

# Package ‘mlr3fselect’

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**Title** Feature Selection for 'mlr3'

**Version** 0.12.0

**Description** Feature selection package of the 'mlr3' ecosystem. It selects the optimal feature set for any 'mlr3' learner. The package works with several optimization algorithms e.g. Random Search, Recursive Feature Elimination, and Genetic Search. Moreover, it can automatically optimize learners and estimate the performance of optimized feature sets with nested resampling.

**License** LGPL-3

**URL** <https://mlr3fselect.mlr-org.com>,  
<https://github.com/mlr-org/mlr3fselect>

**BugReports** <https://github.com/mlr-org/mlr3fselect/issues>

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'FSelectorFromOptimizer.R' 'FSelectorGeneticSearch.R'  
'FSelectorRFE.R' 'FSelectorRFECV.R' 'FSelectorRandomSearch.R'  
'FSelectorSequential.R' 'FSelectorShadowVariableSearch.R'

'ObjectiveFSelect.R' 'assertions.R' 'auto\_fselector.R'  
 'bibentries.R' 'extract\_inner\_fselect\_archives.R'  
 'extract\_inner\_fselect\_results.R' 'fselect.R'  
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mlr3fselect-package     *mlr3fselect: Feature Selection for 'mlr3'*

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## Description

Feature selection package of the 'mlr3' ecosystem. It selects the optimal feature set for any 'mlr3' learner. The package works with several optimization algorithms e.g. Random Search, Recursive Feature Elimination, and Genetic Search. Moreover, it can automatically optimize learners and estimate the performance of optimized feature sets with nested resampling.

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## See Also

Useful links:

- <https://mlr3fselect.mlr-org.com>
- <https://github.com/mlr-org/mlr3fselect>
- Report bugs at <https://github.com/mlr-org/mlr3fselect/issues>

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ArchiveFSelect

*Class for Logging Evaluated Feature Sets*

---

## Description

The `ArchiveFSelect` stores all evaluated feature sets and performance scores.

## Details

The `ArchiveFSelect` is a container around a `data.table::data.table()`. Each row corresponds to a single evaluation of a feature set. See the section on Data Structure for more information. The archive stores additionally a `mlr3::BenchmarkResult` (`$benchmark_result`) that records the resampling experiments. Each experiment corresponds to a single evaluation of a feature set. The table (`$data`) and the benchmark result (`$benchmark_result`) are linked by the `uhash` column. If the archive is passed to `as.data.table()`, both are joined automatically.

### Data structure

The table (`$data`) has the following columns:

- One column for each feature of the task (`$search_space`).
- One column for each performance measure (`$codomain`).
- `runtime_learners` (`numeric(1)`)  
Sum of training and predict times logged in learners per [mlr3::ResampleResult](#) / evaluation. This does not include potential overhead time.
- `timestamp` (`POSIXct`)  
Time stamp when the evaluation was logged into the archive.
- `batch_nr` (`integer(1)`)  
Feature sets are evaluated in batches. Each batch has a unique batch number.
- `uhash` (`character(1)`)  
Connects each feature set to the resampling experiment stored in the [mlr3::BenchmarkResult](#).

### Analysis

For analyzing the feature selection results, it is recommended to pass the archive to `as.data.table()`. The returned data table is joined with the benchmark result which adds the [mlr3::ResampleResult](#) for each feature set.

The archive provides various getters (e.g. `$learners()`) to ease the access. All getters extract by position (`i`) or unique hash (`uhash`). For a complete list of all getters see the methods section.

The benchmark result (`$benchmark_result`) allows to score the feature sets again on a different measure. Alternatively, measures can be supplied to `as.data.table()`.

### S3 Methods

- `as.data.table.ArchiveFSelect(x, exclude_columns = "uhash", measures = NULL)`  
Returns a tabular view of all evaluated feature sets.  
[ArchiveFSelect](#) -> `data.table::data.table()`
  - `x` ([ArchiveFSelect](#))
  - `exclude_columns` (`character()`)  
Exclude columns from table. Set to `NULL` if no column should be excluded.
  - `measures` (list of [mlr3::Measure](#))  
Score feature sets on additional measures.

### Super class

[bbotk::Archive](#) -> `ArchiveFSelect`

### Public fields

`benchmark_result` ([mlr3::BenchmarkResult](#))  
Benchmark result.

**Active bindings**

ties\_method (character(1))  
Method to handle ties.

**Methods****Public methods:**

- [ArchiveFSelect\\$new\(\)](#)
- [ArchiveFSelect\\$learner\(\)](#)
- [ArchiveFSelect\\$learners\(\)](#)
- [ArchiveFSelect\\$predictions\(\)](#)
- [ArchiveFSelect\\$resample\\_result\(\)](#)
- [ArchiveFSelect\\$print\(\)](#)
- [ArchiveFSelect\\$best\(\)](#)
- [ArchiveFSelect\\$clone\(\)](#)

**Method new():** Creates a new instance of this [R6](#) class.

*Usage:*

```
ArchiveFSelect$new(
  search_space,
  codomain,
  check_values = TRUE,
  ties_method = "least_features"
)
```

*Arguments:*

search\_space ([paradox::ParamSet](#))

Search space. Internally created from provided [mlr3::Task](#) by instance.

codomain ([bbotk::Codomain](#))

Specifies codomain of objective function i.e. a set of performance measures. Internally created from provided [mlr3::Measures](#) by instance.

check\_values (logical(1))

If TRUE (default), hyperparameter configurations are check for validity.

ties\_method (character(1))

The method to break ties when selecting sets while optimizing and when selecting the best set. Can be "least\_features" or "random". The option "least\_features" (default) selects the feature set with the least features. If there are multiple best feature sets with the same number of features, one is selected randomly. The random method returns a random feature set from the best feature sets. Ignored if multiple measures are used.

**Method learner():** Retrieve [mlr3::Learner](#) of the i-th evaluation, by position or by unique hash uhash. i and uhash are mutually exclusive. Learner does not contain a model. Use [\\$learners\(\)](#) to get learners with models.

*Usage:*

```
ArchiveFSelect$learner(i = NULL, uhash = NULL)
```

*Arguments:*

`i` (integer(1))  
 The iteration value to filter for.  
`uhash` (logical(1))  
 The uhash value to filter for.

**Method** `learners()`: Retrieve list of trained `mlr3::Learner` objects of the `i`-th evaluation, by position or by unique hash `uhash`. `i` and `uhash` are mutually exclusive.

*Usage:*

```
ArchiveFSelect$learners(i = NULL, uhash = NULL)
```

*Arguments:*

`i` (integer(1))  
 The iteration value to filter for.  
`uhash` (logical(1))  
 The uhash value to filter for.

**Method** `predictions()`: Retrieve list of `mlr3::Prediction` objects of the `i`-th evaluation, by position or by unique hash `uhash`. `i` and `uhash` are mutually exclusive.

*Usage:*

```
ArchiveFSelect$predictions(i = NULL, uhash = NULL)
```

*Arguments:*

`i` (integer(1))  
 The iteration value to filter for.  
`uhash` (logical(1))  
 The uhash value to filter for.

**Method** `resample_result()`: Retrieve `mlr3::ResampleResult` of the `i`-th evaluation, by position or by unique hash `uhash`. `i` and `uhash` are mutually exclusive.

*Usage:*

```
ArchiveFSelect$resample_result(i = NULL, uhash = NULL)
```

*Arguments:*

`i` (integer(1))  
 The iteration value to filter for.  
`uhash` (logical(1))  
 The uhash value to filter for.

**Method** `print()`: Printer.

*Usage:*

```
ArchiveFSelect$print()
```

*Arguments:*

... (ignored).

