Model Transportability and Privacy Protection

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Aim of this talk

The goal of this talk is to give you insights about our findings when using predictive/statistical/prognostic models in private settings:

1. Definition of the problem.
2. Transportable models and the practical situation.
3. Guideline to build transportable models.

Practical problems of model building

- Starting point: Development of a treatment decision score for newly diagnosed patients using a clinical data set (ProVal-MS study in DIFUTURE, https://difuture.de/, DRKS: 00014034)
- The model: We choosed a random forest [1] variant called transformation forest [3] implemented in the R [4] function `traforest` of the package `trtf` [2].
- The problem: After developing a potential model we recognized that we cannot publish the model or share it with other researchers because the data set was attached to the R object at multiple locations.

⇒ How to deal with these situations and ensure models to not publish privacy protected information?

Model transportability - theoretically

- A model $\hat{f}$ is the result of a learning algorithm a applied to training data $\mathcal{D}$ to estimate an underlying functional dependency f between a response variable y and input features x:

$$\hat{f} = a(\mathcal{D}), \quad \hat{y} = \hat{f}(x)$$

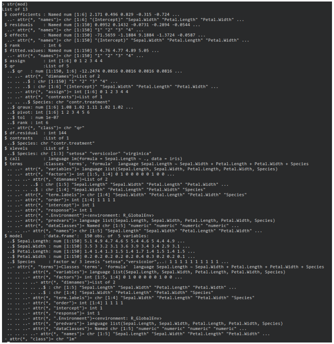
- After the training step, the model is defined by its estimated model parameters $\hat{\theta}$. E.g. the linear model simply equates a linear combination:

$$\hat{f}(x) = x^T\hat{\theta}$$

$\Rightarrow$ After training a model, the training data $\mathcal{D}$ is (in most cases) no longer needed. An exception, for example, is k-NN.

