

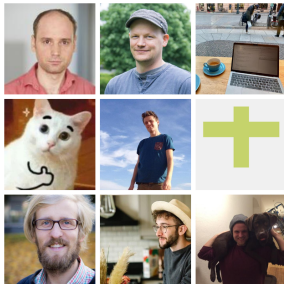
# Object-oriented Machine Learning in R

---



<https://mlr-org.com/>

<https://github.com/mlr-org>



---

**Michel Lang, Bernd Bischl, Jakob Richter, Martin Binder, Marc Becker, Patrick Schratz, Raphael Sonabend, Lennart Schneider and more!**

November 12, 2021

# TODAY'S CONTENT

- Motivation: Why do we want to use mlr3?
- The mlr3verse
- ML Building-Blocks
- Example: Benchmark experiment

# WHAT ARE YOU SUPPOSED TO TAKE AWAY

- Have an overview of most technical possibilities in mlr3
- Know where to find help
- Be able to find the best machine learning method for your problem

# MOTIVATION: MAKING BENCHMARKS EASY!

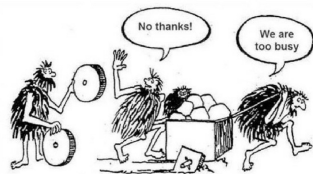
By unifying

- interface to train and predict methods,
- interface to learner's hyperparameters,
- interface to optimizers,
- resampling,
- preprocessing independently from the data,
- parallelization, and
- error handling

methods can be used interchangeably and can be easily benchmarked.

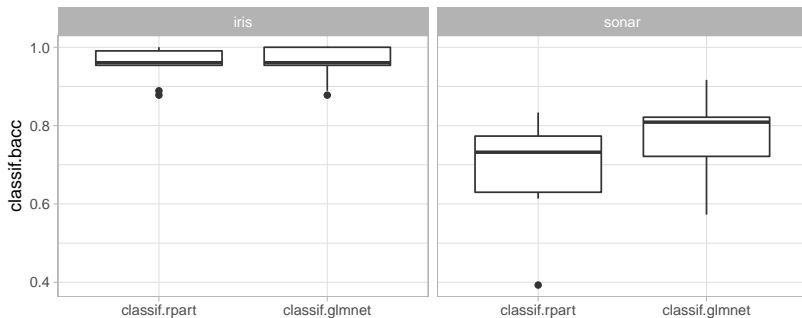
# IS IT WORTH TO "LEARN" MLR3

- Avoid making mistakes by relying on tested functionality
  - predefined performance measures
  - resampling
  - ...
- Easily scale up your benchmark
  - integrated parallelization
  - benchmarking functions
  - on clusters: `batchtools` + `mlr3batchmark`
- New methods can be easily integrated in the `mlr3`verse



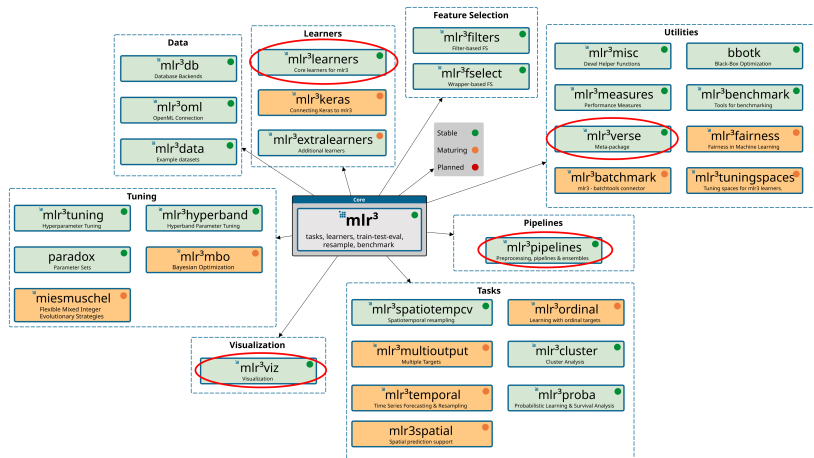
# MLR3: A SHORT EXAMPLE

```
library(mlr3verse)
tasks = list(
  as_task_classif(iris, target = "Species"), # task from df
  tsk("sonar") # example task
)
learners = lrns(c("classif.rpart", "classif.glmnet"))
bmg = benchmark_grid(tasks, learners, rsmp("cv"))
bmr = benchmark(bmg)
autoplot(bmr, measure = msr("classif.bacc")) # balanced accuracy
```



