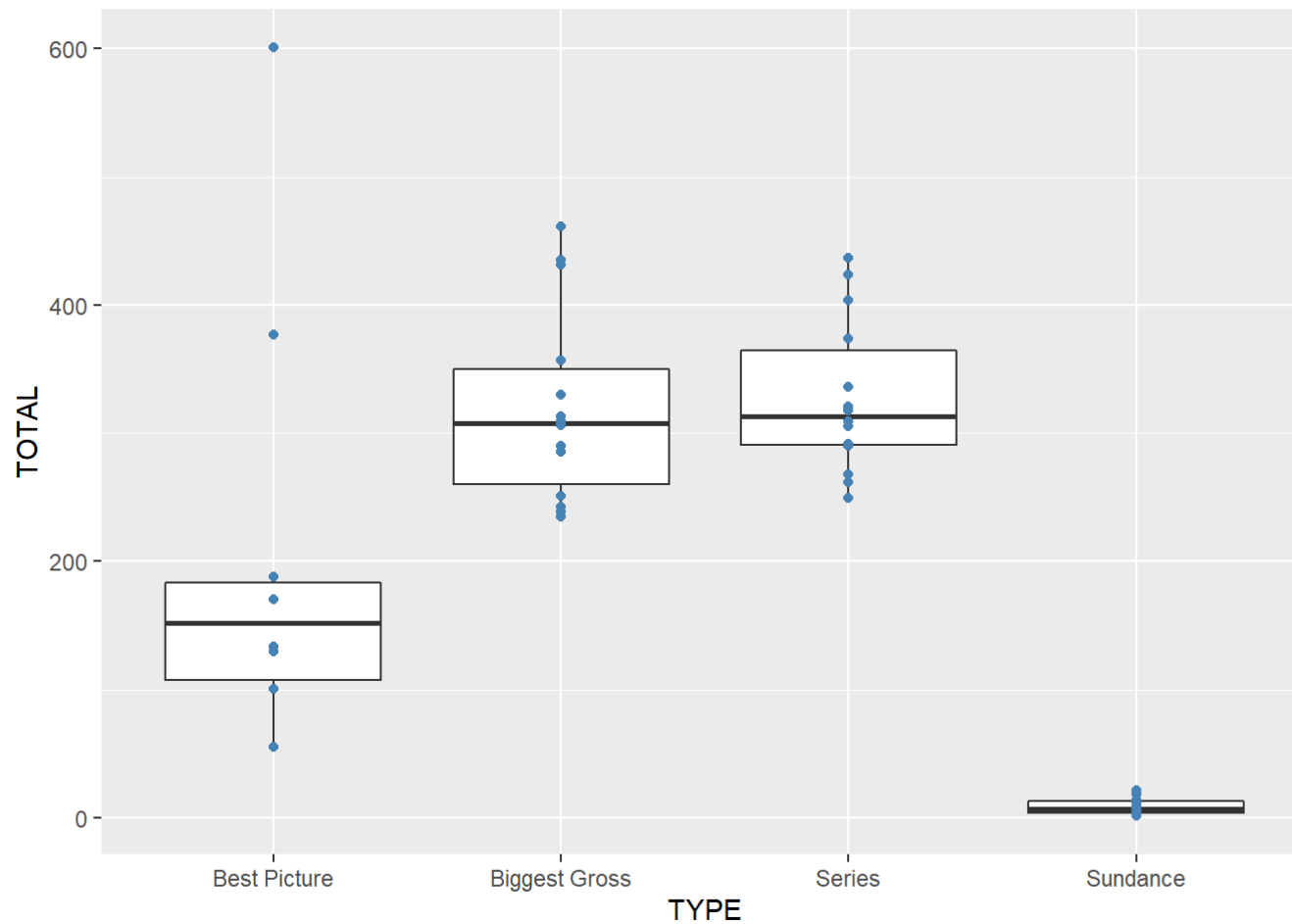
Розподіл кінофільмів за типами:

```
p1 <- ggplot(movie_total, aes(x = MOVIE, y = TOTAL, colour = TYPE)) +
  geom_point() +
  labs(x = "Movie", y = "Revenue") +
  scale_y_continuous(labels = comma) +
  theme_classic() +
  theme(axis.text.x = element_text(angle = 90))
p1
```



Boxplot кінокартин за типами:

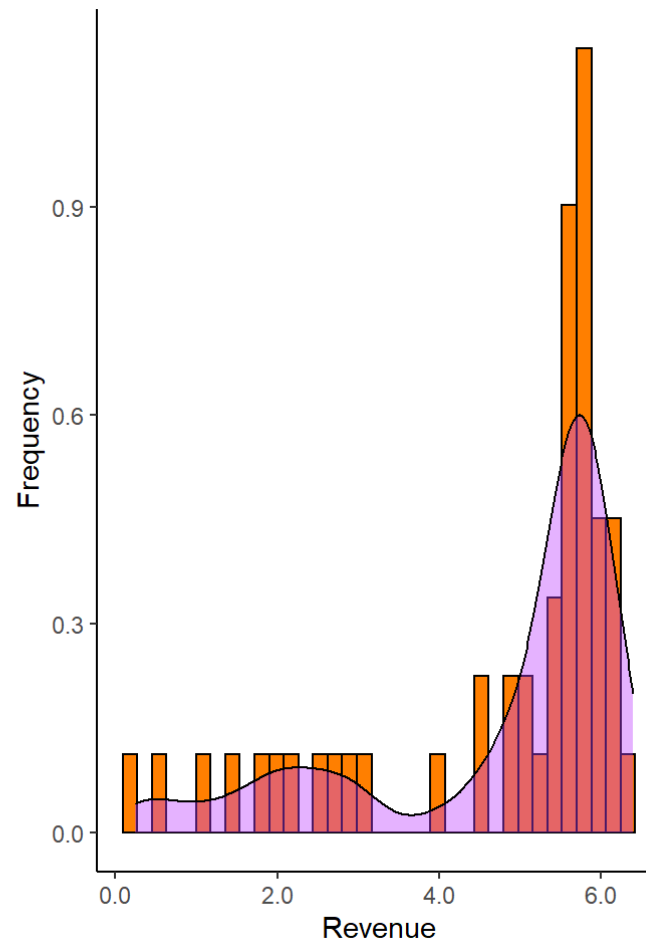
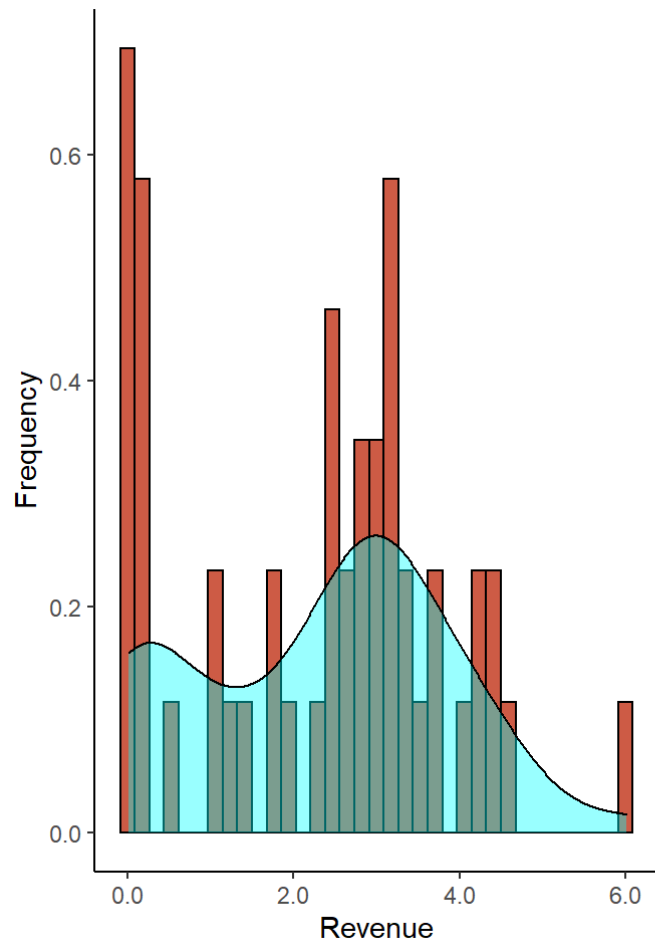
```
p2 <- ggplot(movie_total, aes(x = TYPE, y = TOTAL)) +
  geom_boxplot() +
  geom_point(color = 'steelblue')
p2
```



Гістограми (з і без scale):