**Method** `best()`: Returns the best scoring feature sets.

*Usage:*

```
ArchiveFSelect$best(batch = NULL, ties_method = NULL)
```

*Arguments:*

`batch` (`integer()`)

The batch number(s) to limit the best results to. Default is all batches.

`ties_method` (`character(1)`)

Method to handle ties. If NULL (default), the global ties method set during initialization is used. The default global ties method is `least_features` which selects the feature set with the least features. If there are multiple best feature sets with the same number of features, one is selected randomly. The `random` method returns a random feature set from the best feature sets.

*Returns:* `data.table::data.table()`

**Method** `clone()`: The objects of this class are cloneable with this method.

*Usage:*

```
ArchiveFSelect$clone(deep = FALSE)
```

*Arguments:*

`deep` Whether to make a deep clone.

---

 AutoFSelector

*Class for Automatic Feature Selection*


---

**Description**

The `AutoFSelector` wraps a `mlr3::Learner` and augments it with an automatic feature selection. The `auto_fselector()` function creates an `AutoFSelector` object.

**Details**

The `AutoFSelector` is a `mlr3::Learner` which wraps another `mlr3::Learner` and performs the following steps during `$train()`:

1. The wrapped (inner) learner is trained on the feature subsets via resampling. The feature selection can be specified by providing a `FSelector`, a `bbotk::Terminator`, a `mlr3::Resampling` and a `mlr3::Measure`.
2. A final model is fit on the complete training data with the best-found feature subset.

During `$predict()` the `AutoFSelector` just calls the `predict` method of the wrapped (inner) learner.

**Resources**

There are several sections about feature selection in the [mlr3book](#).

- Estimate Model Performance with [nested resampling](#).

The [gallery](#) features a collection of case studies and demos about optimization.

## Nested Resampling

Nested resampling can be performed by passing an `AutoFSelector` object to `mlr3::resample()` or `mlr3::benchmark()`. To access the inner resampling results, set `store_fselect_instance = TRUE` and execute `mlr3::resample()` or `mlr3::benchmark()` with `store_models = TRUE` (see examples). The `mlr3::Resampling` passed to the `AutoFSelector` is meant to be the inner resampling, operating on the training set of an arbitrary outer resampling. For this reason it is not feasible to pass an instantiated `mlr3::Resampling` here.

## Super class

`mlr3::Learner` -> `AutoFSelector`

## Public fields

`instance_args` (`list()`)  
All arguments from construction to create the `FSelectInstanceSingleCrit`.

`fselector` (`FSelector`)  
Optimization algorithm.

## Active bindings

`archive` (`[ArchiveFSelect]`)  
Returns `FSelectInstanceSingleCrit` archive.

`learner` (`mlr3::Learner`)  
Trained learner.

`fselect_instance` (`FSelectInstanceSingleCrit`)  
Internally created feature selection instance with all intermediate results.

`fselect_result` (`data.table::data.table`)  
Short-cut to `$result` from `FSelectInstanceSingleCrit`.

`predict_type` (`character(1)`)  
Stores the currently active predict type, e.g. "response". Must be an element of `$predict_types`.

`hash` (`character(1)`)  
Hash (unique identifier) for this object.

`phash` (`character(1)`)  
Hash (unique identifier) for this partial object, excluding some components which are varied systematically during tuning (parameter values) or feature selection (feature names).

## Methods

### Public methods:

- `AutoFSelector$new()`
- `AutoFSelector$base_learner()`
- `AutoFSelector$importance()`
- `AutoFSelector$selected_features()`
- `AutoFSelector$oob_error()`
- `AutoFSelector$loglik()`



- [AutoFSelector#print\(\)](#)
- [AutoFSelector\\$clone\(\)](#)

**Method** `new()`: Creates a new instance of this [R6](#) class.

*Usage:*

```
AutoFSelector$new(
  fselector,
  learner,
  resampling,
  measure = NULL,
  terminator,
  store_fselect_instance = TRUE,
  store_benchmark_result = TRUE,
  store_models = FALSE,
  check_values = FALSE,
  callbacks = list(),
  ties_method = "least_features"
)
```

*Arguments:*

`fselector` ([FSelector](#))

Optimization algorithm.

`learner` ([mlr3::Learner](#))

Learner to optimize the feature subset for.

`resampling` ([mlr3::Resampling](#))

Resampling that is used to evaluate the performance of the feature subsets. Uninstantiated resamplings are instantiated during construction so that all feature subsets are evaluated on the same data splits. Already instantiated resamplings are kept unchanged.

`measure` ([mlr3::Measure](#))

Measure to optimize. If NULL, default measure is used.

`terminator` ([Terminator](#))

Stop criterion of the feature selection.

`store_fselect_instance` (`logical(1)`)

If TRUE (default), stores the internally created [FSelectInstanceSingleCrit](#) with all intermediate results in slot `$fselect_instance`. Is set to TRUE, if `store_models = TRUE`

`store_benchmark_result` (`logical(1)`)

Store benchmark result in archive?

`store_models` (`logical(1)`). Store models in benchmark result?

`check_values` (`logical(1)`)

Check the parameters before the evaluation and the results for validity?

`callbacks` (list of [CallbackFSelect](#))

List of callbacks.

`ties_method` (`character(1)`)

The method to break ties when selecting sets while optimizing and when selecting the best set. Can be "least\_features" or "random". The option "least\_features" (default) selects the feature set with the least features. If there are multiple best feature sets with the same number of features, one is selected randomly. The random method returns a random feature set from the best feature sets. Ignored if multiple measures are used.

**Method** `base_learner()`: Extracts the base learner from nested learner objects like `GraphLearner` in **mlr3pipelines**. If `recursive = 0`, the (tuned) learner is returned.

*Usage:*

```
AutoFSelector$base_learner(recursive = Inf)
```

*Arguments:*

```
recursive (integer(1))
```

Depth of recursion for multiple nested objects.

*Returns:* [Learner](#).

**Method** `importance()`: The importance scores of the final model.

*Usage:*

```
AutoFSelector$importance()
```

*Returns:* `Named numeric()`.

**Method** `selected_features()`: The selected features of the final model. These features are selected internally by the learner.

*Usage:*

```
AutoFSelector$selected_features()
```

*Returns:* `character()`.

**Method** `oob_error()`: The out-of-bag error of the final model.

*Usage:*

```
AutoFSelector$oob_error()
```

*Returns:* `numeric(1)`.

**Method** `loglik()`: The log-likelihood of the final model.

*Usage:*

```
AutoFSelector$loglik()
```

*Returns:* `logLik`. `Printer`.

**Method** `print()`:

*Usage:*

```
AutoFSelector$print()
```

*Arguments:*

... (ignored).

**Method** `clone()`: The objects of this class are cloneable with this method.

*Usage:*

```
AutoFSelector$clone(deep = FALSE)
```

*Arguments:*

`deep` Whether to make a deep clone.

**Examples**

```
# Automatic Feature Selection

# split to train and external set
task = tsk("penguins")
split = partition(task, ratio = 0.8)

# create auto fselector
afs = auto_fselector(
  fselector = fs("random_search"),
  learner = lrn("classif.rpart"),
  resampling = rsmp("holdout"),
  measure = msr("classif.ce"),
  term_evals = 4)

# optimize feature subset and fit final model
afs$train(task, row_ids = split$train)

# predict with final model
afs$predict(task, row_ids = split$test)

# show result
afs$fselect_result

# model slot contains trained learner and fselect instance
afs$model

# shortcut trained learner
afs$learner

# shortcut fselect instance
afs$fselect_instance

# Nested Resampling

afs = auto_fselector(
  fselector = fs("random_search"),
  learner = lrn("classif.rpart"),
  resampling = rsmp("holdout"),
  measure = msr("classif.ce"),
  term_evals = 4)

resampling_outer = rsmp("cv", folds = 3)
rr = resample(task, afs, resampling_outer, store_models = TRUE)

# retrieve inner feature selection results.
extract_inner_fselect_results(rr)

# performance scores estimated on the outer resampling
rr$score()
```

```
# unbiased performance of the final model trained on the full data set
rr$aggregate()
```

---

auto\_fselector      *Function for Automatic Feature Selection*

---

### Description

The `AutoFSelector` wraps a `mlr3::Learner` and augments it with an automatic feature selection. The `auto_fselector()` function creates an `AutoFSelector` object.