# **mlr3verse**

# THE MLR3VERSE

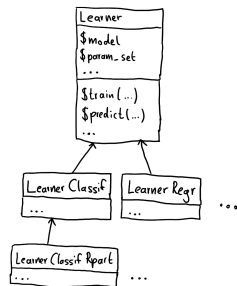




# Principles of mlr3

# MLR3 PHILOSOPHY

- Object-orientation with **R6**
  - Make use of inheritance
  - Make slight use of reference semantics
- Embrace **data.table**:
  - Internal objects are stored in tabular structure.
  - List columns to arrange complex objects
- Be **light on dependencies**:
  - R6, `data.table`, `lgr`, ...
  - Special packages are loaded from `mlr3` extension libraries



# MLR3: OBJECTS AND FUNCTIONS

## User created objects:

- Tasks: data + meta information
- Learner: ml algorithm + hyperparameter + model
- Measure: formula + meta information
- Resampling: strategy (+ indices)

## Further objects:

- Prediction, ResampleResult, BenchmarkResult, ...

## Functions to create objects:

- `tsk()`, `as_task_*()`: Task
- `lrn()`, `lrns()`: Learners
- `msr()`, `msrs()`: Measures
- `rsmp()`: Resampling strategies

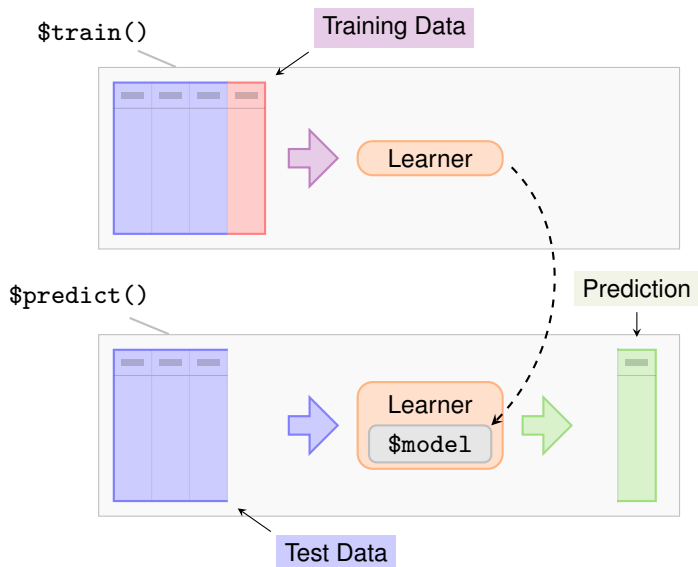
Hint: calling e.g. just `lrns()` prints all available learners in the `mlr_learners` dictionary.

Dictionaries can get populated by add-on packages (e.g. `mlr3extralearners`)

## Functions:

- `resample()`
- `benchmark_grid()` + `benchmark()`
- `future::plan()`: enables parallelization
- `mlr3viz::autoplot()`: visualizes mlr3 objects

# LEARNING ALGORITHMS



# TRAIN, PREDICT, SCORE

```
task = as_task_classif(iris, target = "Species")
```

Objects have *fields* that contain information about the object.

```
c(task$nrow, task$ncol)
```

```
#> [1] 150    5
```

Some can be overwritten:

```
learner = lrn("classif.fnn")
```

```
learner$param_set
```

```
#> <ParamSet>
```

```
#>           id    class lower upper nlevels default  value
#>      <char>   <char> <num> <num>   <num>  <list> <list>
#> 1:           k ParamInt     1   Inf     Inf      1
#> 2: algorithm ParamFct    NA    NA      3 kd_tree
```

```
learner$param_set$values$k = 4
```