Model transportability - in practise i

- Most R models are storing the data at some place, e.g. creating a linear model with the iris data and looking at the structure (with `str`) reveals much more then just the model parameters:



```
> str(mod)
List of 13
 $ coefficients : Named num [1:6] 2.171 0.496 0.829 -0.315 -0.724 ...
  ..- attr(*, "names")= chr [1:6] "(Intercept)" "Sepal.Width" "Petal.Length" "Petal.Width" ...
 $ residuals    : Named num [1:150] 0.0952 0.1432 -0.0731 -0.2894 -0.0544 ...
  ..- attr(*, "names")= chr [1:150] "1" "2" "3" "4" ...
 $ effects      : Named num [1:150] -71.5659 -1.1884 9.1884 -1.3724 -0.0587 ...
  ..- attr(*, "names")= chr [1:150] "(Intercept)" "Sepal.Width" "Petal.Length" "Petal.Width" ...
 $ rank         : int 6
 $ fitted.values: Named num [1:150] 5 4.76 4.77 4.89 5.05 ...
  ..- attr(*, "names")= chr [1:150] "1" "2" "3" "4" ...
 $ assign       : int [1:6] 0 1 2 3 4 4
 $ qr           :List of 5
  ..$ qr   : num [1:150, 1:6] -12.2474 0.0816 0.0816 0.0816 0.0816 ...
  .. ..- attr(*, "dimnames")=List of 2
  .. .. ..$ : chr [1:150] "1" "2" "3" "4" ...
  .. .. ..$ : chr [1:6] "(Intercept)" "Sepal.Width" "Petal.Length" "Petal.Width" ...
  .. ..- attr(*, "assign")= int [1:6] 0 1 2 3 4 4
  .. ..- attr(*, "contrasts")=List of 1
  .. .. ..$ Species: chr "contr.treatment"
  ..$ qraux: num [1:6] 1.08 1.02 1.11 1.02 1.02 ...
  ..$ pivot: int [1:6] 1 2 3 4 5 6
  ..$ tol  : num 1e-07
  ..$ rank : int 6
  ..- attr(*, "class")= chr "qr"
 $ df.residual  : int 144
 $ contrasts    :List of 1
  ..$ Species: chr "contr.treatment"
 $ xlevels      :List of 1
  ..$ Species: chr [1:3] "setosa" "versicolor" "virginica"
 $ call         : language lm(formula = Sepal.Length ~ ., data = iris)
 $ terms        :Classes 'terms', 'formula'  language Sepal.Length ~ Sepal.Width + Petal.Length + Petal.Width + Species
  .. ..- attr(*, "variables")= language list(Sepal.Length, Sepal.Width, Petal.Length, Petal.Width, Species)
  .. ..- attr(*, "factors")= int [1:5, 1:4] 0 1 0 0 0 0 0 1 0 0 ...
  .. .. ..- attr(*, "dimnames")=List of 2
  .. .. .. ..$ : chr [1:5] "Sepal.Length" "Sepal.Width" "Petal.Length" "Petal.Width" ...
  .. .. .. ..$ : chr [1:4] "Sepal.Width" "Petal.Length" "Petal.Width" "Species"
  .. ..- attr(*, "term.labels")= chr [1:4] "Sepal.Width" "Petal.Length" "Petal.Width" "Species"
  .. ..- attr(*, "order")= int [1:4] 1 1 1 1
  .. ..- attr(*, "intercept")= int 1
  .. ..- attr(*, "response")= int 1
  .. ..- attr(*, ".Environment")=<environment: R_GlobalEnv>
  .. ..- attr(*, "predvars")= language list(Sepal.Length, Sepal.Width, Petal.Length, Petal.Width, Species)
  .. ..- attr(*, "dataClasses")= Named chr [1:5] "numeric" "numeric" "numeric" "numeric" ...
  .. .. ..- attr(*, "names")= chr [1:5] "Sepal.Length" "Sepal.Width" "Petal.Length" "Petal.Width" ...
 $ model        :'data.frame':  150 obs. of  5 variables:
  ..$ Sepal.Length: num [1:150] 5.1 4.9 4.7 4.6 5 5.4 4.6 5 4.4 4.9 ...
  ..$ Sepal.Width : num [1:150] 3.5 3 3.2 3.1 3.6 3.9 3.4 3.4 2.9 3.1 ...
  ..$ Petal.Length: num [1:150] 1.4 1.4 1.3 1.5 1.4 1.7 1.4 1.5 1.4 1.5 ...
  ..$ Petal.Width : num [1:150] 0.2 0.2 0.2 0.2 0.2 0.4 0.3 0.2 0.2 0.1 ...
  ..$ Species     : Factor w/ 3 levels "setosa","versicolor",..: 1 1 1 1 1 1 1 1 1 1 ...
  ..- attr(*, "terms")=Classes 'terms', 'formula'  language Sepal.Length ~ Sepal.Width + Petal.Length + Petal.Width + Species
  .. .. ..- attr(*, "variables")= language list(Sepal.Length, Sepal.Width, Petal.Length, Petal.Width, Species)
  .. .. ..- attr(*, "factors")= int [1:5, 1:4] 0 1 0 0 0 0 0 1 0 0 ...
  .. .. .. ..- attr(*, "dimnames")=List of 2
  .. .. .. .. ..$ : chr [1:5] "Sepal.Length" "Sepal.Width" "Petal.Length" "Petal.Width" ...
  .. .. .. .. ..$ : chr [1:4] "Sepal.Width" "Petal.Length" "Petal.Width" "Species"
  .. .. ..- attr(*, "term.labels")= chr [1:4] "Sepal.Width" "Petal.Length" "Petal.Width" "Species"
  .. .. ..- attr(*, "order")= int [1:4] 1 1 1 1
  .. .. ..- attr(*, "intercept")= int 1
  .. .. ..- attr(*, "response")= int 1
  .. .. ..- attr(*, ".Environment")=<environment: R_GlobalEnv>
  .. .. ..- attr(*, "predvars")= language list(Sepal.Length, Sepal.Width, Petal.Length, Petal.Width, Species)
  .. .. ..- attr(*, "dataClasses")= Named chr [1:5] "numeric" "numeric" "numeric" "numeric" ...
  .. .. .. ..- attr(*, "names")= chr [1:5] "Sepal.Length" "Sepal.Width" "Petal.Length" "Petal.Width" ...
 - attr(*, "class")= chr "lm"
```

Figure 1: Structure of an R `lm` object.