### Usage

```
auto_fselector(
  fselector,
  learner,
  resampling,
  measure = NULL,
  term_evals = NULL,
  term_time = NULL,
  terminator = NULL,
  store_fselect_instance = TRUE,
  store_benchmark_result = TRUE,
  store_models = FALSE,
  check_values = FALSE,
  callbacks = list(),
  ties_method = "least_features"
)
```

### Arguments

fselector	( <a href="#">FSelector</a> ) Optimization algorithm.
learner	( <a href="#">mlr3::Learner</a> ) Learner to optimize the feature subset for.
resampling	( <a href="#">mlr3::Resampling</a> ) Resampling that is used to evaluate the performance of the feature subsets. Uninstantiated resamplings are instantiated during construction so that all feature subsets are evaluated on the same data splits. Already instantiated resamplings are kept unchanged.
measure	( <a href="#">mlr3::Measure</a> ) Measure to optimize. If NULL, default measure is used.
term_evals	( <code>integer(1)</code> ) Number of allowed evaluations. Ignored if terminator is passed.

term_time	(integer(1)) Maximum allowed time in seconds. Ignored if terminator is passed.
terminator	( <a href="#">Terminator</a> ) Stop criterion of the feature selection.
store_fselect_instance	(logical(1)) If TRUE (default), stores the internally created <a href="#">FSelectInstanceSingleCrit</a> with all intermediate results in slot \$fselect_instance. Is set to TRUE, if store_models = TRUE
store_benchmark_result	(logical(1)) Store benchmark result in archive?
store_models	(logical(1)). Store models in benchmark result?
check_values	(logical(1)) Check the parameters before the evaluation and the results for validity?
callbacks	(list of <a href="#">CallbackFSelect</a> ) List of callbacks.
ties_method	(character(1)) The method to break ties when selecting sets while optimizing and when selecting the best set. Can be "least_features" or "random". The option "least_features" (default) selects the feature set with the least features. If there are multiple best feature sets with the same number of features, one is selected randomly. The random method returns a random feature set from the best feature sets. Ignored if multiple measures are used.

## Details

The [AutoFSelector](#) is a [mlr3::Learner](#) which wraps another [mlr3::Learner](#) and performs the following steps during `$train()`:

1. The wrapped (inner) learner is trained on the feature subsets via resampling. The feature selection can be specified by providing a [FSelector](#), a [bbotk::Terminator](#), a [mlr3::Resampling](#) and a [mlr3::Measure](#).
2. A final model is fit on the complete training data with the best-found feature subset.

During `$predict()` the [AutoFSelector](#) just calls the predict method of the wrapped (inner) learner.

## Value

[AutoFSelector](#).

## Resources

There are several sections about feature selection in the [mlr3book](#).

- Estimate Model Performance with [nested resampling](#).

The [gallery](#) features a collection of case studies and demos about optimization.

## Nested Resampling

Nested resampling can be performed by passing an `AutoFSelector` object to `mlr3::resample()` or `mlr3::benchmark()`. To access the inner resampling results, set `store_fselect_instance = TRUE` and execute `mlr3::resample()` or `mlr3::benchmark()` with `store_models = TRUE` (see examples). The `mlr3::Resampling` passed to the `AutoFSelector` is meant to be the inner resampling, operating on the training set of an arbitrary outer resampling. For this reason it is not feasible to pass an instantiated `mlr3::Resampling` here.

## Examples

```
# Automatic Feature Selection

# split to train and external set
task = tsk("penguins")
split = partition(task, ratio = 0.8)

# create auto fselector
afs = auto_fselector(
  fselector = fs("random_search"),
  learner = lrn("classif.rpart"),
  resampling = rsmp("holdout"),
  measure = msr("classif.ce"),
  term_evals = 4)

# optimize feature subset and fit final model
afs$train(task, row_ids = split$train)

# predict with final model
afs$predict(task, row_ids = split$test)

# show result
afs$fselect_result

# model slot contains trained learner and fselect instance
afs$model

# shortcut trained learner
afs$learner

# shortcut fselect instance
afs$fselect_instance

# Nested Resampling

afs = auto_fselector(
  fselector = fs("random_search"),
  learner = lrn("classif.rpart"),
  resampling = rsmp("holdout"),
  measure = msr("classif.ce"),
  term_evals = 4)
```

```

resampling_outer = rsmp("cv", folds = 3)
rr = resample(task, afs, resampling_outer, store_models = TRUE)

# retrieve inner feature selection results.
extract_inner_fselect_results(rr)

# performance scores estimated on the outer resampling
rr$score()

# unbiased performance of the final model trained on the full data set
rr$aggregate()

```

---

CallbackFSelect

*Create Feature Selection Callback*


---

### Description

Specialized [bbotk::CallbackOptimization](#) for feature selection. Callbacks allow customizing the behavior of processes in `mlr3fselect`. The `callback_fselect()` function creates a `CallbackFSelect`. Predefined callbacks are stored in the dictionary `mlr_callbacks` and can be retrieved with `clbk()`. For more information on callbacks see `callback_fselect()`.

### Super classes

```
mlr3misc::Callback -> bbotk::CallbackOptimization -> CallbackFSelect
```

### Public fields

`on_eval_after_design` (function())

Stage called after design is created. Called in `ObjectiveFSelect$eval_many()`.

`on_eval_after_benchmark` (function())

Stage called after feature sets are evaluated. Called in `ObjectiveFSelect$eval_many()`.

`on_eval_before_archive` (function())

Stage called before performance values are written to the archive. Called in `ObjectiveFSelect$eval_many()`.

### Methods

#### Public methods:

- `CallbackFSelect$clone()`

**Method** `clone()`: The objects of this class are cloneable with this method.

*Usage:*

```
CallbackFSelect$clone(deep = FALSE)
```

*Arguments:*

`deep` Whether to make a deep clone.

**Examples**

```
# Write archive to disk
callback_fselect("mlr3fselect.backup",
  on_optimization_end = function(callback, context) {
    saveRDS(context$instance$archive, "archive.rds")
  }
)
```

---

callback_fselect	<i>Create Feature Selection Callback</i>
------------------	--

---

**Description**

Function to create a [CallbackFSelect](#). Predefined callbacks are stored in the [dictionary mlr\\_callbacks](#) and can be retrieved with [clbk\(\)](#).

Feature selection callbacks can be called from different stages of feature selection. The stages are prefixed with `on_*`.

```
Start Feature Selection
  - on_optimization_begin
  Start FSelect Batch
    - on_optimizer_before_eval
    Start Evaluation
      - on_eval_after_design
      - on_eval_after_benchmark
      - on_eval_before_archive
    End Evaluation
      - on_optimizer_after_eval
  End FSelect Batch
    - on_result
    - on_optimization_end
End Feature Selection
```

See also the section on parameters for more information on the stages. A feature selection callback works with [bbotk::ContextOptimization](#) and [ContextEval](#).