But are also checked for feasibility:

```
learner$param_set$values$k = -1
```

```
#> Error in self$assert(xs): Assertion on 'xs' failed: k: Element 1
is not >= 1.
```

# TRAIN, PREDICT, SCORE

```
str(learner$model)
```

```
#> NULL
```

```
learner$train(task, row_ids = (1:75) * 2 - 1)
```

```
str(learner$model)
```

```
#> List of 4
```

```
#> $ formula:Class 'formula' language Species ~ .
```

```
#> $ data :Classes 'data.table' and 'data.frame':
```

```
75 obs. of 5 variables:
```

```
#> ..$ Species : Factor w/ 3 levels "setosa","versicolor",...: 1 1 1 1 1 1
```

```
#> ..$ Petal.Length: num [1:75] 1.4 1.3 1.4 1.4 1.4 1.5 1.4 1.2 1.3 1.7 ...
```

```
#> ..$ Petal.Width : num [1:75] 0.2 0.2 0.2 0.3 0.2 0.2 0.1 0.2 0.4 0.3 ...
```

```
#> ..$ Sepal.Length: num [1:75] 5.1 4.7 5 4.6 4.4 5.4 4.8 5.8 5.4 5.7 ...
```

```
#> ..$ Sepal.Width : num [1:75] 3.5 3.2 3.6 3.4 2.9 3.7 3 4 3.9 3.8 ...
```

```
#> ..- attr(*, ".internal.selfref")=<externalptr>
```

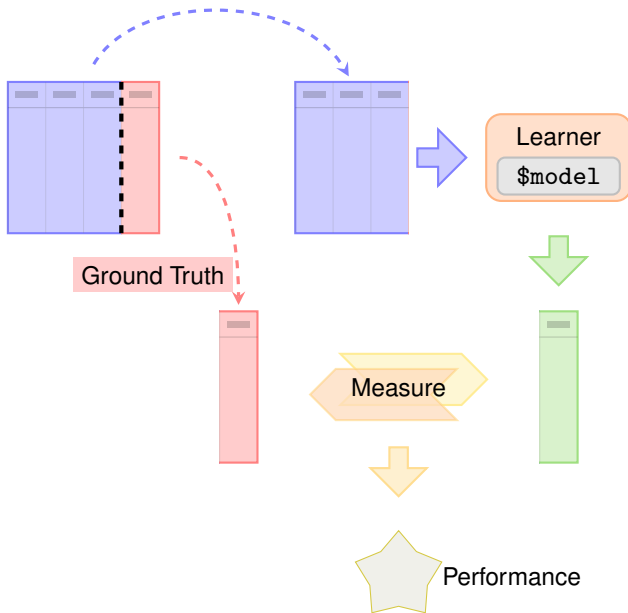
```
#> $ pv :List of 1
```

```
#> ..$ k: int 4
```

```
#> $ kkn : NULL
```

```
pred = learner$predict(task, row_ids = (1:75) * 2)
```

# PERFORMANCE EVALUATION



# TRAIN, PREDICT, SCORE

```
pred$confusion
```

```
#>           truth  
#> response  setosa versicolor virginica  
#>   setosa      25          0          0  
#> versicolor    0          24          2  
#>  virginica    0           1         23
```

```
pred$score()
```

```
#> classif.ce  
#>          0.04
```

```
pred$score(msr("classif.bacc"))
```

```
#> classif.bacc  
#>          0.96
```

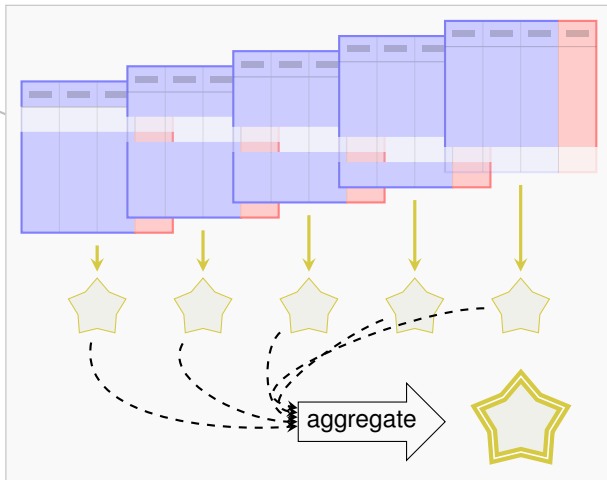
```
head(as.data.table(pred), 4)
```

```
#>   row_ids truth response  
#>   <int> <fctr>  <fctr>  
#> 1:      2 setosa  setosa  
#> 2:      4 setosa  setosa  
#> 3:      6 setosa  setosa  
#> 4:      8 setosa  setosa
```



