In OSIC Pulmonary Fibrosis Progression competition
on Kaggle, participants are tasked to determine the likelihood of recovery (**prognosis**) of several
patients affected by a lung disease. For each patient, the maximum volume of air they can exhale after a maximum inhalation (**FVC**, Forced Vital Capacity) is measured over the weeks, for approximately 1-2 years of time.

In addition, we have the following information about these people:

- A **chest computer scan** obtained at time `Week=0`
- Their **age**
- Their **sex**
- Their **smoking status**: currently smokes, ex-smoker, never smoked

The challenge is to **assess the lung function's health by forecasting the FVC** (I'm not asking myself here, if it's the good or bad way to do that). What I like about this competition, is that there are **many ways to approach it**. Here's a non-exhaustive list:

1.One way could be to **construct a Statistical/Machine Learning (ML) model on the whole dataset**, and study the (conditional) distribution of the FVC, knowing the scan, age,
sex, and smoking status. In this first approach we consider that disease evolution can be generalized
among categories of patients sharing the same patterns. A Bayesian ML model could capture the uncertainty around predictions, or we
could use a more or less sophisticated bootstrapping procedure for the same purpose. Or, even, consider that ML model residuals are irregularly spaced time series.

2.Another way, the *quick and dirty* one I'll present here, **considers each patient's case individually**. Age, sex, smoking status and
the chest scan are not used, but the measurement week is. If we are only interested in forecasting the **FVC**, the approach will be fine. But if we want to understand how
each one of the factors we previously described influence the FVC, either individually or in conjunction, then the first approach is better.

0 – Functions

These are the functions that I use in the analysis. The first one extracts a patient's information from the whole database, based on his/her identifier. The second one fits a smoothing spline to a patient's data, and forecasts his/her FVC.

get patient data

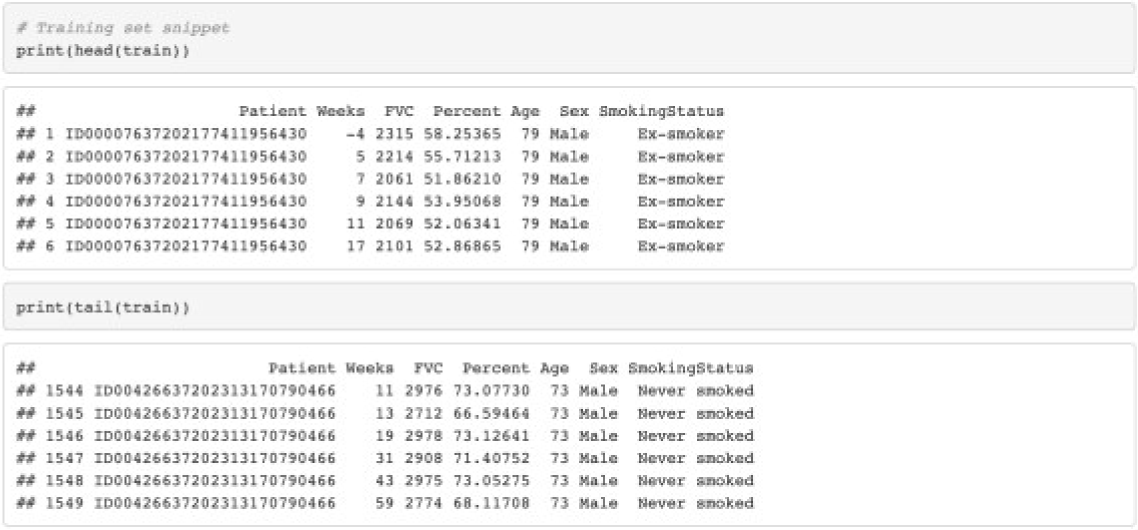
```
suppressPackageStartupMessages(library(dplyr))

# 0 - 1 get patient data -----
get_patient_data <- function(id, train)
{
  df <- dplyr::select(dplyr::filter(train, Patient == id), c(Weeks,
FVC))
  df$log_Weeks <- log(13 + df$Weeks) # the relative timing of FVC
measurements (varies widely)
  df$log_FVC <- log(df$FVC) # transformed response variable
  df$Patient <- id
  return(df)
}
```