**Usage**

```
callback_fselect(
  id,
  label = NA_character_,
  man = NA_character_,
  on_optimization_begin = NULL,
  on_optimizer_before_eval = NULL,
  on_eval_after_design = NULL,
  on_eval_after_benchmark = NULL,
```



```

    on_eval_before_archive = NULL,
    on_optimizer_after_eval = NULL,
    on_result = NULL,
    on_optimization_end = NULL
)

```

## Arguments

id	(character(1)) Identifier for the new instance.
label	(character(1)) Label for the new instance.
man	(character(1)) String in the format [pkg]::[topic] pointing to a manual page for this object. The referenced help package can be opened via method \$help().
on_optimization_begin	(function()) Stage called at the beginning of the optimization. Called in Optimizer\$optimize(). The context available is <a href="#">bbotk::ContextOptimization</a> .
on_optimizer_before_eval	(function()) Stage called after the optimizer proposes points. Called in OptimInstance\$eval_batch(). The context available is <a href="#">bbotk::ContextOptimization</a> .
on_eval_after_design	(function()) Stage called after design is created. Called in ObjectiveFSelect\$eval_many(). The context available is <a href="#">ContextEval</a> .
on_eval_after_benchmark	(function()) Stage called after feature sets are evaluated. Called in ObjectiveFSelect\$eval_many(). The context available is <a href="#">ContextEval</a> .
on_eval_before_archive	(function()) Stage called before performance values are written to the archive. Called in ObjectiveFSelect\$eval_many(). The context available is <a href="#">ContextEval</a> .
on_optimizer_after_eval	(function()) Stage called after points are evaluated. Called in OptimInstance\$eval_batch(). The context available is <a href="#">bbotk::ContextOptimization</a> .
on_result	(function()) Stage called after result are written. Called in OptimInstance\$assign_result(). The context available is <a href="#">bbotk::ContextOptimization</a> .
on_optimization_end	(function()) Stage called at the end of the optimization. Called in Optimizer\$optimize(). The context available is <a href="#">bbotk::ContextOptimization</a> .

## Details

When implementing a callback, each function must have two arguments named `callback` and `context`.

A callback can write data to the state (`$state`), e.g. settings that affect the callback itself. Avoid writing large data the state. This can slow down the feature selection when the evaluation of configurations is parallelized.

Feature selection callbacks access two different contexts depending on the stage. The stages `on_eval_after_design`, `on_eval_after_benchmark`, `on_eval_before_archive` access [ContextEval](#). This context can be used to customize the evaluation of a batch of feature sets. Changes to the state of callback are lost after the evaluation of a batch and changes to the `fselect` instance or the `fselector` are not possible. Persistent data should be written to the archive via `$aggregated_performance` (see [ContextEval](#)). The other stages access [ContextOptimization](#). This context can be used to modify the `fselect` instance, `archive`, `fselector` and final result. There are two different contexts because the evaluation can be parallelized i.e. multiple instances of [ContextEval](#) exists on different workers at the same time.

## Examples

```
# Write archive to disk
callback_fselect("mlr3fselect.backup",
  on_optimization_end = function(callback, context) {
    saveRDS(context$instance$archive, "archive.rds")
  }
)
```

---

ContextEval

*Evaluation Context*


---

## Description

The [ContextEval](#) allows [CallbackFSelects](#) to access and modify data while a batch of feature sets is evaluated. See the section on active bindings for a list of modifiable objects. See [callback\\_fselect\(\)](#) for a list of stages that access [ContextEval](#).

## Details

This context is re-created each time a new batch of feature sets is evaluated. Changes to `$objective_fselect`, `$design` `$benchmark_result` are discarded after the function is finished. Modification on the data table in `$aggregated_performance` are written to the archive. Any number of columns can be added.

## Super class

```
mlr3misc::Context -> ContextEval
```

## Public fields

`objective_fselect` [ObjectiveFSelect](#).

**Active bindings**

- `xss` (`list()`)  
The feature sets of the latest batch.
- `design` (`data.table::data.table`)  
The benchmark design of the latest batch.
- `benchmark_result` (`mlr3::BenchmarkResult`)  
The benchmark result of the latest batch.
- `aggregated_performance` (`data.table::data.table`)  
Aggregated performance scores and training time of the latest batch. This data table is passed to the archive. A callback can add additional columns which are also written to the archive.

**Methods****Public methods:**

- `ContextEval$new()`
- `ContextEval$clone()`

**Method** `new()`: Creates a new instance of this [R6](#) class.

*Usage:*

```
ContextEval$new(objective_fselect)
```

*Arguments:*

`objective_fselect` [ObjectiveFSelect](#).

`id` (`character(1)`)

Identifier for the new callback.

**Method** `clone()`: The objects of this class are cloneable with this method.

*Usage:*

```
ContextEval$clone(deep = FALSE)
```

*Arguments:*

`deep` Whether to make a deep clone.

---

extract\_inner\_fselect\_archives

*Extract Inner Feature Selection Archives*

---

**Description**

Extract inner feature selection archives of nested resampling. Implemented for [mlr3::ResampleResult](#) and [mlr3::BenchmarkResult](#). The function iterates over the [AutoFSelector](#) objects and binds the archives to a `data.table::data.table()`. [AutoFSelector](#) must be initialized with `store_fselect_instance = TRUE` and `resample()` or `benchmark()` must be called with `store_models = TRUE`.

**Usage**

```
extract_inner_fselect_archives(x, exclude_columns = "uhash")
```

**Arguments**

`x` ([mlr3::ResampleResult](#) | [mlr3::BenchmarkResult](#)).

`exclude_columns` ([character\(\)](#))  
Exclude columns from result table. Set to NULL if no column should be excluded.

**Value**

[data.table::data.table\(\)](#).

**Data structure**

The returned data table has the following columns:

- `experiment` ([integer\(1\)](#))  
Index, giving the according row number in the original benchmark grid.
- `iteration` ([integer\(1\)](#))  
Iteration of the outer resampling.
- One column for each feature of the task.
- One column for each performance measure.
- `runtime_learners` ([numeric\(1\)](#))  
Sum of training and predict times logged in learners per [mlr3::ResampleResult](#) / evaluation.  
This does not include potential overhead time.
- `timestamp` ([POSIXct](#))  
Time stamp when the evaluation was logged into the archive.
- `batch_nr` ([integer\(1\)](#))  
Feature sets are evaluated in batches. Each batch has a unique batch number.
- `resample_result` ([mlr3::ResampleResult](#))  
Resample result of the inner resampling.
- `task_id` ([character\(1\)](#)).
- `learner_id` ([character\(1\)](#)).
- `resampling_id` ([character\(1\)](#)).

**Examples**

```
# Nested Resampling on Palmer Penguins Data Set

# create auto fselector
at = auto_fselector(
  fselector = fs("random_search"),
  learner = lrn("classif.rpart"),
  resampling = rsmpl("holdout"),
```

```

measure = msr("classif.ce"),
term_evals = 4)

resampling_outer = rsmp("cv", folds = 2)
rr = resample(tsk("penguins"), at, resampling_outer, store_models = TRUE)

# extract inner archives
extract_inner_fselect_archives(rr)

```

---

```
extract_inner_fselect_results
```

*Extract Inner Feature Selection Results*

---

## Description

Extract inner feature selection results of nested resampling. Implemented for [mlr3::ResampleResult](#) and [mlr3::BenchmarkResult](#).

## Usage

```
extract_inner_fselect_results(x, fselect_instance, ...)
```

## Arguments

<code>x</code>	( <a href="#">mlr3::ResampleResult</a>   <a href="#">mlr3::BenchmarkResult</a> ).
<code>fselect_instance</code>	(logical(1)) If TRUE, instances are added to the table.
<code>...</code>	(any) Additional arguments.