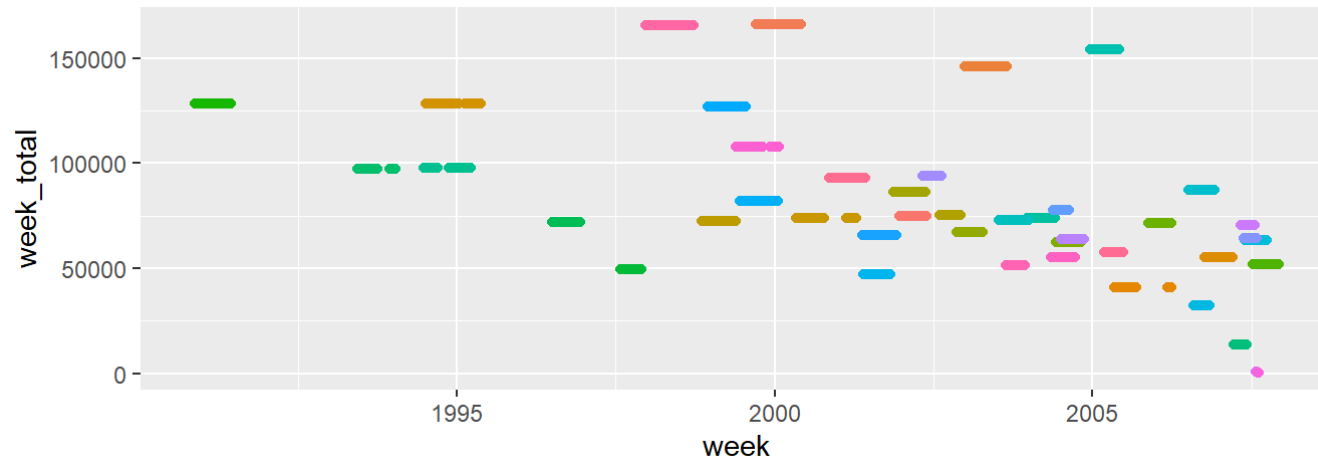
```
pla <- ggplot(movie_total %>% filter(TOTAL != 0), aes(x = TOTAL/100)) +
  geom_histogram(aes(y=..density..), fill = "coral3", color = 'black', bins = 35) +
  geom_density(alpha=.4, fill="cyan1") +
  scale_x_continuous(labels = comma) +
  scale_y_continuous() +
```

```
labs(x = "Revenue", y = "Frequency") +  
theme_classic()  
p2a <- ggplot(movie_total %>% filter(TOTAL != 0), aes(x = log(TOTAL))) +  
  geom_histogram(aes(y=..density..), fill = "darkorange1", color = 'black', bins = 35) +  
  geom_density(alpha=.4, fill="darkorchid1") +  
  scale_x_continuous(labels = comma) +  
  scale_y_continuous() +  
  labs(x = "Revenue", y = "Frequency") +  
  theme_classic()  
ggarrange(pla, p2a)
```

```
mV <- movie_weekend %>% filter(WEEKEND_DATE >= as.Date("1990-01-01")) %>% select(MOVIE, WEEKEND_PER_THEATER, WEEK
END_DATE) %>% group_by(MOVIE) %>%
  summarise(week_total = sum(WEEKEND_PER_THEATER), week = WEEKEND_DATE)
ggplot(mV, aes(x=week, y=week_total, colour = MOVIE)) +
  geom_point() +
  theme(legend.position = "bottom",
```

```
legend.text = element_text(size = 6.5),
legend.box.margin = margin(1, 1, 1, 5))
```

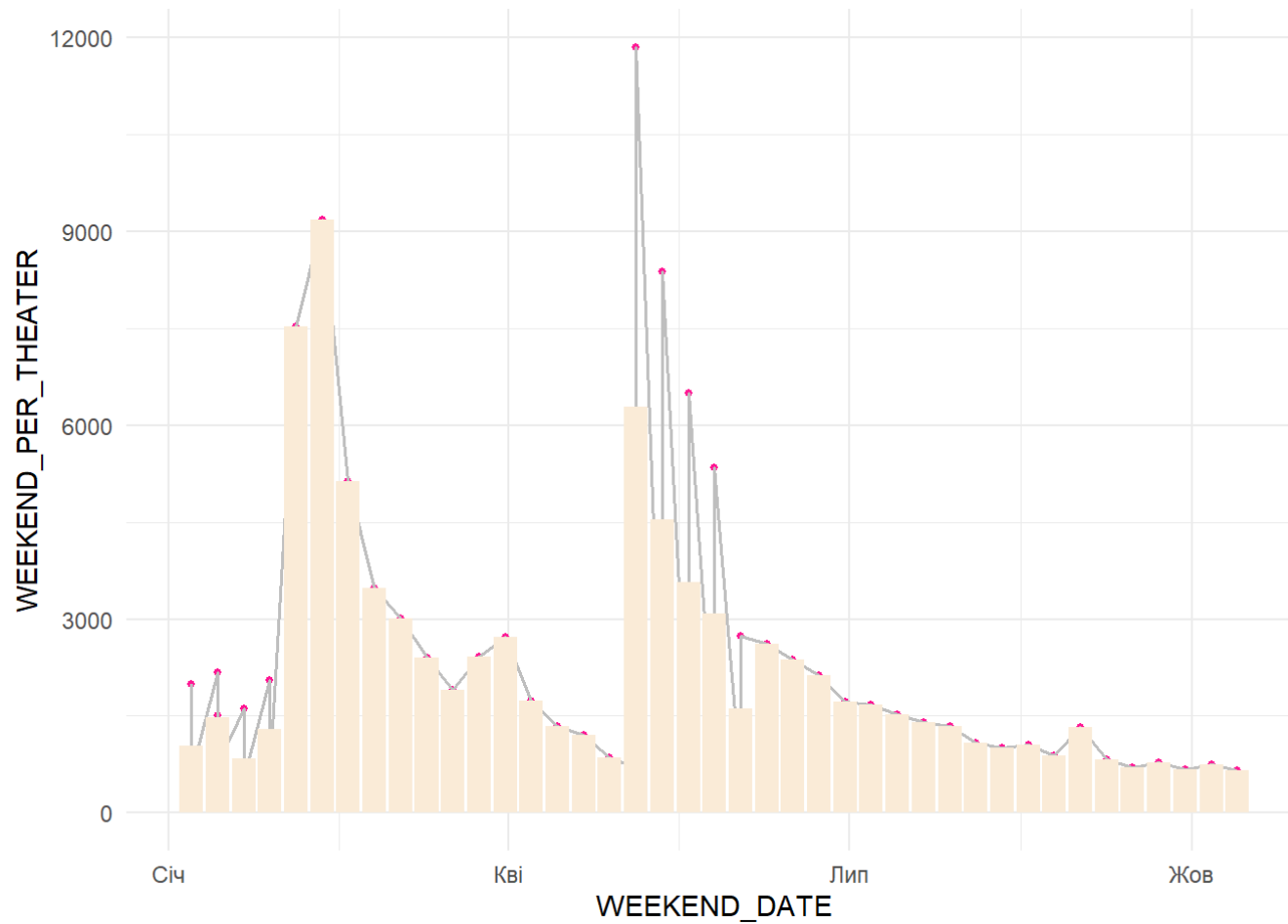


MOVIE

• A Beautiful Mind	• Harry Potter 1: Sorcerer's Stone	• Last Mimzy, The	• Run Lola Run	• Spider-Man
• American Beauty	• Harry Potter 2: Chamber of Secrets	• Lion King, The	• Shakespeare in Love	• Spider-Man
• Chicago	• Harry Potter 3: Prisoner of Azkaban	• Lord of the Rings: Return	• Shrek	• Spider-Man
• Crash	• Harry Potter 4: Goblet of Fire	• Million Dollar Baby	• Shrek 2	• Star Wars
• Departed, The	• Harry Potter 5: Order of the Phoenix	• Pirates 1: Curse of the Black Pearl	• Shrek the Third	• Super Siz
• Forrest Gump	• Home Alone	• Pirates 2: Dead Man's Chest	• Spider-Man	• Thirteen
• Gladiator	• In the Company of Men	• Pirates 3: At World's End	• Spider-Man 2	• Titanic
• Gods and Monsters	• Independence Day	• Quinceanera	• Spider-Man 3	• Upside of
• Good Girl, The	• Jurassic Park	• Road Home, The	• Spider-Man 4	• You Can

```
ggplot(movie_weekend %>% filter(WEEKEND_DATE >= as.Date("2000-01-01") & WEEKEND_DATE <= as.Date("2000-10-20")
                             & WEEKEND_PER_THEATER >= 200), aes(x = WEEKEND_DATE, y = WEEKEND_PER_THEATER)) +
  geom_point(color = "deeppink1", size = 1) +
```

```
geom_line(color = "grey", size = 0.7) +  
geom_bar(position = "dodge", stat = "summary", fun.y = "mean", fill = "antiquewhite", size = 2) +  
theme_minimal()
```



```
mw <- movie_weekend %>%
  filter(WEEKEND_DATE >= as.Date("2000-01-01")) %>%
  select(MOVIE, WEEKEND_DATE, WEEKEND_PER_THEATER) %>%
  group_by(MOVIE) %>%
  summarise(MOVIE, week_total = cumsum(WEEKEND_PER_THEATER), week = WEEKEND_DATE)
mw
```

```
## # A tibble: 656 x 3
## # Groups:   MOVIE [36]
##   MOVIE          week_total week
##   <chr>          <int> <date>
## 1 A Beautiful Mind      701 2001-12-21
## 2 A Beautiful Mind     15521 2001-12-28
## 3 A Beautiful Mind     24461 2002-01-04
## 4 A Beautiful Mind     31311 2002-01-11
## 5 A Beautiful Mind     36591 2002-01-18
## 6 A Beautiful Mind     41746 2002-01-25
## 7 A Beautiful Mind     45481 2002-02-01
## 8 A Beautiful Mind     48321 2002-02-08
## 9 A Beautiful Mind     52211 2002-02-15
## 10 A Beautiful Mind    54776 2002-02-22
## # ... with 646 more rows
```