# RESAMPLING

`resample()`



# RESAMPLING

- Resample description: How to split the data

```
cv5 = rsmp("cv", folds = 5)
```

- Use the `resample()` function for resampling:

```
task = tsk("iris")  
learner = lrn("classif.rpart")  
rr = resample(task, learner, cv5, store_models = TRUE)
```

(`store_models = TRUE` so we can access models in `rr` later.)

- We get a `ResamplingResult` object:

```
print(rr)  
#> <ResampleResult> of 5 iterations  
#> * Task: iris  
#> * Learner: classif.rpart  
#> * Warnings: 0 in 0 iterations  
#> * Errors: 0 in 0 iterations
```

# RESAMPLING

- Predictions of individual folds

```
predictions = rr$predictions()
predictions[[1]]

#> <PredictionClassif> for 30 observations:
#>      row_ids      truth  response
#>          1      setosa    setosa
#>          2      setosa    setosa
#>         11      setosa    setosa
#> ---
#>        147 virginica virginica
#>        148 virginica virginica
#>        149 virginica virginica
```

# RESAMPLING

- Predictions of individual folds

```
predictions = rr$predictions()
predictions[[1]]

#> <PredictionClassif> for 30 observations:
#>      row_ids      truth  response
#>          1      setosa    setosa
#>          2      setosa    setosa
#>         11      setosa    setosa
#> ---
#>        147 virginica virginica
#>        148 virginica virginica
#>        149 virginica virginica
```

- Score of individual folds

```
scores = rr$score()
scores[1:3, c("iteration", "classif.ce")]

#>      iteration classif.ce
#>      <int>      <num>
#> 1:          1      0.033
#> 2:          2      0.100
#> 3:          3      0.033
```

# RESAMPLING

- Access to models of individual folds (only if `$store_models = TRUE`)

```
rr$learners[[1]]$importance()  
#>   Petal.Width Petal.Length Sepal.Length  Sepal.Width  
#>           70           62           39           25
```

# RESAMPLING

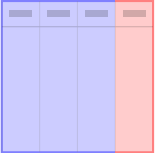



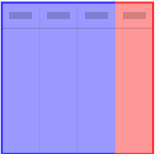



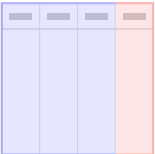



- Access to models of individual folds (only if `$store_models = TRUE`)

```
rr$learners[[1]]$importance()  
#>   Petal.Width Petal.Length Sepal.Length  Sepal.Width  
#>           70           62           39           25
```

- Aggregate over multiple folds:

```
sapply(rr$learners, function(x) x$importance()) %>%  
  apply(1, mean)  
#>   Petal.Width Petal.Length Sepal.Length  Sepal.Width  
#>           71           66           44           29
```

# PERFORMANCE COMPARISON: BENCHMARK

	Learner 1	Learner 2	Learner 3
			
			
			

# PERFORMANCE COMPARISON

- Multiple Learners, multiple Tasks:

```
library("mlr3learners")
learners = list(lrn("classif.rpart"), lrn("classif.kknn"))
tasks = list(tsk("iris"), tsk("sonar"), tsk("wine"))
```

- Set up the *design* and execute benchmark:

```
design = benchmark_grid(tasks, learners, cv5)
bmr = benchmark(design)
```

- We get a BenchmarkResult object which shows that kknn outperforms rpart:

```
bmr_ag = bmr$aggregate()
bmr_ag[, c("task_id", "learner_id", "classif.ce")]

#>   task_id    learner_id classif.ce
#>   <char>      <char>      <num>
#> 1:   iris classif.rpart    0.060
#> 2:   iris classif.kknn    0.047
#> 3:  sonar classif.rpart    0.265
#> 4:  sonar classif.kknn    0.163
#> 5:   wine classif.rpart    0.118
#> 6:   wine classif.kknn    0.039
```



# BENCHMARK RESULT

What exactly is a `BenchmarkResult` object?