## Details

The function iterates over the [AutoFSelector](#) objects and binds the feature selection results to a [data.table::data.table\(\)](#). [AutoFSelector](#) must be initialized with `store_fselect_instance = TRUE` and `resample()` or `benchmark()` must be called with `store_models = TRUE`. Optionally, the instance can be added for each iteration.

## Value

[data.table::data.table\(\)](#).

## Data structure

The returned data table has the following columns:

- `experiment (integer(1))`  
Index, giving the according row number in the original benchmark grid.
- `iteration (integer(1))`  
Iteration of the outer resampling.
- One column for each feature of the task.
- One column for each performance measure.
- `features (character())`  
Vector of selected feature set.
- `task_id (character(1))`.
- `learner_id (character(1))`.
- `resampling_id (character(1))`.

## Examples

```
# Nested Resampling on Palmer Penguins Data Set

# create auto fselector
at = auto_fselector(
  fselector = fs("random_search"),
  learner = lrn("classif.rpart"),
  resampling = rsmpl("holdout"),
  measure = msr("classif.ce"),
  term_evals = 4)

resampling_outer = rsmpl("cv", folds = 2)
rr = resample(tsk("iris"), at, resampling_outer, store_models = TRUE)

# extract inner results
extract_inner_fselect_results(rr)
```

---

 fs

*Syntactic Sugar for FSelect Construction*


---

## Description

Functions to retrieve objects, set parameters and assign to fields in one go. Relies on `mlr3misc::dictionary_sugar_get()` to extract objects from the respective `mlr3misc::Dictionary`:

- `fs()` for a [FSelector](#) from `mlr_fselectors`.
- `fss()` for a list of [FSelectors](#) from `mlr_fselectors`.
- `trm()` for a [Terminator](#) from `mlr_terminators`.
- `trms()` for a list of [Terminators](#) from `mlr_terminators`.

**Usage**

```
fs(.key, ...)

fss(.keys, ...)
```

**Arguments**

<code>.key</code>	(character(1)) Key passed to the respective <a href="#">dictionary</a> to retrieve the object.
<code>...</code>	(named list()) Named arguments passed to the constructor, to be set as parameters in the <a href="#">paradox::ParamSet</a> , or to be set as public field. See <a href="#">mlr3misc::dictionary_sugar_get()</a> for more details.
<code>.keys</code>	(character()) Keys passed to the respective <a href="#">dictionary</a> to retrieve multiple objects.

**Value**

[R6::R6Class](#) object of the respective type, or a list of [R6::R6Class](#) objects for the plural versions.

**Examples**

```
# random search with batch size of 5
fs("random_search", batch_size = 5)

# run time terminator with 20 seconds
trm("run_time", secs = 20)
```

---

fselect

*Function for Feature Selection*


---

**Description**

Function to optimize the features of a [mlr3::Learner](#). The function internally creates a [FSelectInstanceSingleCrit](#) or [FSelectInstanceMultiCrit](#) which describes the feature selection problem. It executes the feature selection with the [FSelector](#) (method) and returns the result with the fselect instance (`$result`). The [ArchiveFSelect](#) (`$archive`) stores all evaluated hyperparameter configurations and performance scores.

**Usage**

```
fselect(
  fselector,
  task,
  learner,
  resampling,
  measures = NULL,
```

```

term_evals = NULL,
term_time = NULL,
terminator = NULL,
store_benchmark_result = TRUE,
store_models = FALSE,
check_values = FALSE,
callbacks = list(),
ties_method = "least_features"
)

```

### Arguments

fselector	(FSelector) Optimization algorithm.
task	(mlr3::Task) Task to operate on.
learner	(mlr3::Learner) Learner to optimize the feature subset for.
resampling	(mlr3::Resampling) Resampling that is used to evaluate the performance of the feature subsets. Uninstantiated resamplings are instantiated during construction so that all feature subsets are evaluated on the same data splits. Already instantiated resamplings are kept unchanged.
measures	(mlr3::Measure or list of mlr3::Measure) A single measure creates a FSelectInstanceSingleCrit and multiple measures a FSelectInstanceMultiCrit. If NULL, default measure is used.
term_evals	(integer(1)) Number of allowed evaluations. Ignored if terminator is passed.
term_time	(integer(1)) Maximum allowed time in seconds. Ignored if terminator is passed.
terminator	(Terminator) Stop criterion of the feature selection.
store_benchmark_result	(logical(1)) Store benchmark result in archive?
store_models	(logical(1)). Store models in benchmark result?
check_values	(logical(1)) Check the parameters before the evaluation and the results for validity?
callbacks	(list of CallbackFSelect) List of callbacks.
ties_method	(character(1)) The method to break ties when selecting sets while optimizing and when selecting the best set. Can be "least_features" or "random". The option "least_features" (default) selects the feature set with the least features. If there are multiple best feature sets with the same number of features, one is selected randomly. The random method returns a random feature set from the best feature sets. Ignored if multiple measures are used.



## Details

The `mlr3::Task`, `mlr3::Learner`, `mlr3::Resampling`, `mlr3::Measure` and `Terminator` are used to construct a `FSelectInstanceSingleCrit`. If multiple performance `Measures` are supplied, a `FSelectInstanceMultiCrit` is created. The parameter `term_evals` and `term_time` are shortcuts to create a `Terminator`. If both parameters are passed, a `TerminatorCombo` is constructed. For other `Terminators`, pass one with `terminator`. If no termination criterion is needed, set `term_evals`, `term_time` and `terminator` to `NULL`.

## Value

`FSelectInstanceSingleCrit` | `FSelectInstanceMultiCrit`

## Resources

There are several sections about feature selection in the [mlr3book](#).

- Getting started with [wrapper feature selection](#).
- Do a [sequential forward selection](#) Palmer Penguins data set.

The [gallery](#) features a collection of case studies and demos about optimization.

- Utilize the built-in feature importance of models with [Recursive Feature Elimination](#).
- Run a feature selection with [Shadow Variable Search](#).
- [Feature Selection](#) on the Titanic data set.

## Analysis

For analyzing the feature selection results, it is recommended to pass the archive to `as.data.table()`. The returned data table is joined with the benchmark result which adds the `mlr3::ResampleResult` for each feature set.

The archive provides various getters (e.g. `$learners()`) to ease the access. All getters extract by position (`i`) or unique hash (`uhash`). For a complete list of all getters see the methods section.

The benchmark result (`$benchmark_result`) allows to score the feature sets again on a different measure. Alternatively, measures can be supplied to `as.data.table()`.

## Examples

```
# Feature selection on the Palmer Penguins data set
task = tsk("pima")
learner = lrn("classif.rpart")

# Run feature selection
instance = fselect(
  fselector = fs("random_search"),
  task = task,
  learner = learner,
  resampling = rsmpl("holdout"),
  measures = msr("classif.ce"),
  term_evals = 4)
```

```
# Subset task to optimized feature set
task$select(instance$result_feature_set)

# Train the learner with optimal feature set on the full data set
learner$train(task)

# Inspect all evaluated configurations
as.data.table(instance$archive)
```

---

```
FSelectInstanceMultiCrit
```

```
Class for Multi Criteria Feature Selection
```

---

## Description

The `FSelectInstanceMultiCrit` specifies a feature selection problem for `FSelectors`. The function `fsi()` creates a `FSelectInstanceMultiCrit` and the function `fselect()` creates an instance internally.

## Resources

There are several sections about feature selection in the [mlr3book](#).

- Learn about [multi-objective optimization](#).

The [gallery](#) features a collection of case studies and demos about optimization.

## Analysis

For analyzing the feature selection results, it is recommended to pass the archive to `as.data.table()`. The returned data table is joined with the benchmark result which adds the `mlr3::ResampleResult` for each feature set.

The archive provides various getters (e.g. `$learners()`) to ease the access. All getters extract by position (`i`) or unique hash (`uhash`). For a complete list of all getters see the methods section.