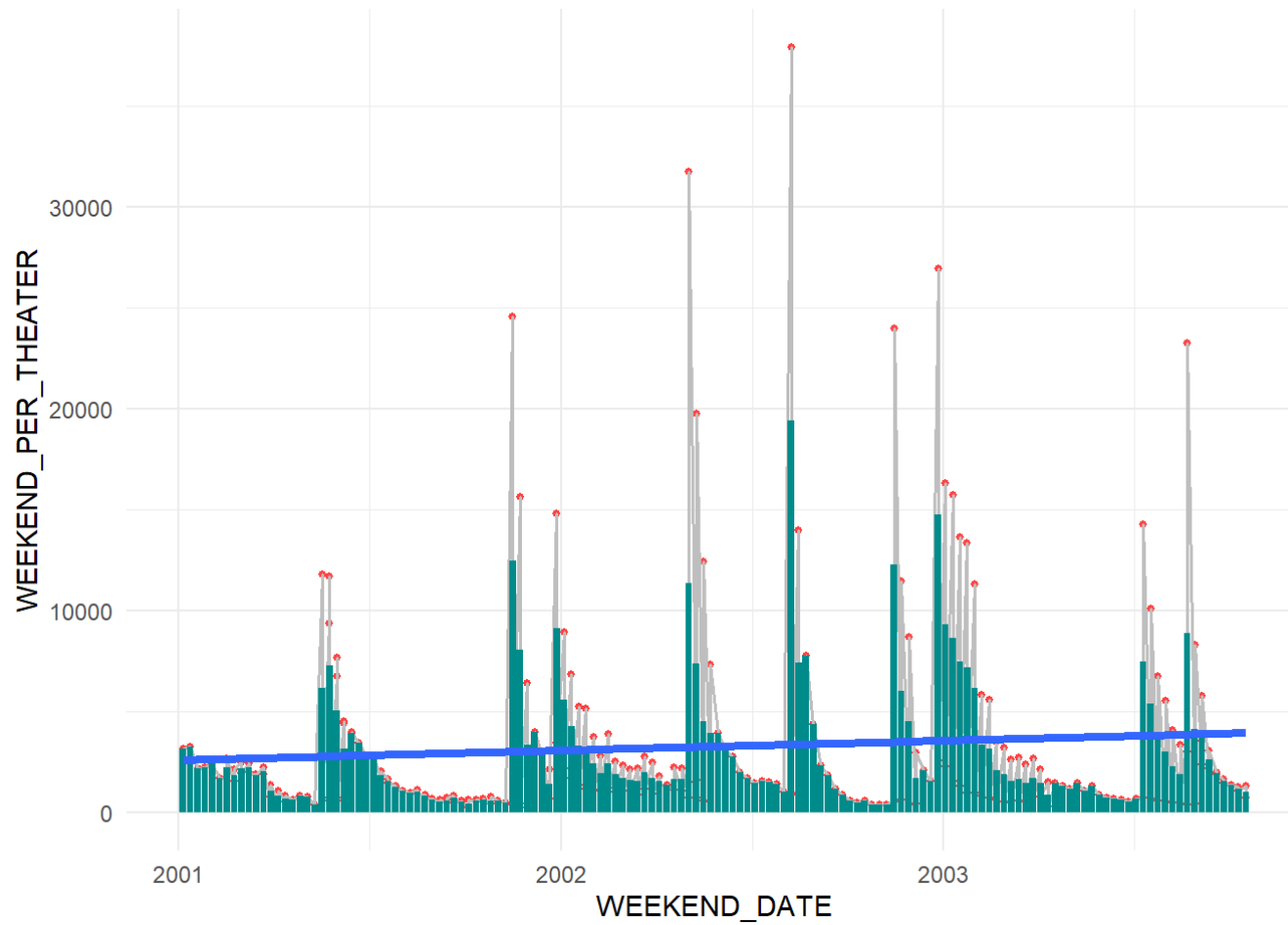
```
movie_weekend %>% filter(WEEKEND_DATE >= as.Date("2000-01-01") & WEEKEND_DATE <= as.Date("2000-12-12")
                        & WEEKEND_PER_THEATER >= 200)
```

```
##   NUMBER      MOVIE WEEK_NUM WEEKEND_PER_THEATER WEEKEND_DATE
## 1      2  American Beauty      17           1998   2000-01-07
## 2      2  American Beauty      18           2168   2000-01-14
## 3      2  American Beauty      19           1614   2000-01-21
```

## 4	2	American Beauty	20	2047	2000-01-28
## 5	2	American Beauty	21	7523	2000-02-04
## 6	2	American Beauty	22	9185	2000-02-11
## 7	2	American Beauty	23	5132	2000-02-18
## 8	2	American Beauty	24	3483	2000-02-25
## 9	2	American Beauty	25	3010	2000-03-03
## 10	2	American Beauty	26	2408	2000-03-10
## 11	2	American Beauty	27	1902	2000-03-17
## 12	2	American Beauty	28	2422	2000-03-24
## 13	2	American Beauty	29	2717	2000-03-31
## 14	2	American Beauty	30	1731	2000-04-07
## 15	2	American Beauty	31	1341	2000-04-14
## 16	2	American Beauty	32	1201	2000-04-21
## 17	2	American Beauty	33	848	2000-04-28
## 18	2	American Beauty	34	711	2000-05-05
## 19	2	American Beauty	35	724	2000-05-12
## 20	2	American Beauty	36	640	2000-05-19
## 21	2	American Beauty	37	827	2000-05-26
## 22	2	American Beauty	38	479	2000-06-02
## 23	12	Gladiator	1	11851	2000-05-05
## 24	12	Gladiator	2	8374	2000-05-12
## 25	12	Gladiator	3	6494	2000-05-19
## 26	12	Gladiator	4	5353	2000-05-26
## 27	12	Gladiator	5	2741	2000-06-02
## 28	12	Gladiator	6	2614	2000-06-09
## 29	12	Gladiator	7	2366	2000-06-16
## 30	12	Gladiator	8	2126	2000-06-23
## 31	12	Gladiator	9	1720	2000-06-30
## 32	12	Gladiator	10	1677	2000-07-07
## 33	12	Gladiator	11	1520	2000-07-14
## 34	12	Gladiator	12	1408	2000-07-21
## 35	12	Gladiator	13	1343	2000-07-28
## 36	12	Gladiator	14	1090	2000-08-04
## 37	12	Gladiator	15	1014	2000-08-11
## 38	12	Gladiator	16	1045	2000-08-18
## 39	12	Gladiator	17	889	2000-08-25
## 40	12	Gladiator	18	1325	2000-09-01

## 41	12	Gladiator	19	828	2000-09-08
## 42	12	Gladiator	20	703	2000-09-15
## 43	12	Gladiator	21	782	2000-09-22
## 44	12	Gladiator	22	672	2000-09-29
## 45	12	Gladiator	23	742	2000-10-06
## 46	12	Gladiator	24	663	2000-10-13
## 47	35	Run Lola Run	29	497	2000-01-07
## 48	35	Run Lola Run	30	1505	2000-01-14
## 49	35	Run Lola Run	31	364	2000-01-21
## 50	44	Star Wars: Phantom Menace	28	611	2000-01-07
## 51	44	Star Wars: Phantom Menace	29	766	2000-01-14
## 52	44	Star Wars: Phantom Menace	30	557	2000-01-21
## 53	44	Star Wars: Phantom Menace	31	558	2000-01-28
## 54	49	You Can Count on Me	1	14771	2000-11-10
## 55	49	You Can Count on Me	2	8614	2000-11-17
## 56	49	You Can Count on Me	3	9708	2000-11-24
## 57	49	You Can Count on Me	4	7368	2000-12-01
## 58	49	You Can Count on Me	5	5607	2000-12-08