fit and forecast FVC

```
# 0 - 2 fit, predict and plot -----
fit_predict <- function(df, plot_=TRUE)
{
  min_week <- 13
  n <- nrow(df)

  test_seq_week <- seq(-12, 133)
  log_test_seq_week <- log(min_week + test_seq_week)


    # Fit a smoothing spline, using Leave-one-out cross-validation for
regularization
    fit_obj <- stats::smooth.spline(x = df$log_Weeks,
                                    y = df$log_FVC,
                                    cv = TRUE)

    resids <- residuals(fit_obj)
    mean_resids <- mean(resids)
    conf <- max(exp(sd(resids)), 70) # https://www.kaggle.com/c/osic-pulmonary-
fibrosis-progression/overview/evaluation

    preds <- predict(fit_obj, x=log_test_seq_week)

    res <- list(Weeks_pred = test_seq_week, FVC_pred = exp(preds$y))
    conf_sqrt_n <- conf/sqrt(n)
    ubound <- res$FVC_pred + mean_resids + 1.96*conf_sqrt_n # strong
hypothesis
    lbound  <- res$FVC_pred + mean_resids - 1.96*conf_sqrt_n


  if (plot_)
  {
    leg.txt <- c("Measured FVC", "Interpolated/Extrapolated FVC", "95%
Confidence interval bound")

    plot(df$Weeks, df$FVC, col="blue", type="l", lwd=3,
         xlim = c(-12, 133),
         ylim = c(min(min(lbound), min(df$FVC)),
                  max(max(ubound), max(df$FVC)) ),
         xlab = "Week", ylab = "FVC",
         main = paste0("Patient: ", df$Patient[1]))
    lines(res$Weeks_pred, res$FVC_pred)
    lines(res$Weeks_pred, ubound, lty=2, col="red")
    lines(res$Weeks_pred, lbound, lty=2, col="red")
    abline(v = max(df$Weeks), lty=2)
    legend("bottomright", legend = leg.txt,
          lwd=c(3, 1, 1), lty=c(1, 1, 2),
          col = c("blue", "black", "red"))
  }

  return(invisible(list(res = res,
              conf = rep(conf, length(res$FVC_pred)),
              mean = res$FVC_pred,
              ubound = ubound,
              lbound = lbound,
              resids = resids)))
}
```

1 - Import the whole dataset

```
# Training set data
train <- read.csv("~/Documents/Kaggle/OSIC_August2020/train.csv")

# Training set snippet
print(head(train))
print(tail(train))
```



```
# Training set snippet
print(head(train))
```