The benchmark result (`$benchmark_result`) allows to score the feature sets again on a different measure. Alternatively, measures can be supplied to `as.data.table()`.

## Super classes

```
bbotk::OptimInstance -> bbotk::OptimInstanceMultiCrit -> FSelectInstanceMultiCrit
```

## Active bindings

```
result_feature_set (list of character())
  Feature sets for task subsetting.
```

**Methods****Public methods:**

- [FSelectInstanceMultiCrit\\$new\(\)](#)
- [FSelectInstanceMultiCrit\\$assign\\_result\(\)](#)
- [FSelectInstanceMultiCrit\\$print\(\)](#)
- [FSelectInstanceMultiCrit\\$clone\(\)](#)

**Method** `new()`: Creates a new instance of this [R6](#) class.

*Usage:*

```
FSelectInstanceMultiCrit$new(
  task,
  learner,
  resampling,
  measures,
  terminator,
  store_benchmark_result = TRUE,
  store_models = FALSE,
  check_values = FALSE,
  callbacks = list()
)
```

*Arguments:*

`task` ([mlr3::Task](#))

Task to operate on.

`learner` ([mlr3::Learner](#))

Learner to optimize the feature subset for.

`resampling` ([mlr3::Resampling](#))

Resampling that is used to evaluate the performance of the feature subsets. Uninstantiated resamplings are instantiated during construction so that all feature subsets are evaluated on the same data splits. Already instantiated resamplings are kept unchanged.

`measures` (list of [mlr3::Measure](#))

Measures to optimize. If NULL, [mlr3](#)'s default measure is used.

`terminator` ([Terminator](#))

Stop criterion of the feature selection.

`store_benchmark_result` (logical(1))

Store benchmark result in archive?

`store_models` (logical(1)). Store models in benchmark result?

`check_values` (logical(1))

Check the parameters before the evaluation and the results for validity?

`callbacks` (list of [CallbackFSelect](#))

List of callbacks.

**Method** `assign_result()`: The [FSelector](#) object writes the best found feature subsets and estimated performance values here. For internal use.

*Usage:*

```
FSelectInstanceMultiCrit$assign_result(xdt, ydt)
```

*Arguments:*

xdt (data.table::data.table())  
 x values as data.table. Each row is one point. Contains the value in the *search space* of the FSelectInstanceMultiCrit object. Can contain additional columns for extra information.

ydt (data.table::data.table())  
 Optimal outcomes, e.g. the Pareto front.

**Method print():** Printer.

*Usage:*

```
FSelectInstanceMultiCrit$print(...)
```

*Arguments:*

... (ignored).

**Method clone():** The objects of this class are cloneable with this method.

*Usage:*

```
FSelectInstanceMultiCrit$clone(deep = FALSE)
```

*Arguments:*

deep Whether to make a deep clone.

**Examples**

```
# Feature selection on Palmer Penguins data set

task = tsk("penguins")

# Construct feature selection instance
instance = fsi(
  task = task,
  learner = lrn("classif.rpart"),
  resampling = rsmp("cv", folds = 3),
  measures = msrs(c("classif.ce", "time_train")),
  terminator = trm("evals", n_evals = 4)
)

# Choose optimization algorithm
fselector = fs("random_search", batch_size = 2)

# Run feature selection
fselector$optimize(instance)

# Optimal feature sets
instance$result_feature_set

# Inspect all evaluated sets
as.data.table(instance$archive)
```

---

FSelectInstanceSingleCrit

*Class for Single Criterion Feature Selection*


---

## Description

The `FSelectInstanceSingleCrit` specifies a feature selection problem for `FSelectors`. The function `fsi()` creates a `FSelectInstanceSingleCrit` and the function `fselect()` creates an instance internally.

The instance contains an `ObjectiveFSelect` object that encodes the black box objective function a `FSelector` has to optimize. The instance allows the basic operations of querying the objective at design points (`$eval_batch()`). This operation is usually done by the `FSelector`. Evaluations of feature subsets are performed in batches by calling `mlr3::benchmark()` internally. The evaluated feature subsets are stored in the `Archive` (`$archive`). Before a batch is evaluated, the `bbotk::Terminator` is queried for the remaining budget. If the available budget is exhausted, an exception is raised, and no further evaluations can be performed from this point on. The `FSelector` is also supposed to store its final result, consisting of a selected feature subset and associated estimated performance values, by calling the method `instance$assign_result()`.

## Default Measures

If no measure is passed, the default measure is used. The default measure depends on the task type.

Task	Default Measure	Package
"classif"	"classif.ce"	<b>mlr3</b>
"regr"	"regr.mse"	<b>mlr3</b>
"surv"	"surv.cindex"	<b>mlr3proba</b>
"dens"	"dens.logloss"	<b>mlr3proba</b>
"classif_st"	"classif.ce"	<b>mlr3spatial</b>
"regr_st"	"regr.mse"	<b>mlr3spatial</b>
"clust"	"clust.dunn"	<b>mlr3cluster</b>

## Resources

There are several sections about feature selection in the [mlr3book](#).

- Getting started with [wrapper feature selection](#).
- Do a [sequential forward selection](#) Palmer Penguins data set.

The [gallery](#) features a collection of case studies and demos about optimization.

- Utilize the built-in feature importance of models with [Recursive Feature Elimination](#).
- Run a feature selection with [Shadow Variable Search](#).
- [Feature Selection](#) on the Titanic data set.

## Analysis

For analyzing the feature selection results, it is recommended to pass the archive to `as.data.table()`. The returned data table is joined with the benchmark result which adds the `mlr3::ResampleResult` for each feature set.

The archive provides various getters (e.g. `$learners()`) to ease the access. All getters extract by position (`i`) or unique hash (`uhash`). For a complete list of all getters see the methods section.

The benchmark result (`$benchmark_result`) allows to score the feature sets again on a different measure. Alternatively, measures can be supplied to `as.data.table()`.

## Super classes

`bbotk::OptimInstance` -> `bbotk::OptimInstanceSingleCrit` -> `FSelectInstanceSingleCrit`

## Active bindings

`result_feature_set` (`character()`)  
Feature set for task subsetting.

## Methods

### Public methods:

- `FSelectInstanceSingleCrit$new()`
- `FSelectInstanceSingleCrit$assign_result()`
- `FSelectInstanceSingleCrit$print()`
- `FSelectInstanceSingleCrit$clone()`

**Method** `new()`: Creates a new instance of this `R6` class.

*Usage:*

```
FSelectInstanceSingleCrit$new(
  task,
  learner,
  resampling,
  measure,
  terminator,
  store_benchmark_result = TRUE,
  store_models = FALSE,
  check_values = FALSE,
  callbacks = list(),
  ties_method = "least_features"
)
```

*Arguments:*

`task` (`mlr3::Task`)

Task to operate on.

`learner` (`mlr3::Learner`)

Learner to optimize the feature subset for.

resampling ([mlr3::Resampling](#))  
 Resampling that is used to evaluate the performance of the feature subsets. Uninstantiated resamplings are instantiated during construction so that all feature subsets are evaluated on the same data splits. Already instantiated resamplings are kept unchanged.

measure ([mlr3::Measure](#))  
 Measure to optimize. If NULL, default measure is used.

terminator ([Terminator](#))  
 Stop criterion of the feature selection.

store\_benchmark\_result (logical(1))  
 Store benchmark result in archive?

store\_models (logical(1)). Store models in benchmark result?

check\_values (logical(1))  
 Check the parameters before the evaluation and the results for validity?

callbacks (list of [CallbackFSelect](#))  
 List of callbacks.

ties\_method (character(1))  
 The method to break ties when selecting sets while optimizing and when selecting the best set. Can be "least\_features" or "random". The option "least\_features" (default) selects the feature set with the least features. If there are multiple best feature sets with the same number of features, one is selected randomly. The random method returns a random feature set from the best feature sets. Ignored if multiple measures are used.