Model transportability - in practise ii

- Here, the data is directly stored in the `$model` slot:

```
$ model        :'data.frame':  150 obs. of  5 variables:
 ..$ Sepal.Length: num [1:150] 5.1 4.9 4.7 4.6 5 5.4 4.6 5 4.4 4.9 ...
 ..$ Sepal.Width : num [1:150] 3.5 3 3.2 3.1 3.6 3.9 3.4 3.4 2.9 3.1 ...
 ..$ Petal.Length: num [1:150] 1.4 1.4 1.3 1.5 1.4 1.7 1.4 1.5 1.4 1.5 ...
 ..$ Petal.Width : num [1:150] 0.2 0.2 0.2 0.2 0.2 0.4 0.3 0.2 0.2 0.1 ...
 ..$ Species     : Factor w/ 3 levels "setosa","versicolor",..: 1 1 1 1 1 1 1 1 1 1 ...
 ..- attr(*, "terms")=Classes 'terms', 'formula'  language Sepal.Length ~ Sepal.Width + Petal.Length + Petal.Width + Species
 .. .. ..- attr(*, "variables")= language list(Sepal.Length, Sepal.Width, Petal.Length, Petal.Width, Species)
 .. .. ..- attr(*, "factors")= int [1:5, 1:4] 0 1 0 0 0 0 0 1 0 0 ...
 .. .. .. ..- attr(*, "dimnames")=List of 2
 .. .. .. .. ..$ : chr [1:5] "Sepal.Length" "Sepal.Width" "Petal.Length" "Petal.Width" ...
 .. .. .. .. ..$ : chr [1:4] "Sepal.Width" "Petal.Length" "Petal.Width" "Species"
 .. .. ..- attr(*, "term.labels")= chr [1:4] "Sepal.Width" "Petal.Length" "Petal.Width" "Species"
 .. .. ..- attr(*, "order")= int [1:4] 1 1 1 1
 .. .. ..- attr(*, "intercept")= int 1
 .. .. ..- attr(*, "response")= int 1
 .. .. ..- attr(*, ".Environment")=<environment: R_GlobalEnv>
 .. .. ..- attr(*, "predvars")= language list(Sepal.Length, Sepal.Width, Petal.Length, Petal.Width, Species)
 .. .. ..- attr(*, "dataClasses")= Named chr [1:5] "numeric" "numeric" "numeric" "numeric" ...
 .. .. .. ..- attr(*, "names")= chr [1:5] "Sepal.Length" "Sepal.Width" "Petal.Length" "Petal.Width" ...
- attr(*, "class")= chr "lm"
```

Figure 2: Structure of an R `lm` object.

- **But**, parts of the data, the response variable $y = \hat{y} + \hat{\varepsilon}$, can be recreated by accessing the fitted values $\hat{y}$ (`$fitted.values`) and the residuals $\hat{\varepsilon}$ (`$residuals`):

Model transportability - in practise iii

```
> str(mod)
List of 13
 $ coefficients : Named num [1:6] 2.171 0.496 0.829 -0.315 -0.724 ...
  ..- attr(*, "names")= chr [1:6] "(Intercept)" "Sepal.Width" "Petal.Length" "Petal.Width" ...
 $ residuals    : Named num [1:150] 0.0952 0.1432 -0.0731 -0.2894 -0.0544 ...
  ..- attr(*, "names")= chr [1:150] "1" "2" "3" "4" ...
 $ effects      : Named num [1:150] -71.5659 -1.1884 9.1884 -1.3724 -0.0587 ...
  ..- attr(*, "names")= chr [1:150] "(Intercept)" "Sepal.Width" "Petal.Length" "Petal.Width" ...
 $ rank         : int 6
 $ fitted.values: Named num [1:150] 5 4.76 4.77 4.89 5.05 ...
  ..- attr(*, "names")= chr [1:150] "1" "2" "3" "4" ...
 $ assign       : int [1:6] 0 1 2 3 4 4
 $ qr           :List of 5
```

Figure 3: Structure of an R `lm` object.

⇒ Not just the data, but also everything that enables a recalculation of the data set or parts of it leads to privacy breaches.

How to fix this problem?

Solution 1: Remove crucial parts from the object.

$\Rightarrow$ Sometimes data is hidden at various locations.

Solution 2: Re-implement the algorithm.

$\Rightarrow$ Takes too much time for complex algorithms.

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Solution 1: Remove crucial parts from the object.

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Solution 2: Re-implement the algorithm.

$\Rightarrow$ Takes too much time for complex algorithms.

We will focus on solution 1.

Challenges when removing data

- Nested data structures. Sometimes, a method depends on another method and hence stores data in each of these sub-objects. E.g. the `traforest` implementation uses other `R` objects such as `lm` objects.
- Method to calculate predictions sometimes depends on the data.
- Sometimes transformations of the data are stored. Cholesky decomposition, SVD, or QU decomposition from which original data can be recreated.

$\Rightarrow$ Each method and the resulting object requires an extensive investigation of its structure.