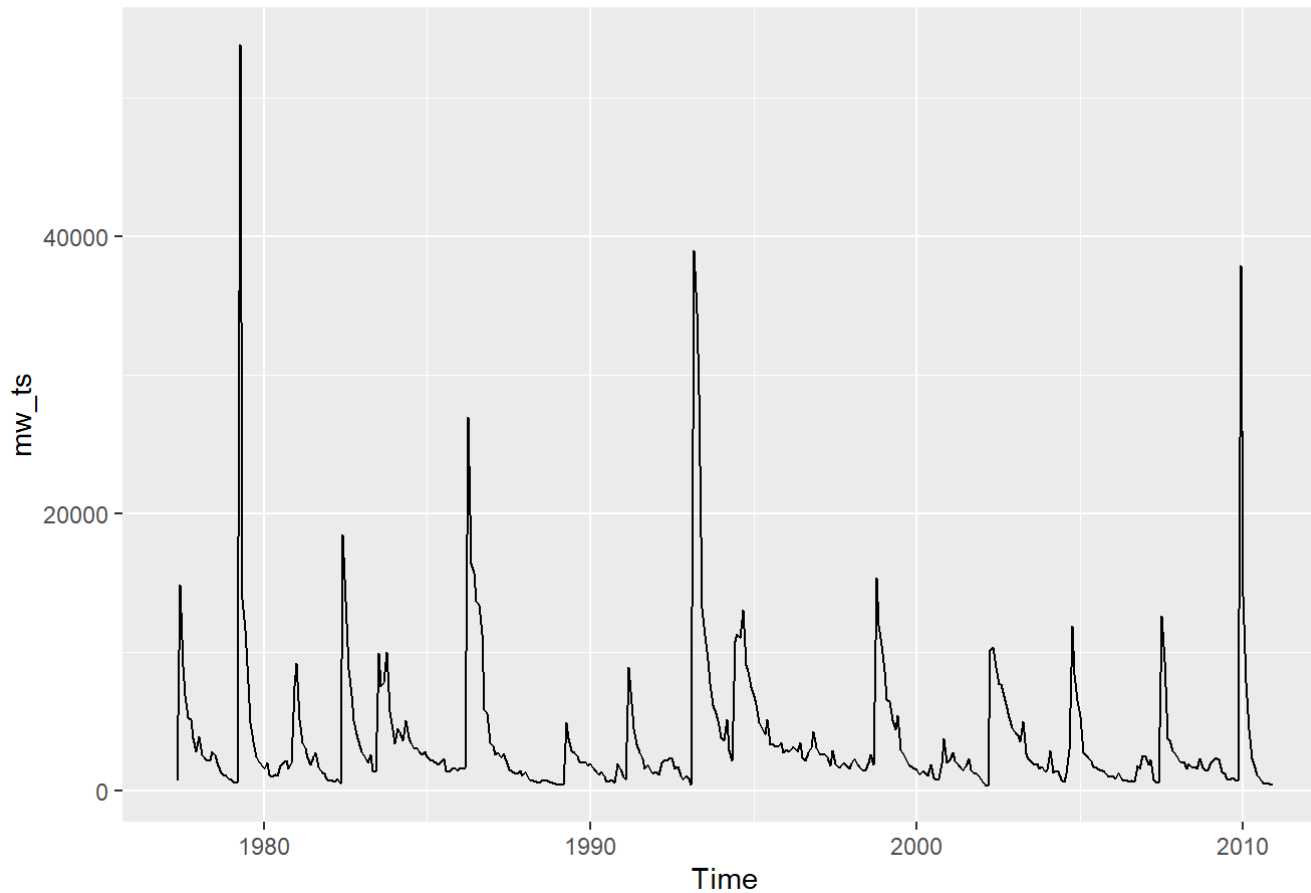
```
ggplot(movie_weekend %>% filter(WEEKEND_DATE >= as.Date("2001-01-01") & WEEKEND_DATE <= as.Date("2003-10-20")),
  aes(x = WEEKEND_DATE, y = WEEKEND_PER_THEATER)) +
  geom_point(color = "brown1", size = 1) +
  geom_line(color = "grey", size = 0.7) +
  geom_bar(position = "dodge", stat = "summary", fun.y = "mean", fill = "cyan4", size = 2) +
  geom_smooth(method="lm", se=FALSE, size = 1.5) +
  theme_minimal()
```



```
mw_ts <- ts(movie_weekend$WEEKEND_PER_THEATER, frequency=12, start = c(1977, 05), end = c(2010, 12))
str(mw_ts)
```

```
## Time-Series [1:404] from 1977 to 2011: 701 14820 8940 6850 5280 5155 3735 2840 3890 2565 ...
```

```
autoplot(mw_ts)
```



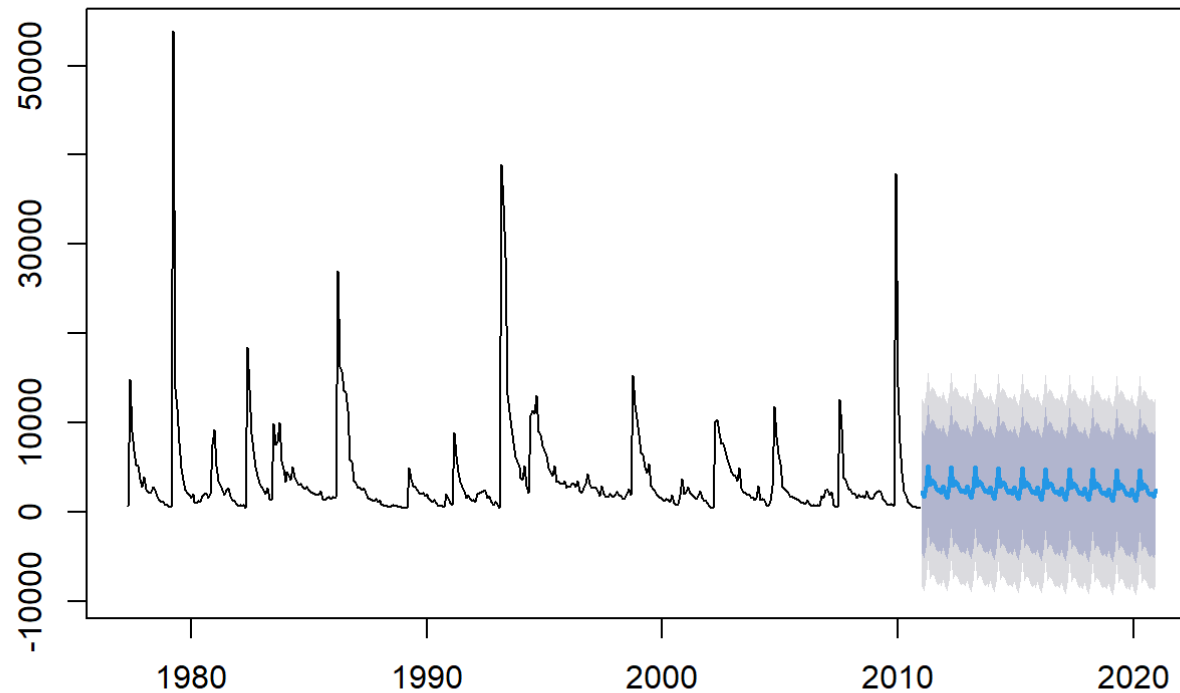
```
df_ts <- data.frame(revenue = mw_ts, as.numeric(time(mw_ts)))  
names(df_ts) <- c("revenue", "time")  
fit.consMR <- tslm(  
  revenue ~ season + trend - 1,  
  data=df_ts)  
summary(fit.consMR)
```



```
##
## Call:
## tslm(formula = revenue ~ season + trend - 1, data = df_ts)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -5769  -2416  -1365    319  47098
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## season1    3904.590    1018.457   3.834 0.000147 ***
## season2    3349.409    1019.448   3.286 0.001110 **
## season3    4531.531    1020.444   4.441 1.17e-05 ***
## season4    6848.744    1021.443   6.705 7.07e-11 ***
## season5    4708.995    1004.337   4.689 3.81e-06 ***
## season6    5277.708    1005.333   5.250 2.51e-07 ***
## season7    5080.833    1006.332   5.049 6.83e-07 ***
## season8    4467.517    1007.336   4.435 1.20e-05 ***
## season9    4058.259    1008.343   4.025 6.85e-05 ***
## season10   4309.531    1009.355   4.270 2.46e-05 ***
## season11   3922.862    1010.370   3.883 0.000121 ***
## season12   4698.664    1011.390   4.646 4.64e-06 ***
## trend       -4.213         2.239  -1.882 0.060639 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 5248 on 391 degrees of freedom
## Multiple R-squared:  0.3595, Adjusted R-squared:  0.3382
## F-statistic: 16.88 on 13 and 391 DF,  p-value: < 2.2e-16
```