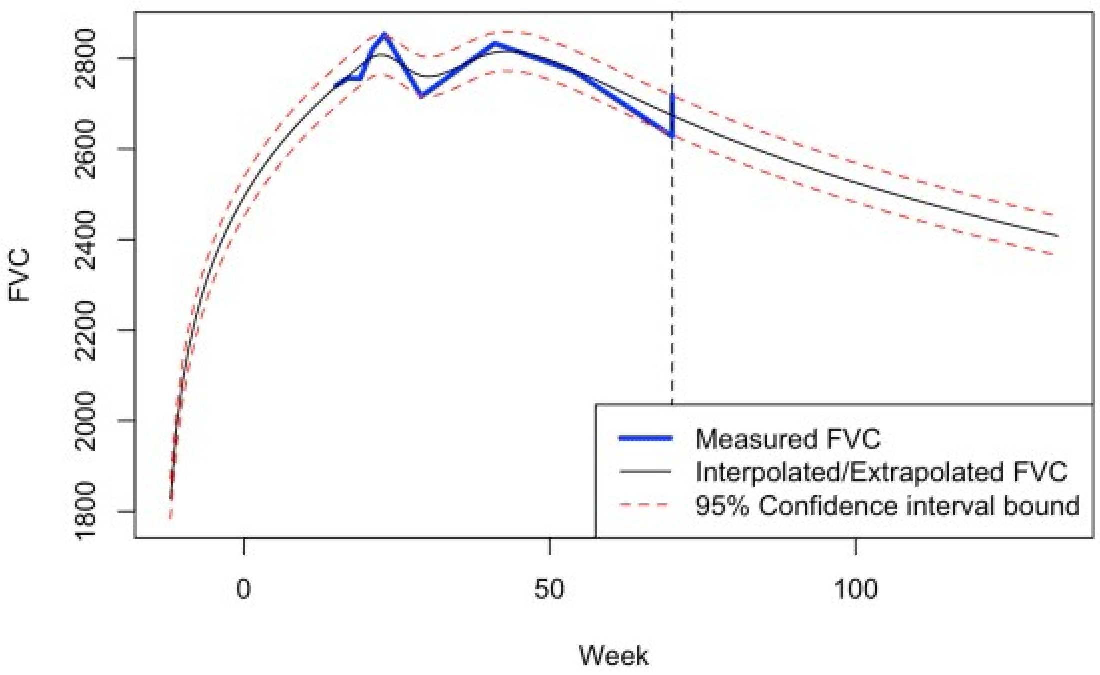
```
##                        Patient Weeks  FVC  Percent Age  Sex SmokingStatus
## 1 ID00007637202177411956430    -4 2315 58.25365  79 Male     Ex-smoker
## 2 ID00007637202177411956430     5 2214 55.71213  79 Male     Ex-smoker
## 3 ID00007637202177411956430     7 2061 51.86210  79 Male     Ex-smoker
## 4 ID00007637202177411956430     9 2144 53.95068  79 Male     Ex-smoker
## 5 ID00007637202177411956430    11 2069 52.06341  79 Male     Ex-smoker
## 6 ID00007637202177411956430    17 2101 52.86865  79 Male     Ex-smoker
```

```
print(tail(train))
```

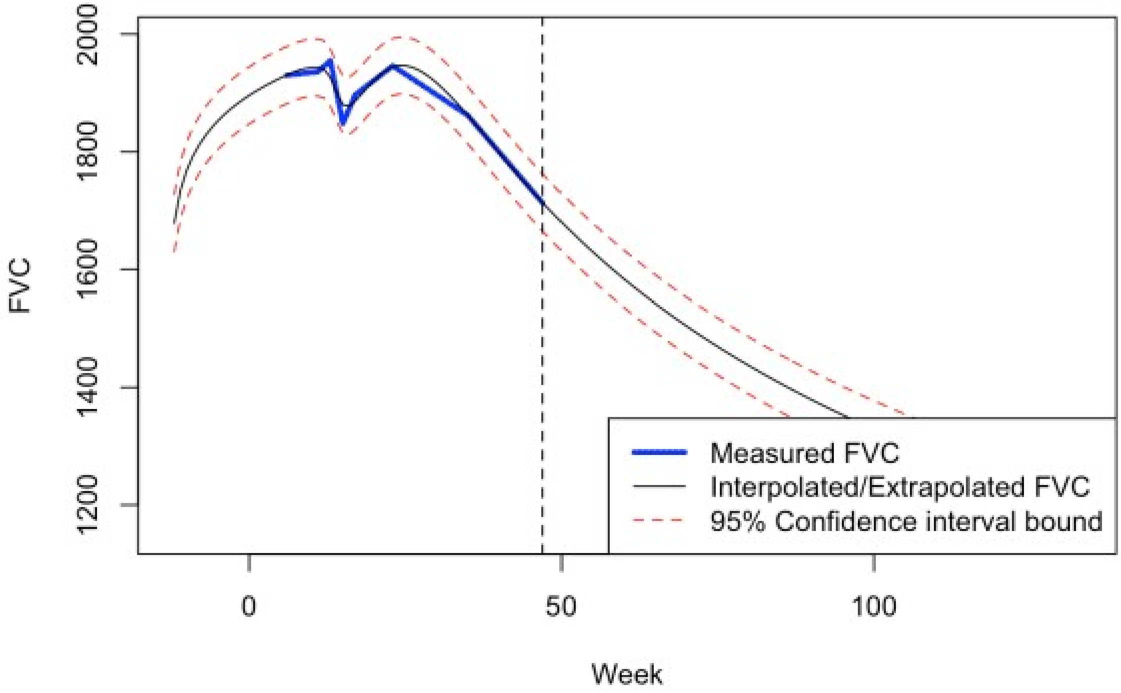
```
##                           Patient Weeks  FVC  Percent Age  Sex SmokingStatus
## 1544 ID00426637202313170790466    11 2976 73.07730  73 Male  Never smoked
## 1545 ID00426637202313170790466    13 2712 66.59464  73 Male  Never smoked
## 1546 ID00426637202313170790466    19 2978 73.12641  73 Male  Never smoked
## 1547 ID00426637202313170790466    31 2908 71.40752  73 Male  Never smoked
## 1548 ID00426637202313170790466    43 2975 73.05275  73 Male  Never smoked
## 1549 ID00426637202313170790466    59 2774 68.11708  73 Male  Never smoked
```