Model transportability - example `traforest`

Making a `traforest` object transportible requires to remove all data:

```
> tf_cmod = trtf::traforest(m, formula = y ~ horTh | age, control = ctrl,
+   ntree = 50, mtry = 1, trace = TRUE, data = GBSG2)
  |======================================================================| 100%
>
> tf_cmod$data = NULL
> tf_cmod$info$model$model = NULL
> tf_cmod$info$call$data = NULL
> tf_cmod$fitted = NULL
> tf_cmod$mltobj$object$data = NULL
```

Figure 4: Training of a `traforest` model and removing all the data from the object.

Model transportability - example `traforest`

Trying to predict with this data-free object throws an error:

```
> tf_cmod = trtf::traforest(m, formula = y ~ horTh | age, control = ctrl,
+   ntree = 50, mtry = 1, trace = TRUE, data = GBSG2)
  |======================================================================| 100%
>
> tf_cmod$data = NULL
> tf_cmod$info$model$model = NULL
> tf_cmod$info$call$data = NULL
> tf_cmod$fitted = NULL
> tf_cmod$mltobj$object$data = NULL
> predict(tf_cmod, newdata = GBSG2)
Error in 1:ncol(nd) : argument of length 0
```

Figure 5: Predicting a `traforest` object after removing all data.

- We have to adjust the predict function to get predictions with a transportable `traforest` object.
- Even worse, for the `traforest` we also have to adjust the train method.

How did we fix that issue?

- Carefully searching for data in an object is mandatory:
    - First overview over the structure of an object using the `str` command.
    - We designed an R package called `rmmodeldata` (`github.com/difuture-lmu/rmmodeldata`) to search through an object to detect numbers. Use this method to search for individual numbers of the original data.
    - Always ask yourself if there are transformations of the original data and try to get detailed information about suspicious objects.
- Remove these parts and, if necessary, re-write parts of the original code to ensure proper functionality.
- Our package `rmmodeldata` contains wrapper around selected methods (`traforest`, `lm`, `ctree`) to get an object without data and still ensure working functionality.

Model transportability - example `traforest`

Using `rmmodeldata` returns a transportable `traforest` object which can be used to calculate predictions:

```
> tf_cmod_wd = rmmodeldata::traforest(m, formula = y ~ horTh | age, control = ctrl,
+   ntree = 50, mtry = 1, trace = TRUE, data = GBSG2)
[2022-06-27 16:30:27] Using `rmmodeldata::traforest`
[2022-06-27 16:30:27] Using `rmmodeldata::cforest`
  |======================================================================| 100%
[2022-06-27 16:30:51] Remove data `$data`
[2022-06-27 16:30:51] Remove data `$info$model$model`
[2022-06-27 16:30:51] Remove data `$info$call$data`
[2022-06-27 16:30:51] Remove data `$fitted`
[2022-06-27 16:30:51] Remove data `$mltobj$object$data`
> tf_cmod$data
NULL
> tf_cmod$info$model$model
NULL
> tf_cmod$info$call$data
NULL
> tf_cmod$fitted
NULL
> tf_cmod$mltobj$object$data
NULL
> pred = predict(tf_cmod_wd, newdata = GBSG2)
[2022-06-27 16:31:01] Using `rmmodeldata::predict.traforest.nodat`
[2022-06-27 16:31:01] Using `rmmodeldata::predict.cforest.nodat`
> str(pred)
 num [1:686, 1:686] 1.61 0 0 0 1.67 ...
 - attr(*, "dimnames")=List of 2
  ..$ : NULL
  ..$ : chr [1:686] "1" "2" "3" "4" ...
```

Figure 6: Training of a `traforest` model and predicting using `rmmodeldata`.

Advantages and disadvantages of transportability

Advantages

- The model object does not contain confidential data.
- The object size becomes smaller. Especially striking for big data situations.
- We have to deal with the object and are getting a better understanding about the functionality of the method.

Disadvantages

- The data is gone, obviously.
- Reproducibility is more elaborate without data.
- Read and understand other code can quickly become exhausting.

General considerations

- When developing a package/method, think about how to make the results independent of the data. E.g. include an option `store_data = FALSE` to return models without data.
- If possible, and not too time consuming, implement the method by yourself. Not feasible for most complex algorithms such as Boosting, Random Forests, etc.
- Making a model object transportable requires a lot of post processing of the object and advanced knowledge about the programming language and methods.

Thanks for your attention!
Any Questions?

References

[1] L. Breiman. Random forests. *Machine learning*, 45(1):5–32, 2001.

[2] T. Hothorn. *trtf: Transformation Trees and Forests*, 2020. R package version 0.3-7.

[3] T. Hothorn and A. Zeileis. Transformation forests. *arXiv preprint arXiv:1701.02110*, 2017.

[4] R Core Team. *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria, 2022.