**Method** `assign_result()`: The [FSelector](#) writes the best found feature subset and estimated performance value here. For internal use.

*Usage:*

```
FSelectInstanceSingleCrit$assign_result(xdt, y)
```

*Arguments:*

xdt (`data.table::data.table()`)

x values as `data.table`. Each row is one point. Contains the value in the *search space* of the [FSelectInstanceMultiCrit](#) object. Can contain additional columns for extra information.

y (`numeric(1)`)

Optimal outcome.

**Method** `print()`: Printer.

*Usage:*

```
FSelectInstanceSingleCrit$print(...)
```

*Arguments:*

... (ignored).

**Method** `clone()`: The objects of this class are cloneable with this method.

*Usage:*

```
FSelectInstanceSingleCrit$clone(deep = FALSE)
```

*Arguments:*

deep Whether to make a deep clone.

## Examples

```
# Feature selection on Palmer Penguins data set

task = tsk("penguins")
learner = lrn("classif.rpart")

# Construct feature selection instance
instance = fsi(
  task = task,
  learner = learner,
  resampling = rsmpl("cv", folds = 3),
  measures = msr("classif.ce"),
  terminator = trm("evals", n_evals = 4)
)

# Choose optimization algorithm
fselector = fs("random_search", batch_size = 2)

# Run feature selection
fselector$optimize(instance)

# Subset task to optimal feature set
task$select(instance$result_feature_set)

# Train the learner with optimal feature set on the full data set
learner$train(task)

# Inspect all evaluated sets
as.data.table(instance$archive)
```

---

FSelector

*Class for Feature Selection Algorithms*

---

## Description

The [FSelector](#) implements the optimization algorithm.

## Details

[FSelector](#) is an abstract base class that implements the base functionality each fselector must provide. A subclass is implemented in the following way:

- Inherit from FSelector.
- Specify the private abstract method `$.optimize()` and use it to call into your optimizer.
- You need to call `instance$eval_batch()` to evaluate design points.



- The batch evaluation is requested at the [FSelectInstanceSingleCrit/FSelectInstanceMultiCrit](#) object instance, so each batch is possibly executed in parallel via `mlr3::benchmark()`, and all evaluations are stored inside of `instance$archive`.
- Before the batch evaluation, the [bbotk::Terminator](#) is checked, and if it is positive, an exception of class "terminated\_error" is generated. In the latter case the current batch of evaluations is still stored in `instance`, but the numeric scores are not sent back to the handling optimizer as it has lost execution control.
- After such an exception was caught we select the best set from `instance$archive` and return it.
- Note that therefore more points than specified by the [bbotk::Terminator](#) may be evaluated, as the Terminator is only checked before a batch evaluation, and not in-between evaluation in a batch. How many more depends on the setting of the batch size.
- Overwrite the private super-method `.assign_result()` if you want to decide how to estimate the final set in the instance and its estimated performance. The default behavior is: We pick the best resample experiment, regarding the given measure, then assign its set and aggregated performance to the instance.

### Private Methods

- `.optimize(instance) -> NULL`  
Abstract base method. Implement to specify feature selection of your subclass. See technical details sections.
- `.assign_result(instance) -> NULL`  
Abstract base method. Implement to specify how the final feature subset is selected. See technical details sections.

### Resources

There are several sections about feature selection in the [mlr3book](#).

- Learn more about [fselectors](#).

The [gallery](#) features a collection of case studies and demos about optimization.

- Utilize the built-in feature importance of models with [Recursive Feature Elimination](#).
- Run a feature selection with [Shadow Variable Search](#).

### Public fields

`id` (`character(1)`)  
Identifier of the object. Used in tables, plot and text output.

### Active bindings

`param_set` [paradox::ParamSet](#)  
Set of control parameters.

`properties` (`character()`)  
Set of properties of the fselector. Must be a subset of `mlr_reflections$fselect_properties`.

`packages` (character())  
Set of required packages. Note that these packages will be loaded via `requireNamespace()`, and are not attached.

`label` (character(1))  
Label for this object. Can be used in tables, plot and text output instead of the ID.

`man` (character(1))  
String in the format `[pkg]::[topic]` pointing to a manual page for this object. The referenced help package can be opened via method `$help()`.

## Methods

### Public methods:

- [FSelector\\$new\(\)](#)
- [FSelector\\$format\(\)](#)
- [FSelector\\$print\(\)](#)
- [FSelector\\$help\(\)](#)
- [FSelector\\$optimize\(\)](#)
- [FSelector\\$clone\(\)](#)

**Method** `new()`: Creates a new instance of this R6 class.

*Usage:*

```
FSelector$new(
  id = "fselector",
  param_set,
  properties,
  packages = character(),
  label = NA_character_,
  man = NA_character_
)
```

*Arguments:*

`id` (character(1))  
Identifier for the new instance.

`param_set` [paradox::ParamSet](#)  
Set of control parameters.

`properties` (character())  
Set of properties of the fselector. Must be a subset of `mlr_reflections$fselect_properties`.

`packages` (character())  
Set of required packages. Note that these packages will be loaded via `requireNamespace()`, and are not attached.

`label` (character(1))  
Label for this object. Can be used in tables, plot and text output instead of the ID.

`man` (character(1))  
String in the format `[pkg]::[topic]` pointing to a manual page for this object. The referenced help package can be opened via method `$help()`.

**Method** `format()`: Helper for print outputs.

*Usage:*

```
FSelector$format(...)
```

*Arguments:*

... (ignored).

*Returns:* (character()).

**Method print():** Print method.

*Usage:*

```
FSelector$print()
```

*Returns:* (character()).

**Method help():** Opens the corresponding help page referenced by field \$man.

*Usage:*

```
FSelector$help()
```

**Method optimize():** Performs the feature selection on a [FSelectInstanceSingleCrit](#) or [FSelectInstanceMultiCrit](#) until termination. The single evaluations will be written into the [ArchiveFSelect](#) that resides in the [FSelectInstanceSingleCrit](#) / [FSelectInstanceMultiCrit](#). The result will be written into the instance object.

*Usage:*

```
FSelector$optimize(inst)
```

*Arguments:*

inst ([FSelectInstanceSingleCrit](#) | [FSelectInstanceMultiCrit](#)).

*Returns:* [data.table::data.table\(\)](#).

**Method clone():** The objects of this class are cloneable with this method.

*Usage:*

```
FSelector$clone(deep = FALSE)
```

*Arguments:*

deep Whether to make a deep clone.

---

fselect\_nested

*Function for Nested Resampling*

---

## Description

Function to conduct nested resampling.