2 - Predict FVC for a few patients (4)

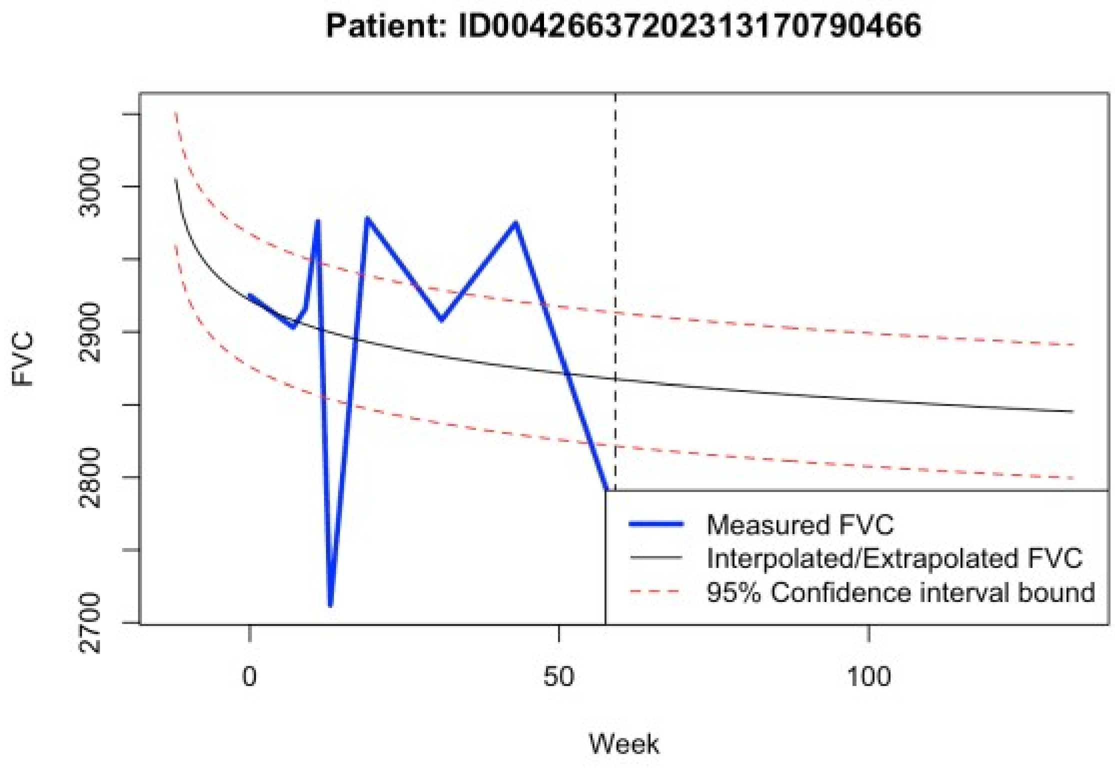
```
# Four patient ids are selected
ids <- c("ID00421637202311550012437", "ID00422637202311677017371",
         "ID00426637202313170790466", "ID00248637202266698862378")

#par(mfrow=c(2, 2))
for(i in 1:length(ids))
{
  # Extract patient's data based on his/her ID
  (df <- get_patient_data(id=ids[i], train))
  # Obtain FVC forecasts, with 95% confidence interval
  # warnings when repeated measures in the same week
  suppressWarnings(fit_predict(df, plot_=TRUE))
}
```