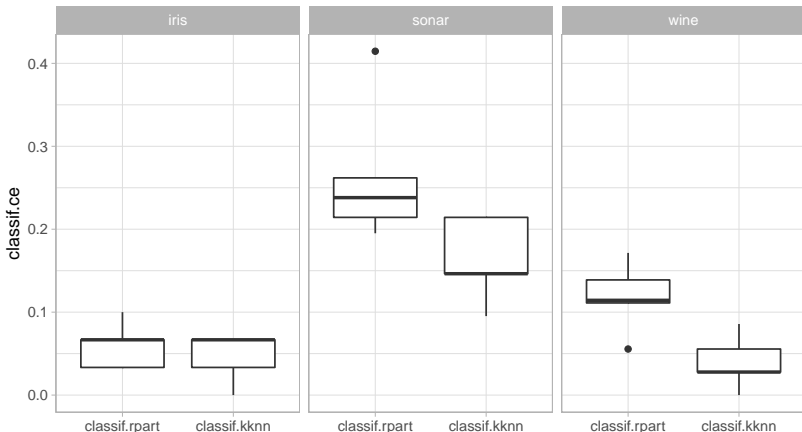
Just like `Prediction` and `ResamplingResult`!

- Table representation using `as.data.table()`
- Active bindings and functions that make information easily accessible

# BENCHMARK RESULT

The `mlr3viz` package contains `autoplot()` functions for many `mlr3` objects

```
library(mlr3viz)
autoplot(bmr)
```



# BENCHMARK RESULT

Many objects can be transformed into a `data.table()`.

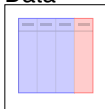
```
as.data.table(bmr)[1:4, -1]
```

#	task	learner	resampling
#	<list>	<list>	<list>
# 1:	<TaskClassif[47]>	<LearnerClassifRpart[36]>	<ResamplingCV[19]>
# 2:	<TaskClassif[47]>	<LearnerClassifRpart[36]>	<ResamplingCV[19]>
# 3:	<TaskClassif[47]>	<LearnerClassifRpart[36]>	<ResamplingCV[19]>
# 4:	<TaskClassif[47]>	<LearnerClassifRpart[36]>	<ResamplingCV[19]>
#	iteration	prediction	
#	<int>	<list>	
# 1:	1	<PredictionClassif[19]>	
# 2:	2	<PredictionClassif[19]>	
# 3:	3	<PredictionClassif[19]>	
# 4:	4	<PredictionClassif[19]>	

# MLR3: SHORT RECAP

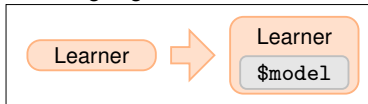
Ingredients:

Data



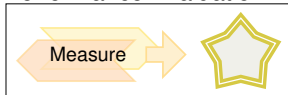
```
TaskClassif,  
TaskRegr,  
tsk()
```

Learning Algorithms



```
lrn() ⇒ Learner,  
↪Learner$train(),  
↪Learner$predict() ⇒ Prediction
```

Performance Evaluation



```
rsmp() ⇒ Resampling,  
msr() ⇒ Measure,  
resample() ⇒ ResamplingResult,  
↪ ResamplingResult$score(),  
↪ ResamplingResult$aggregate()
```

Performance Comparison



```
benchmark_grid(),  
benchmark() ⇒ BenchmarkResult
```

# **mlr3pipelines**

# MLR3PIPELINES

Main author: Martin Binder (LMU)

## Machine Learning Workflows:

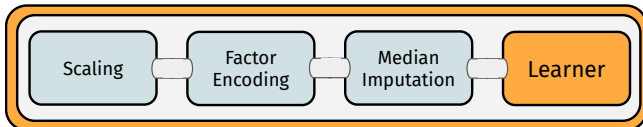
- **Preprocessing:** Feature extraction, feature selection, missing data imputation,...
- **Ensemble methods:** Model averaging, model stacking
- **mlr3:** modular model fitting