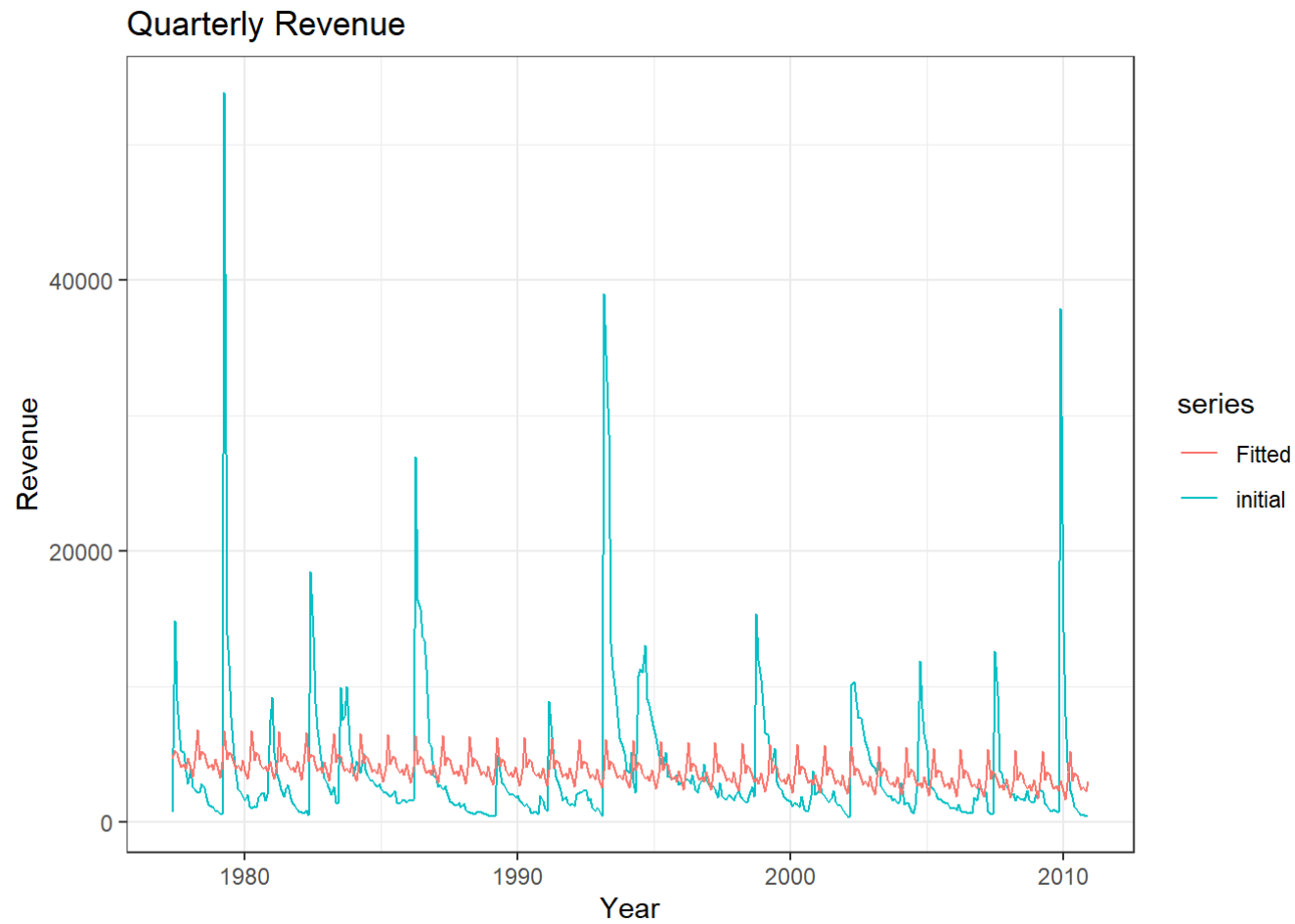
```
my_fc <- forecast(fit.consMR, h=120)  
plot(my_fc)
```

Forecasts from Linear regression model



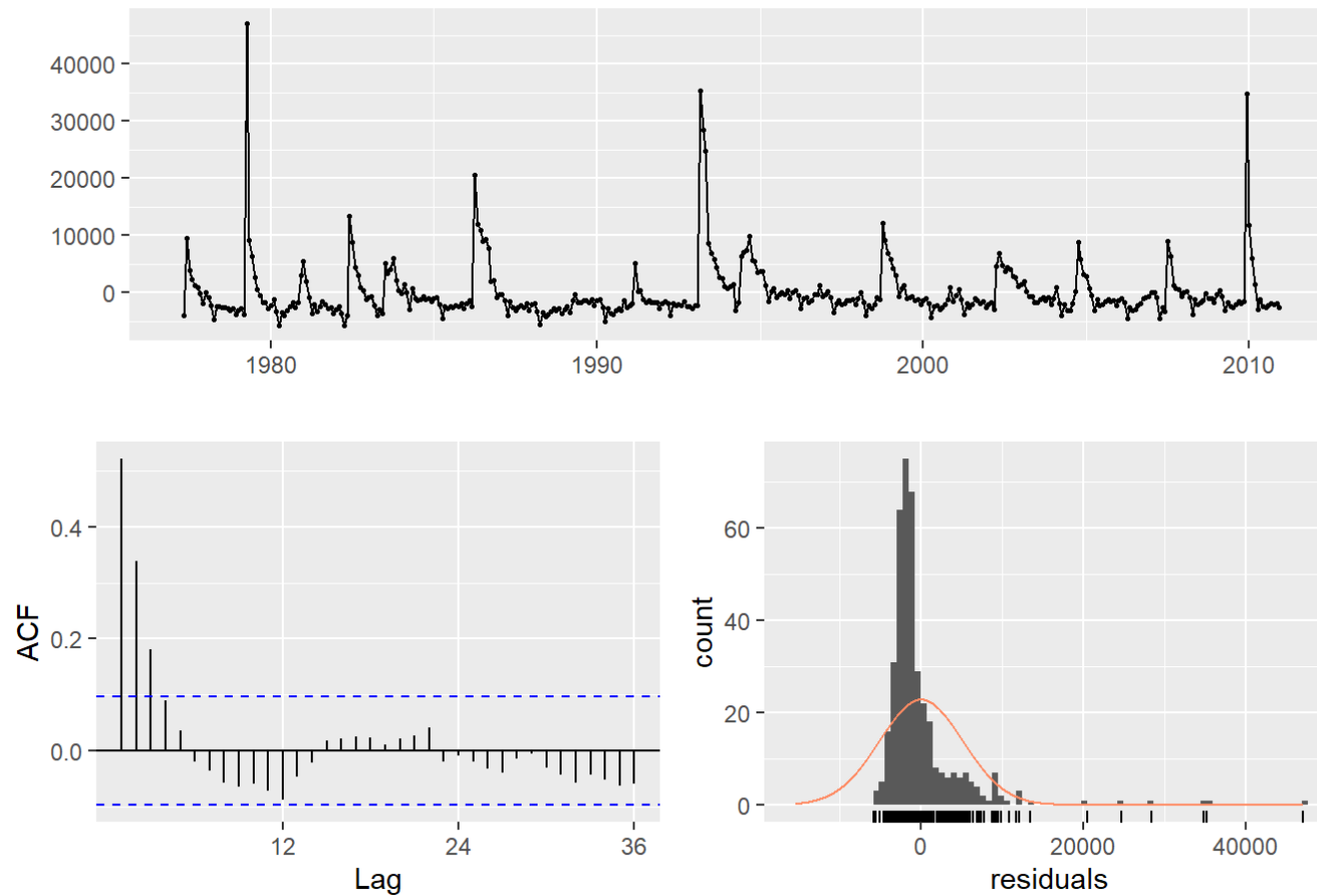
```
autoplot(mw_ts, series="initial") +  
  autolayer(fitted(fit.consMR), series="Fitted") +
```

```
xlab("Year") + ylab("Revenue") +  
ggtitle("Quarterly Revenue") +  
theme_bw()
```



```
checkresiduals(fit.consMR)
```