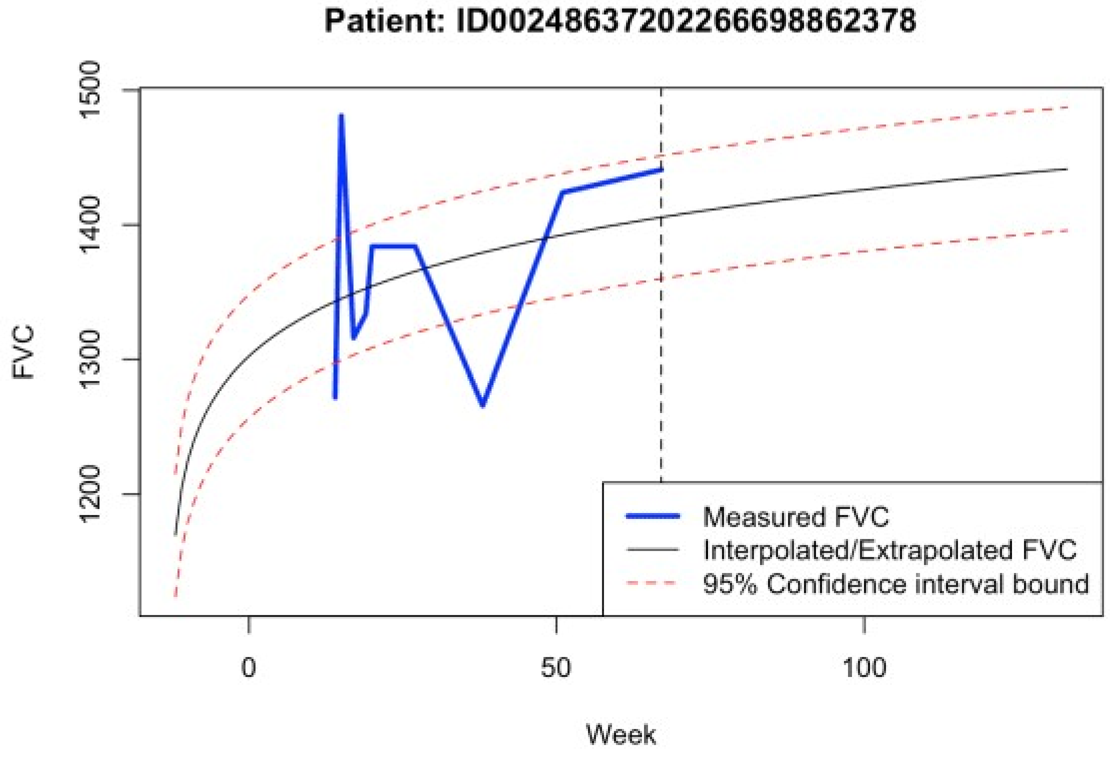


Patient: ID00421637202311550012437



Patient: ID00422637202311677017371





For a *quick and dirty* baseline model, this one seems to produce quite coherent forecasts, which could be used for decision making. Of course, validation data (unseen by the model) could reveal a whole different truth.