⇒ **mlr3pipelines:** modular ML workflows

# MLR3PIPELINES IN ACTION

## Linear Preprocessing Pipeline

```
graph_pp = po("scale") %>>%  
  po("encode") %>>%  
  po("imputemedian") %>>%  
  lrn("classif.rpart")
```

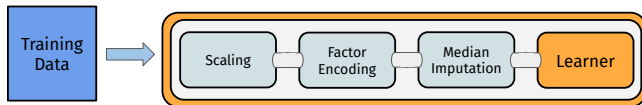


# MLR3PIPELINES IN ACTION

## Linear Preprocessing Pipeline

- `train()`ing: Data propagates and creates `$states`

```
glrn = GraphLearner$new(graph_pp)  
glrn$train(task)
```



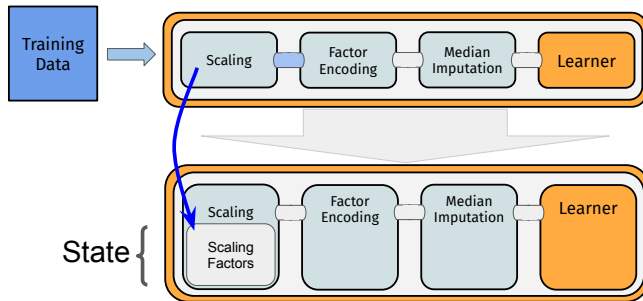


# MLR3PIPELINES IN ACTION

## Linear Preprocessing Pipeline

- `train()`ing: Data propagates and creates `$states`

```
glrn = GraphLearner$new(graph_pp)  
glrn$train(task)
```

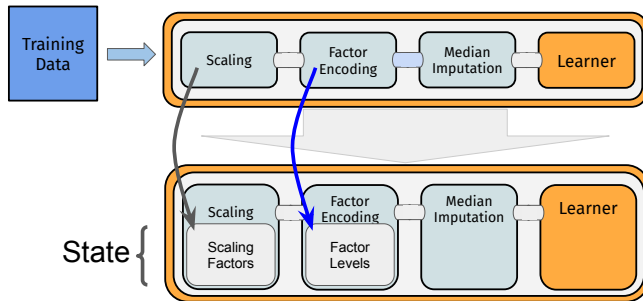


# MLR3PIPELINES IN ACTION

## Linear Preprocessing Pipeline

- `train()`ing: Data propagates and creates `$states`

```
glrn = GraphLearner$new(graph_pp)
glrn$train(task)
```

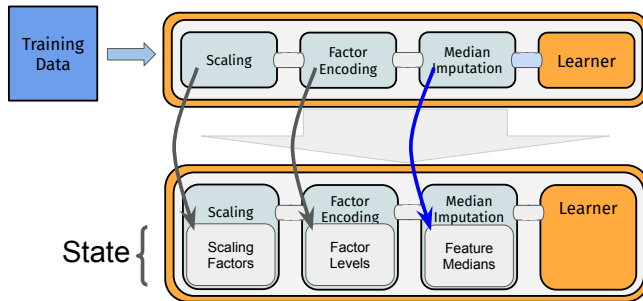


# MLR3PIPELINES IN ACTION

## Linear Preprocessing Pipeline

- `train()`ing: Data propagates and creates `$states`

```
glrn = GraphLearner$new(graph_pp)
glrn$train(task)
```

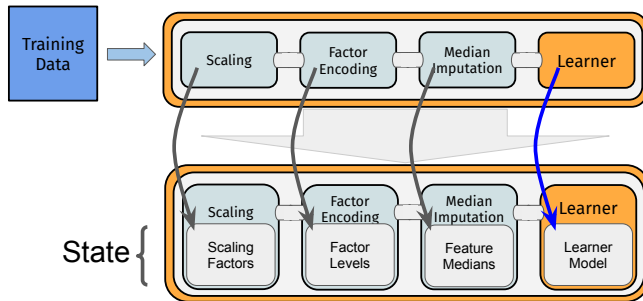


# MLR3PIPELINES IN ACTION

## Linear Preprocessing Pipeline

- `train()`ing: Data propagates and creates `$states`

```
glrn = GraphLearner$new(graph_pp)  
glrn$train(task)
```