Residuals from Linear regression model



```
##  
## Breusch-Godfrey test for serial correlation of order up to 24  
##  
## data: Residuals from Linear regression model  
## LM test = 118.46, df = 24, p-value = 1.822e-14
```

```

h <- 10
fit.lin <- tslm(revenue ~ trend, data=df_ts)
fcasts.lin <- forecast(fit.lin, h = h)
fit.exp <- tslm(revenue ~ trend, data=df_ts, lambda = 0)
fcasts.exp <- forecast(fit.exp, h = h)

t <- time(mw_ts)
t.break1 <- 1970
t.break2 <- 1980
tb1 <- ts(pmax(0, t - t.break1), start = 1977)
tb2 <- ts(pmax(0, t - t.break2), start = 2008)

fit.pw <- tslm(revenue ~ t + tb1 + tb2, data=df_ts)
t.new <- t[length(t)] + seq(h)
tb1.new <- tb1[length(tb1)] + seq(h)
tb2.new <- tb2[length(tb2)] + seq(h)

newdata <- cbind(t=t.new, tb1=tb1.new, tb2=tb2.new) %>%
  as.data.frame()
fcasts.pw <- forecast(fit.pw, newdata = newdata)

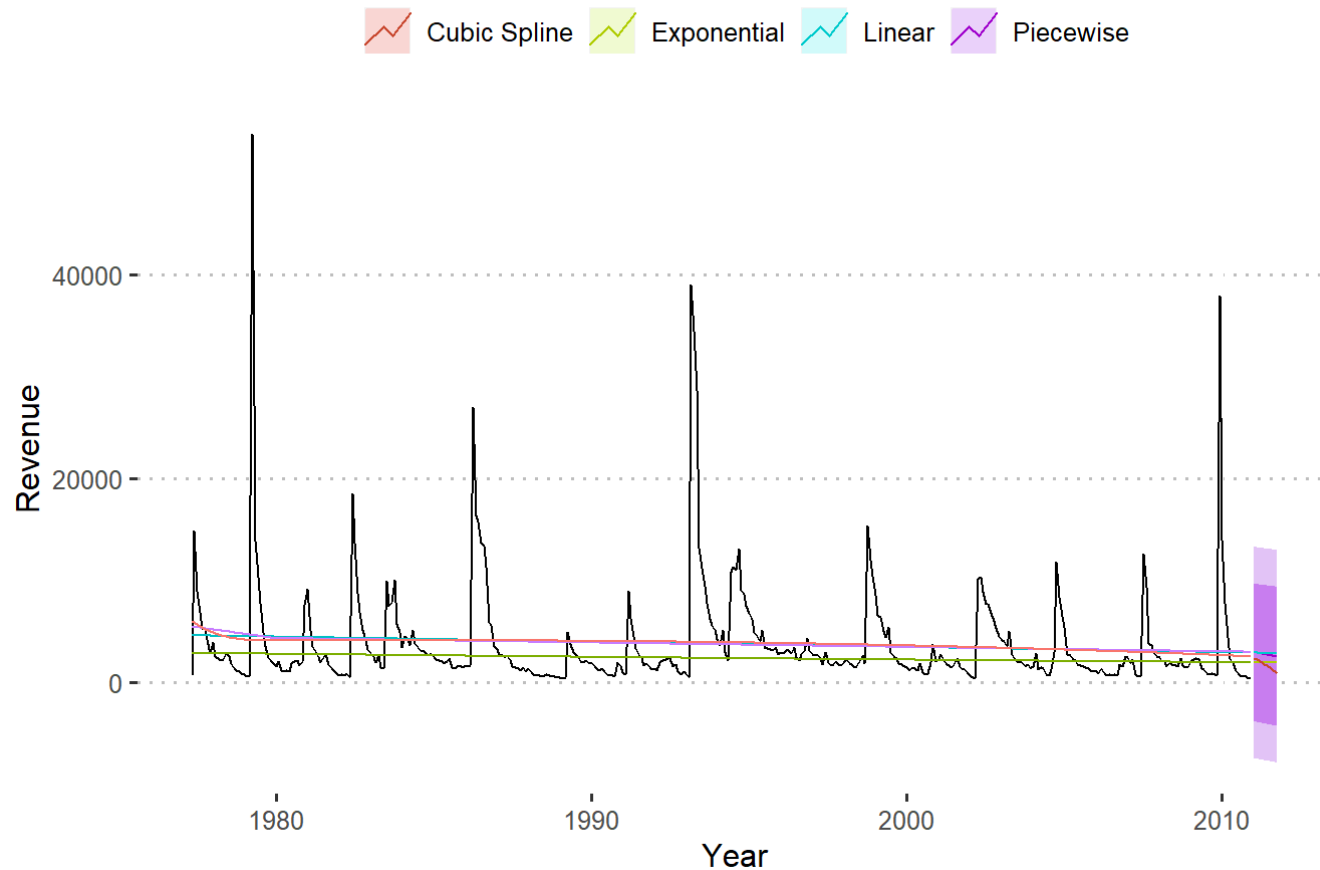
fit.spline <- tslm(revenue ~ t + I(t^2) + I(t^3) +
  I(tb1^3) + I(tb2^3), data=df_ts)
fcasts.spl <- forecast(fit.spline, newdata = newdata)

autoplot(mw_ts) +
  autolayer(fitted(fit.lin), series = "Linear") +
  autolayer(fitted(fit.exp), series = "Exponential") +
  autolayer(fitted(fit.pw), series = "Piecewise") +
  autolayer(fitted(fit.spline), series = "Cubic Spline") +
  autolayer(fcasts.pw, series="Piecewise") +
  autolayer(fcasts.lin, series="Linear", PI=FALSE) +
  autolayer(fcasts.exp, series="Exponential", PI=FALSE) +
  autolayer(fcasts.spl, series="Cubic Spline", PI=FALSE) +
  xlab("Year") + ylab("Revenue") +
  ggtitle("Cinemas' Revenue") +

```

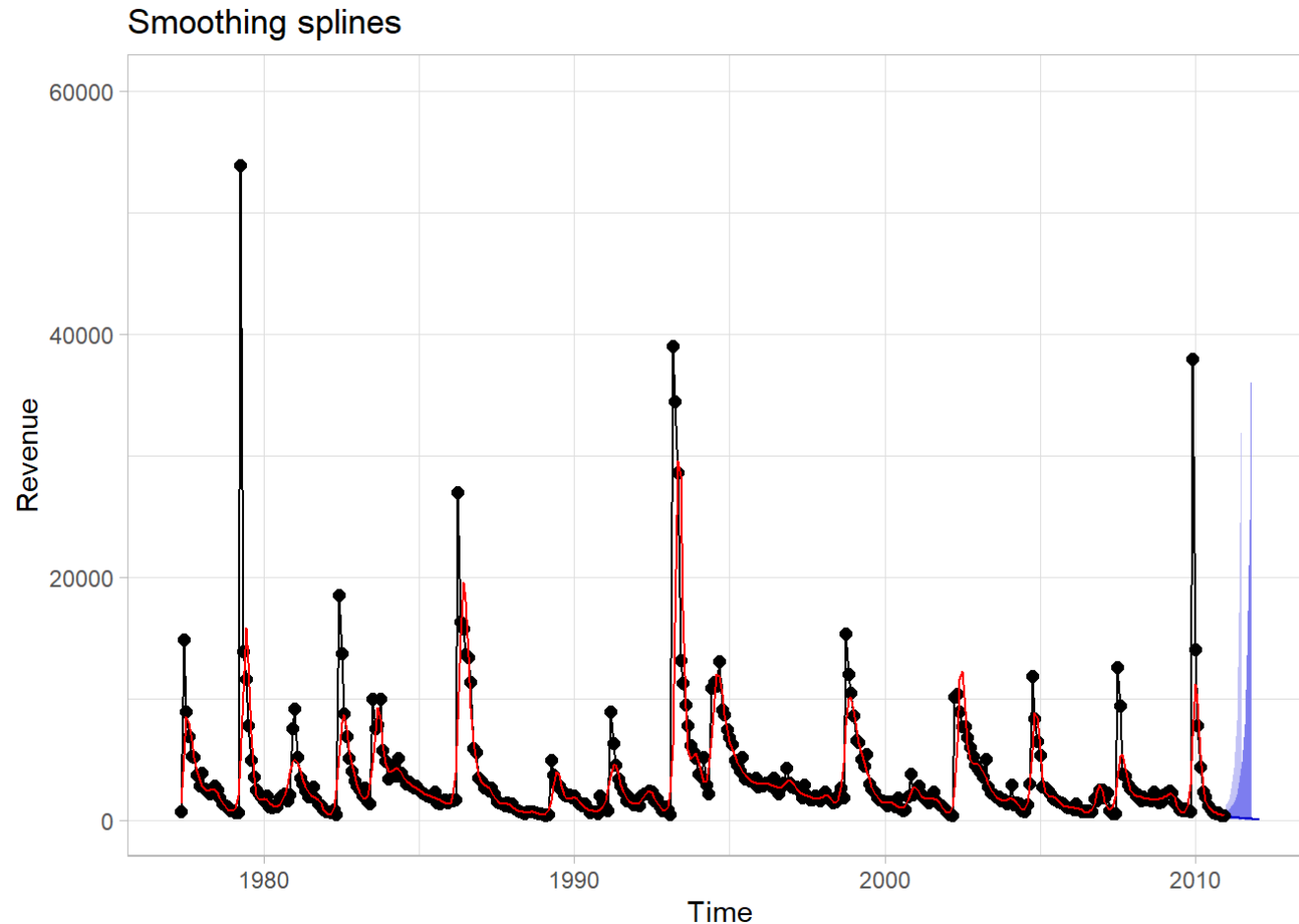
```
guides(colour = guide_legend(title = " ")) +  
theme_pubclean()
```

