

mlr3 pipelines

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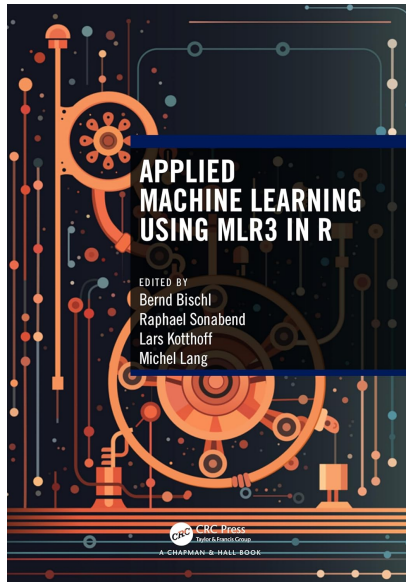
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<https://mlr3book.mlr-org.com/>

```

library(mlr3verse)

tasks = tsks(c("breast_cancer", "sonar"))

glrn_rf_tuned = as_learner(ppl("robustify") %>% auto_tuner(
  tnr("grid_search", resolution = 5),
  lrn("classif.ranger", num.trees = to_tune(200, 500)),
  rsmp("holdout")
))
glrn_rf_tuned$id = "RF"

glrn_stack = as_learner(ppl("robustify") %>% ppl("stacking",
  lrns(c("classif.rpart", "classif.kknn")),
  lrn("classif.log_reg")
))
glrn_stack$id = "Stack"

learners = c(glrn_rf_tuned, glrn_stack)
bmr = benchmark(benchmark_grid(tasks, learners, rsmp("cv", folds = 3)))

bmr$aggregate(msr("classif.acc"))

```

	nr	task_id	learner_id	resampling_id	iters	classif.acc
	<int>	<char>	<char>	<char>	<int>	<num>
1:	1	breast_cancer	RF	cv	3	0.9677912
2:	2	breast_cancer	Stack	cv	3	0.9164992
3:	3	sonar	RF	cv	3	0.8267081
4:	4	sonar	Stack	cv	3	0.7162871

Pipe Operators

- ▷ PipeOp in mlr3-speak
- ▷ `$train()` and a `$predict()` method
- ▷ `$param_set` field that defines the hyperparameters
- ▷ constructed with the `po()` function

```
library(mlr3verse)
po_pca = po("pca", center = TRUE)
```

```
PipeOp: <pca> (not trained)
```

```
values: <center=TRUE>
```

```
Input channels <name [train type, predict type]>:
```

```
  input [Task,Task]
```

```
Output channels <name [train type, predict type]>:
```

```
  output [Task,Task]
```

Pipe Operators Train

```
po_pca$train(tsks("boston_housing"))
```

```
$output
```

```
<TaskRegr:boston_housing> (506 x 18): Boston Housing Prices
```

```
* Target: cmedv
```

```
* Properties: -
```

```
* Features (17):
```

- dbl (15): PC1, PC10, PC11, PC12, PC13, PC14, PC15, PC2, PC3, PC4, PC5, PC6, PC7, PC8, PC9
- fct (2): chas, town

Pipe Operators State

```
po_pca$state
```

```
Standard deviations (1, ..., p=15):
```

```
[1] 1.387078e+03 1.080930e+02 7.750918e+01 2.807860e+01 1.630019e+01  
[6] 6.907191e+00 5.276367e+00 3.876985e+00 2.915733e+00 1.762825e+00  
[11] 1.083099e+00 5.033412e-01 6.944262e-02 4.966327e-02 3.862021e-02
```

```
Rotation (n x k) = (15 x 15):
```

	PC1	PC2	PC3	PC4	PC5
age	9.928068e-03	0.0548286996	-7.652884e-03	0.765442047	-6.282490e-01
b	-2.423736e-02	-0.4607717741	-8.866967e-01	0.022865175	-4.174316e-03
crim	3.405922e-03	0.0218600096	5.015232e-03	0.004508408	-3.219726e-02
dis	-7.572546e-04	-0.0046940019	6.983044e-04	-0.045481910	-3.178385e-03
indus	2.864462e-03	0.0268024509	-9.875540e-03	0.093219299	1.615220e-02
lat	9.848547e-06	-0.0003154347	1.218493e-04	0.000247237	-6.237778e-05
...					

