Data-driven modelling in a nut shell

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Summer school 2023:

Time Series Analysis - with a focus on Modelling and Forecasting in Energy Systems

- **Statistics** is the discipline that concerns the collection, organization, displaying, analysis, interpretation and presentation of data.
- Machine learning is the scientific study of algorithms and statistical models that computer systems use to perform a specific task without using explicit instructions, relying on patterns and inference instead.

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• Maybe what we do in the course: "data-driven modelling for energy engineering"

Depends on the application

- What is the objective:
 - learning about a phenomena, e.g. performance estimation
 - predictions
 - control
- Model structure from prior knowledge?
- Which data is at hand!

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ARMAX, SDE, grey-box: basically some Kalman filter is behind!

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Each technique have different pros and cons. Depends on the application, data, ...

Plot, plot, plot

- Get insights by plotting, it's really the best way to understand your data...of course everything cannot be seen, but be creative!
- Plot all data and plot interesting details

Plots and base R functions

- Scatter plots (plot, pairs)
- Histograms (hist) and box-plots (boxplot)
- Time series plots (ts.plot), ACF (acf), CCF (ccf)

Model selection and the bias-variance tradeoff

We want to find a *suitable model* – the model which is neither too simple (under-fitted) nor too complex (over-fitted):

- Divide the data into a training set and a test set
- Define a fit score (smaller is better e.g. summed squared error)

Under-fitted + Suitable -+ Over-fitted High bing High variance Fit score Test set Training set Model complexity (number of parameters)

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- Information criteria (AIC, BIC)
- Goodness of fit test (likelihood-ratio test, F-test)
- Cross-validation technique (n-fold CV)

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Model selection procedure

- Forward selection (start with a small model and extend)
- Backward selection (start with a large model and remove)

Model validation (use also while finding a model)

After fitting the model then analyse the residuals

If no patterns are left, hence we have white noise residual, then we are done!

Residuals analysis

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- Time series plots of residuals aligned with input series
- Scatter plots of residuals vs. inputs
- ACF and CCF

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Forward selection

Fit a simple model, analyse the residuals: Can you see some patterns left related to some inputs? Improve the model and repeat...

- Good approach for modelling with new data
- Good approach for articles (you get a story)

Well, with experience it helps, but it's never trivial!!

I think it can be challenging because of:

- Know the techniques
- Many choices to make!
- When is the model good enough!?
- We tend to make too complex models
- More like missing data, poor resolution, ...

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Let's help each other!

R intro

Quick tour around in RStudio and R

Open RStudio

R basics

The workflow in R is to apply functions on data variables

```
## A data.frame has attributes in addition to its value
X <- data.frame(col1=1:10, col2=10:1)</pre>
х
## The variables has attributes (X is basically a list)
attributes(X)
## You can add attributes
attr(X, "element1") <- "value1"</pre>
attributes(X)
## Change the column names
names(X) <- c("a", "b")
Х
## Check its class
class(X)
## Define a function (sum squared)
ss <- function(x) { sum(x^2) }
## Apply the function on each row
apply(X, 1, ss)
## or column
apply(X, 2, ss)
```

R basics

The list class is good (everything actually either a list or function in R)

```
L <- list()
## Put in everything you like
L$X <- X
L$vext <- "Helle"
L$value <- 3
L
## Apply a function on each element
lapply(L, class)
## Load a package (more on R packages later)
require(parallel)
## Do this using all the cores of the processor
mclapply(L, class)</pre>
```

R packages (more than 10000 on cran!)

Popular packages:

- Great plotting: ggplot2 and plotly
- Working with really large datasets: data.table
- Making browser apps: shiny
- Integrate c++ code easily: Rcpp
- Use Python in R or R in Python: Several R and Python packages

We will use different packages in the exercises

```
install.packages("Rcpp")
```

Search in R packages https://www.r-pkg.org/, try "splines" and "kernels"

R nice to know and tips

- Matlab R reference guide https://cran.r-project.org/doc/contrib/Hiebeler-matlabR.pdf
- Debugging:
 - browser() and traceback()
 - Easy in RStudio to set breakpoint

R nice to know and tips

Speed issues

- For-loops can be really slow
- Testing speed:

```
## install.packages("microbenchmark")
library(microbenchmark)
x <- numeric(100)
microbenchmark(
    for(i in 1:100){x[i] <- i},
    sapply(1:100, function(i){ return(i) }),
    times=100
)</pre>
```

• If possible use apply functions, if recursive write it in c++

Install the ctsmr package

Tomorrow we will use the $\mathtt{ctsmrTMB}$ package and Thursday the onlineforecast package

If you did not install the *ctsmrTMB* package, do it today to check it works: See instructions on https://github.com/phillipbvetter/ctsmrTMB.

Tomorrow Phillip who is making the package will present it!