Cinemas' Revenue



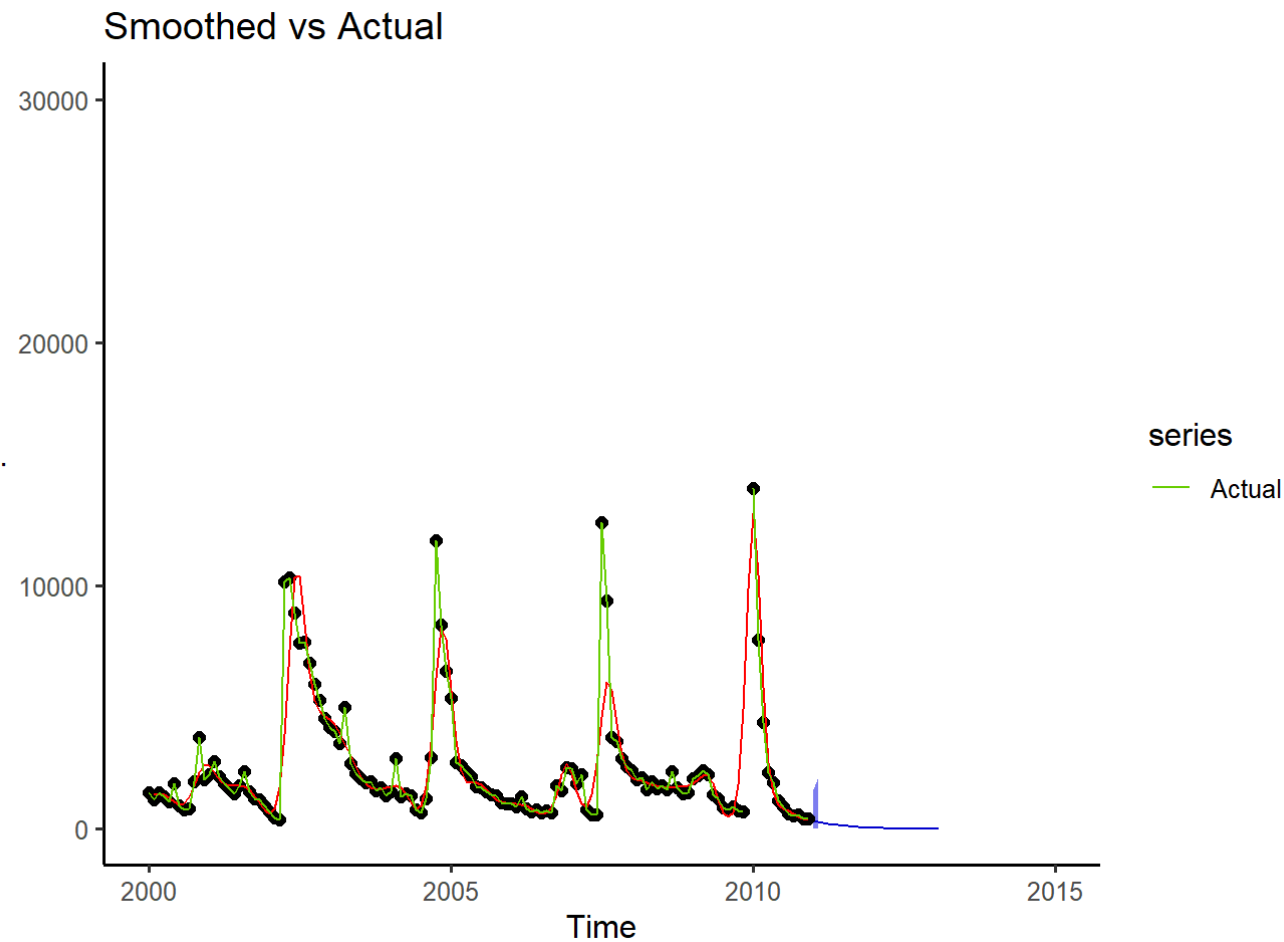
```
splinef(mw_ts, h=14, lambda=-0.05, method = "gcv") %>%  
  autoplot(ylim = c(0, 60000)) +  
  ylab("Revenue") +
```

```
ggtitle("Smoothing splines") +  
theme_light()
```



```
spl_pred <- predict(mw_ts %>% splinef(h=300, lambda=0.3), mw_ts)  
autoplot(spl_pred, ylim = c(0, 30000), xlim = c(2000, 2015)) +  
autolayer(mw_ts) +  
  scale_color_manual(labels = c("Actual", "Forecasted"),
```

```
values=c("chartreuse3", "darkred3")) +  
ggtitle("Smoothed vs Actual") +  
theme_classic2()
```

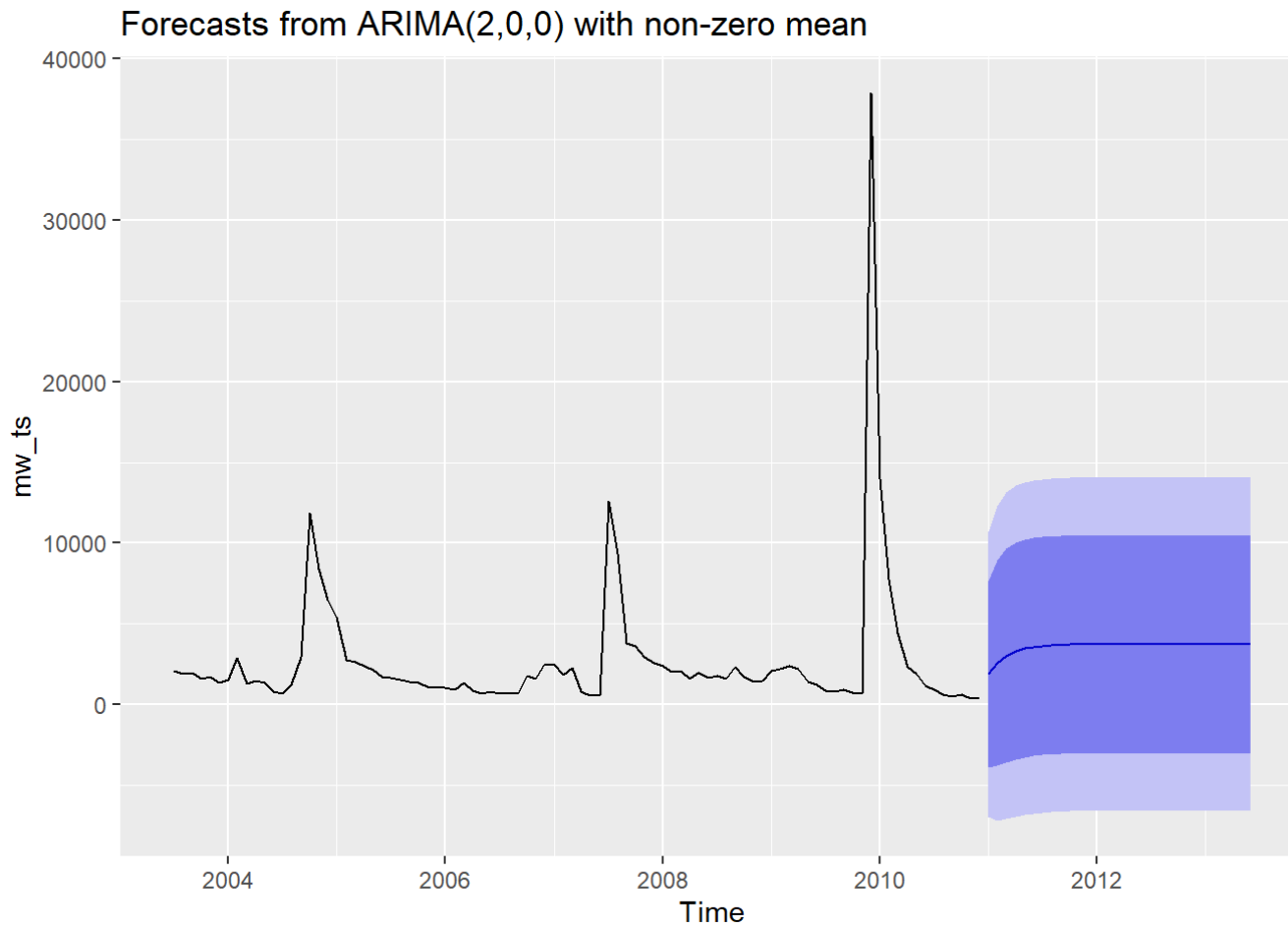


```
spl_model <- splinesf(mw_ts, h=300, lambda=-0.05, method = "gcv")  
accuracy(spl_pred)
```



```
##           ME      RMSE      MAE      MPE      MAPE      MASE      ACF1
## Training set -413.4282 6147.484 2264.153 -12.91916 38.25337 0.5645504 0.2593321
```

```
fit <- auto.arima(mw_ts, seasonal=TRUE)
fit %>% forecast(h=30) %>% autoplot(include=90)
```