Pipe Operators Predict

```
po_pca$predict(tsks("boston_housing"))[[1]]$data()
```

		cmedv	chas	town	PC1	PC2	PC3	PC4
	<num>	<fctr>	<fctr>	<num>	<num>	<num>	<num>	<num>
1:	24.0	0	Nahant	673.7945	-185.6437	32.41160	-6.3736055	-6.980564
2:	21.6	0	Swampscott	658.8871	-230.9396	57.05639	18.8929772	-3.138591
3:	34.7	0	Swampscott	657.8002	-230.0266	60.75298	4.7170875	8.295867
4:	33.4	0	Marblehead	646.6991	-248.5129	68.32003	-6.5170816	17.375165
5:	36.2	0	Marblehead	645.7392	-248.9604	66.23151	0.1865058	11.976457

Graphs

- ▷ collection of pipeline operators that define individual steps in data science pipelines
- ▷ “edges” guide the flow of data
- ▷ connect pipeline operators with the %>>% operator

```
po_scale = po("scale")  
graph = po_pca %>>% po_scale
```

Graph with 2 PipeOps:

ID	State	sccssors	prdcssors
<char>	<char>	<char>	<char>
pca	<prcomp>	scale	
scale	<<UNTRAINED>>		pca

Graphs Training

```
graph$train(tsk("boston_housing"))
```

```
$scale.output
```

```
<TaskRegr:boston_housing> (506 x 18): Boston Housing Prices
```

```
* Target: cmedv
```

```
* Properties: -
```

```
* Features (17):
```

- dbl (15): PC1, PC10, PC11, PC12, PC13, PC14, PC15, PC2, PC3, PC4, PC5, PC6, PC7, PC8, PC9
- fct (2): chas, town

Graphs Predict

```
graph$predict(tsk("boston_housing"))$scale.output$data()
```

	cmedv	chas	town	PC1	PC10	PC11	PC12
	<num>	<fctr>	<fctr>	<num>	<num>	<num>	<num>
1:	24.0	0	Nahant	0.4857654	-1.75305179	0.04865207	0.5157509
2:	21.6	0	Swampscott	0.4750181	-0.25008756	-1.38250786	-0.1003841
3:	34.7	0	Swampscott	0.4742345	-0.33275540	-1.03983952	-1.1393915
4:	33.4	0	Marblehead	0.4662313	0.06778422	-1.07052858	-0.7431648
5:	36.2	0	Marblehead	0.4655392	0.09450762	-1.20760905	-1.2565375

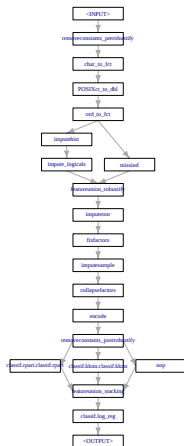
Plotting Graphs

```
graph$plot(horizontal = TRUE)
```



Graphs as Learners

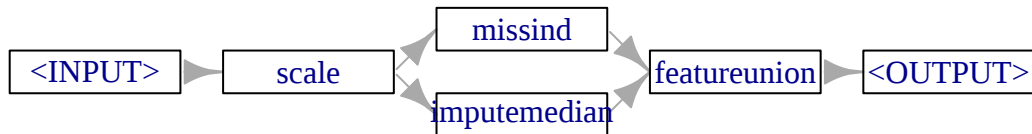
```
glrn_stack = as_learner(ppl("robustify") %>% ppl("stacking",  
  lrns(c("classif.rpart", "classif.kknn")),  
  lrn("classif.log_reg")  
)
```



Non-Sequential Pipelines

- ▷ non-sequential pipelines can perform more complex operations
- ▷ `gunion()` can combine multiple pipe operators, graphs, or mixture, into parallel graph

```
graph = po("scale", center = TRUE, scale = FALSE) %>%  
  gunion(list(  
    po("missind"),  
    po("imputemedian")  
  )) %>%  
  po("featureunion")
```