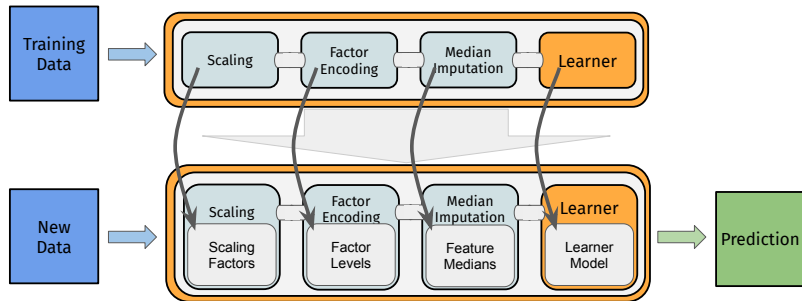


# MLR3PIPELINES IN ACTION

## Linear Preprocessing Pipeline

- `train()`ing: Data propagates and creates `$states`
- `predict()`ion: Data propagates, uses `$states`

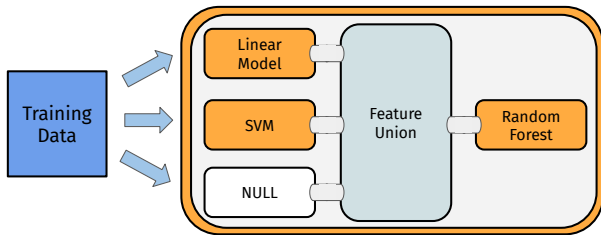
```
glrn$predict(task)
```



# MLR3PIPELINES IN ACTION

## Ensemble Method: Stacking

```
graph_stack = gunion(list(  
  po("learner_cv", learner = lrn("regr.lm")),  
  po("learner_cv", learner = lrn("regr.svm")),  
  po("nop"))) %>>%  
po("featureunion") %>>%  
lrn("regr.ranger")
```

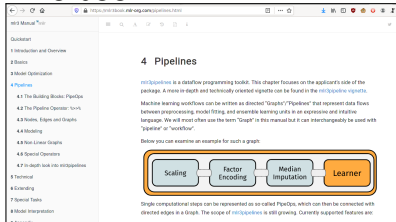


# WHAT WAS NOT COVERED TODAY?

- Error handling (fallback learners), Database backends, Parallelization
- Hyperparameter tuning
- Cost-sensitive classification, survival learning, feature selection, geospatial methods
- Model interpretation (interpretable machine learning)
- ...

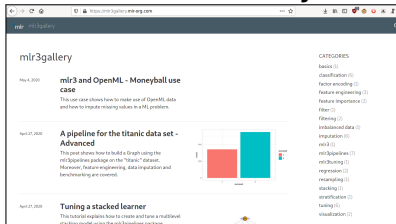
# MLR3 RESOURCES

## mlr3 book



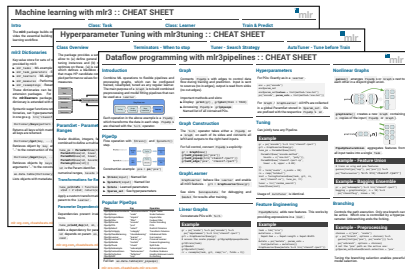
<https://mlr3book.mlr-org.com/>

## mlr3 Use Case Gallery



<https://mlr3gallery.mlr-org.com/>

## Cheat Sheets



<https://cheatsheets.mlr-org.com/>

## More:

- Stackoverflow: <https://stackoverflow.com/tags/mlr3>
- Mattermost channel: [https://lmmisld-lmu-stats-slds.srv.mwn.de/mlr\\_invite/](https://lmmisld-lmu-stats-slds.srv.mwn.de/mlr_invite/)
- GitHub Issue in one of the projects: <https://github.com/mlr-org/>