Random Forest

```
model_data_tbl <-
  movie_weekend %>%
  mutate(trend      = 1:nrow(movie_weekend),
         trend_sqr   = trend^2,
         rev_lag_13  = lag(WEEKEND_PER_THEATER, n = 13),
         rev_lag_52  = lag(WEEKEND_PER_THEATER, n = 52),
         season      = case_when(WEEKEND_PER_THEATER == 0 ~ 0,
                                TRUE ~ 1)
  ) %>%
  filter(!is.na(rev_lag_52))

train_tbl <-
  model_data_tbl %>%
  filter(WEEKEND_DATE <= "2007-03-19")

test_tbl <-
  model_data_tbl %>%
  filter(WEEKEND_DATE >= "2006-10-02" &
         WEEKEND_DATE <= "2007-03-19")

train_tbl %>% head()
```

##	NUMBER	MOVIE	WEEK_NUM	WEEKEND_PER_THEATER	WEEKEND_DATE	trend	trend_sqr	rev_lag_13	rev_lag_52	season
n										
## 1	2	American Beauty	30	1731	2000-04-07	53	2809	1998	701	
1										
## 2	2	American Beauty	31	1341	2000-04-14	54	2916	2168	14820	
1										
## 3	2	American Beauty	32	1201	2000-04-21	55	3025	1614	8940	
1										

## 4	2 American Beauty	33	848	2000-04-28	56	3136	2047	6850
1								
## 5	2 American Beauty	34	711	2000-05-05	57	3249	7523	5280
1								
## 6	2 American Beauty	35	724	2000-05-12	58	3364	9185	5155
1								

```
h2o.init(max_mem_size = "8G")
```

```
## Connection successful!
##
## R is connected to the H2O cluster:
##   H2O cluster uptime:      6 minutes 29 seconds
##   H2O cluster timezone:    Europe/Helsinki
##   H2O data parsing timezone: UTC
##   H2O cluster version:    3.32.0.1
##   H2O cluster version age: 3 months and 1 day
##   H2O cluster name:       H2O_started_from_R_danie_xim214
##   H2O cluster total nodes: 1
##   H2O cluster total memory: 6.93 GB
##   H2O cluster total cores: 8
##   H2O cluster allowed cores: 8
##   H2O cluster healthy:    TRUE
##   H2O Connection ip:      localhost
##   H2O Connection port:    54321
##   H2O Connection proxy:   NA
##   H2O Internal Security:  FALSE
##   H2O API Extensions:     Amazon S3, Algos, AutoML, Core V3, TargetEncoder, Core V4
##   R Version:              R version 4.0.2 (2020-06-22)
```

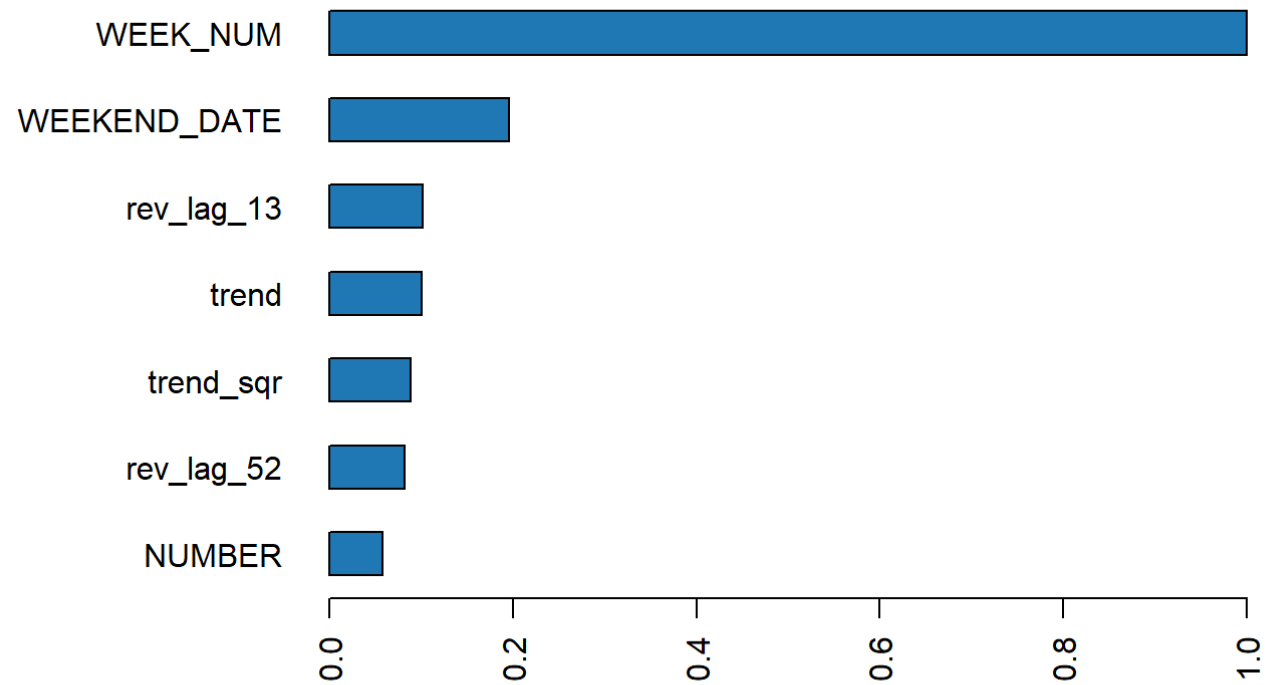
```
h2o.no_progress()
y <- "WEEKEND_PER_THEATER"
```

```
# predictors set: remove response variable and order_date from the set
x <- setdiff(names(train_tbl %>% as.h2o()), c(y, "weekend_date"))

rft_model <-
  h2o.randomForest(
    x = x,
    y = y,
    training_frame = train_tbl %>% as.h2o(),
    nfolds = 10,
    ntrees = 500,
    stopping_metric = "RMSE",
    stopping_rounds = 10,
    stopping_tolerance = 0.005,
    seed = 1975
  )

rft_model %>% h2o.varimp_plot()
```

Variable Importance: DRF



```
rft_model@model$model_summary
```

```
## Model Summary:
##  number_of_trees number_of_internal_trees model_size_in_bytes min_depth max_depth mean_depth min_leaves
## 1                42                   42          333989         18         20    19.88095         574
```

```
## max_leaves mean_leaves
## 1          660    628.61900
```

```
h2o.performance(rft_model, newdata = test_tbl %>% as.h2o())
```

```
## H2ORegressionMetrics: drf
##
## MSE: 178418.9
## RMSE: 422.3966
## MAE: 236.2163
## RMSLE: 0.3098941
## Mean Residual Deviance : 178418.9
```

```
rft_model %>% h2o.r2()
```

```
## [1] 0.7992146
```

Naive Bayes

```
splice <- h2o.uploadFile("C:/Users/danie/Downloads/movietotal-dat.txt", header = TRUE, na.strings = FALSE)

# Set the predictors and response; set the response as a factor:
splice$TYPE <- as.factor(splice$TYPE)
predictors <- c("MOVIE", "TOTAL")
response <- "TYPE"

# Build and train the model:
pros_nb <- h2o.naiveBayes(x = predictors,
                          y = response,
                          training_frame = splice,
```

```
        laplace = 0,  
        nfolds = 5,  
        seed = 1234)  
  
perf <- h2o.performance(pros_nb)  
pred <- h2o.predict(pros_nb, newdata = splice)  
pros_nb %>% h2o.r2()
```

```
## [1] 0.7761132
```