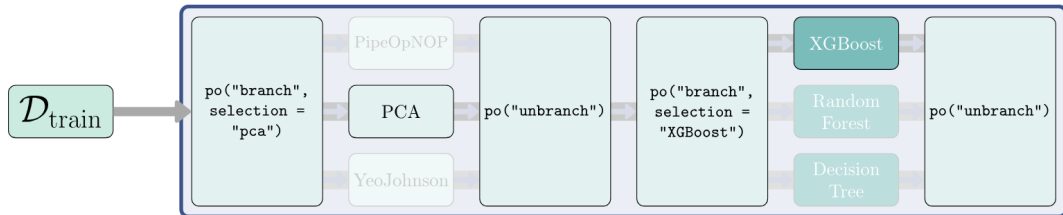
Common Pipeline Patterns

- ▷ pipelines useful for more than one problem – `ppl()` operator to easily construct (partial) pipelines from patterns
- ▷ `ppl("bagging", graph)` creates a bagging ensemble
- ▷ `ppl("branch", graphs)` creates a branch
- ▷ `ppl("robustify")` common preprocessing steps
- ▷ `ppl("stacking", base_learners, super_learner)` creates a stacking ensemble

```
glrn_stack = as_learner(ppl("robustify") %>% ppl("stacking",  
  lrns(c("classif.rpart", "classif.kknn")),  
  lrn("classif.log_reg")  
))
```

Branching

- ▷ `po("branch")` creates alternative paths where data flow is determined by selection hyperparameter
- ▷ easy combined model selection and hyperparameter tuning



Preprocessing – Robustify

1. `po("removeconstants")` removes constant values
2. `po("colapply")` encodes character and ordinal features as categorical, date/time features as numeric
3. `po("imputehist")` imputes numeric features by histogram sampling
4. `po("imputesample")` imputes logical features by sampling from the empirical distribution
5. `po("missind")` adds missing data indicators for imputed numeric and logical variables
6. `po("imputeoor")` encodes missing values of categorical features with a new level
7. `po("fixfactors")` ensures that the same levels are present during training and prediction
8. `po("imputesample")` imputes any introduced missing values
9. `po("collapsefactors")` collapses rare factor levels
10. `po("encode")` one-hot encodes categorical features
11. `po("removeconstants")` removes constant values

Hyperparameters

- ▷ hyperparameters are collected in `$param_set` for convenient tuning

```
graph = po("scale", center = FALSE, scale = TRUE, id = "scale") %>%  
  po("scale", center = TRUE, scale = FALSE, id = "center") %>%  
  lrn("classif.rpart", cp = 1)  
unlist(graph$param_set$values)
```

scale.center	scale.scale	scale.robust	center.center
0	1	0	1
center.scale	center.robust	classif.rpart.cp	classif.rpart.xval
0	0	1	0

Tuning Hyperparameters

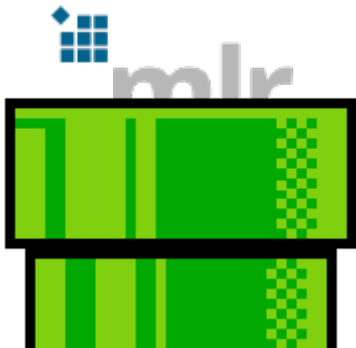
```
graph_learner = as_learner(po("pca") %>% lrn("classif.kknn"))

lrn_knn = lrn("classif.kknn", k = to_tune(1, 32))
po_pca = po("pca", rank. = to_tune(2, 20))
graph_learner = as_learner(po_pca %>% lrn_knn)

glrn_tuned = auto_tuner(tnr("mbo"), graph_learner, rsmp("holdout"),
  term_evals = 10)
glrn_untuned = po("pca") %>% lrn("classif.kknn")
design = benchmark_grid(tsk("sonar"), c(glrn_tuned, glrn_untuned),
  rsmp("cv", folds = 5))
benchmark(design)$aggregate()[, .(learner_id, classif.ce)]
```

	learner_id	classif.ce
	<char>	<num>
1:	pca.classif.kknn.tuned	0.1681765
2:	pca.classif.kknn	0.2257840

<https://mlr-org.com/>
<https://mlr3pipelines.mlr-org.com/>
<https://mlr3book.mlr-org.com/>



Exercises

<https://shorturl.at/9Htr3>
<https://mlr3book.mlr-org.com/>
Exercises for Chapters 7, 8, 9