**Usage**

```
fselect_nested(
  fselector,
  task,
  learner,
  inner_resampling,
  outer_resampling,
  measure = NULL,
  term_evals = NULL,
  term_time = NULL,
  terminator = NULL,
  store_fselect_instance = TRUE,
  store_benchmark_result = TRUE,
  store_models = FALSE,
  check_values = FALSE,
  callbacks = list(),
  ties_method = "least_features"
)
```

**Arguments**

fselector	( <a href="#">FSelector</a> ) Optimization algorithm.
task	( <a href="#">mlr3::Task</a> ) Task to operate on.
learner	( <a href="#">mlr3::Learner</a> ) Learner to optimize the feature subset for.
inner_resampling	( <a href="#">mlr3::Resampling</a> ) Resampling used for the inner loop.
outer_resampling	( <a href="#">mlr3::Resampling</a> ) Resampling used for the outer loop.
measure	( <a href="#">mlr3::Measure</a> ) Measure to optimize. If NULL, default measure is used.
term_evals	( <a href="#">integer(1)</a> ) Number of allowed evaluations. Ignored if terminator is passed.
term_time	( <a href="#">integer(1)</a> ) Maximum allowed time in seconds. Ignored if terminator is passed.
terminator	( <a href="#">Terminator</a> ) Stop criterion of the feature selection.
store_fselect_instance	( <a href="#">logical(1)</a> ) If TRUE (default), stores the internally created <a href="#">FSelectInstanceSingleCrit</a> with all intermediate results in slot \$fselect_instance. Is set to TRUE, if store_models = TRUE

store_benchmark_result	(logical(1)) Store benchmark result in archive?
store_models	(logical(1)). Store models in benchmark result?
check_values	(logical(1)) Check the parameters before the evaluation and the results for validity?
callbacks	(list of <a href="#">CallbackFSelect</a> ) List of callbacks.
ties_method	(character(1)) The method to break ties when selecting sets while optimizing and when selecting the best set. Can be "least_features" or "random". The option "least_features" (default) selects the feature set with the least features. If there are multiple best feature sets with the same number of features, one is selected randomly. The random method returns a random feature set from the best feature sets. Ignored if multiple measures are used.

**Value**

[mlr3::ResampleResult](#)

**Examples**

```
# Nested resampling on Palmer Penguins data set
rr = fselect_nested(
  fselector = fs("random_search"),
  task = tsk("penguins"),
  learner = lrn("classif.rpart"),
  inner_resampling = rsmp("holdout"),
  outer_resampling = rsmp("cv", folds = 2),
  measure = msr("classif.ce"),
  term_evals = 4)

# Performance scores estimated on the outer resampling
rr$score()

# Unbiased performance of the final model trained on the full data set
rr$aggregate()
```

**Description**

Function to construct a [FSelectInstanceSingleCrit](#) or [FSelectInstanceMultiCrit](#).

**Usage**

```

fsi(
  task,
  learner,
  resampling,
  measures = NULL,
  terminator,
  store_benchmark_result = TRUE,
  store_models = FALSE,
  check_values = FALSE,
  callbacks = list(),
  ties_method = "least_features"
)

```

**Arguments**

task	( <a href="#">mlr3::Task</a> ) Task to operate on.
learner	( <a href="#">mlr3::Learner</a> ) Learner to optimize the feature subset for.
resampling	( <a href="#">mlr3::Resampling</a> ) Resampling that is used to evaluate the performance of the feature subsets. Uninstantiated resamplings are instantiated during construction so that all feature subsets are evaluated on the same data splits. Already instantiated resamplings are kept unchanged.
measures	( <a href="#">mlr3::Measure</a> or list of <a href="#">mlr3::Measure</a> ) A single measure creates a <a href="#">FSelectInstanceSingleCrit</a> and multiple measures a <a href="#">FSelectInstanceMultiCrit</a> . If NULL, default measure is used.
terminator	( <a href="#">Terminator</a> ) Stop criterion of the feature selection.
store_benchmark_result	( <a href="#">logical(1)</a> ) Store benchmark result in archive?
store_models	( <a href="#">logical(1)</a> ). Store models in benchmark result?
check_values	( <a href="#">logical(1)</a> ) Check the parameters before the evaluation and the results for validity?
callbacks	(list of <a href="#">CallbackFSelect</a> ) List of callbacks.
ties_method	( <a href="#">character(1)</a> ) The method to break ties when selecting sets while optimizing and when selecting the best set. Can be "least_features" or "random". The option "least_features" (default) selects the feature set with the least features. If there are multiple best feature sets with the same number of features, one is selected randomly. The random method returns a random feature set from the best feature sets. Ignored if multiple measures are used.

## Resources

There are several sections about feature selection in the [mlr3book](#).

- Getting started with [wrapper feature selection](#).
- Do a [sequential forward selection](#) Palmer Penguins data set.

The [gallery](#) features a collection of case studies and demos about optimization.

- Utilize the built-in feature importance of models with [Recursive Feature Elimination](#).
- Run a feature selection with [Shadow Variable Search](#).
- [Feature Selection](#) on the Titanic data set.

## Default Measures

If no measure is passed, the default measure is used. The default measure depends on the task type.

Task	Default Measure	Package
"classif"	"classif.ce"	<b>mlr3</b>
"regr"	"regr.mse"	<b>mlr3</b>
"surv"	"surv.cindex"	<b>mlr3proba</b>
"dens"	"dens.logloss"	<b>mlr3proba</b>
"classif_st"	"classif.ce"	<b>mlr3spatial</b>
"regr_st"	"regr.mse"	<b>mlr3spatial</b>
"clust"	"clust.dunn"	<b>mlr3cluster</b>

## Examples

```
# Feature selection on Palmer Penguins data set
```

```
task = tsk("penguins")
learner = lrn("classif.rpart")

# Construct feature selection instance
instance = fsi(
  task = task,
  learner = learner,
  resampling = rsmpl("cv", folds = 3),
  measures = msr("classif.ce"),
  terminator = trm("evals", n_evals = 4)
)
```

```
# Choose optimization algorithm
fselector = fs("random_search", batch_size = 2)
```

```
# Run feature selection
fselector$optimize(instance)
```

```
# Subset task to optimal feature set
```

```

task$select(instance$result_feature_set)

# Train the learner with optimal feature set on the full data set
learner$train(task)

# Inspect all evaluated sets
as.data.table(instance$archive)

```

---

```
mlr3fselect.backup
```

*Backup Benchmark Result Callback*

---

### Description

This [CallbackFSelect](#) writes the [mlr3::BenchmarkResult](#) after each batch to disk.

### Examples

```

clbk("mlr3fselect.backup", path = "backup.rds")

# Run feature selection on the Palmer Penguins data set
instance = fselect(
  fselector = fs("random_search"),
  task = tsk("pima"),
  learner = lrn("classif.rpart"),
  resampling = rsmp("holdout"),
  measures = msr("classif.ce"),
  term_evals = 4,
  callbacks = clbk("mlr3fselect.backup", path = tempfile(fileext = ".rds")))

```

---

```
mlr3fselect.one_se_rule
```

*One Standard Error Rule Callback*

---

### Description

Selects the smallest feature set within one standard error of the best as the result. If there are multiple feature sets with the same performance and number of features, the first one is selected.

### Source

Kuhn, Max, Johnson, Kjell (2013). "Applied Predictive Modeling." In chapter Over-Fitting and Model Tuning, 61–92. Springer New York, New York, NY. ISBN 978-1-4614-6849-3.



**Examples**

```

clbk("mlr3fselect.one_se_rule")

# Run feature selection on the pima data set with the callback
instance = fselect(
  fselector = fs("random_search"),
  task = tsk("pima"),
  learner = lrn("classif.rpart"),
  resampling = rsmp("cv", folds = 3),
  measures = msr("classif.ce"),
  term_evals = 10,
  callbacks = clbk("mlr3fselect.one_se_rule"))
# Smallest feature set within one standard error of the best
instance$result

```

---

```
mlr3fselect.svm_rfe   SVM-RFE Callback
```

---

**Description**

Runs a recursive feature elimination with a [mlr3learners::LearnerClassifSVM](#). The SVM must be configured with `type = "C-classification"` and `kernel = "linear"`.

**Source**

Guyon I, Weston J, Barnhill S, Vapnik V (2002). "Gene Selection for Cancer Classification using Support Vector Machines." *Machine Learning*, **46**(1), 389–422. ISSN 1573-0565, [doi:10.1023/A:1012487302797](#).

**Examples**

```

clbk("mlr3fselect.svm_rfe")

library(mlr3learners)

# Create instance with classification svm with linear kernel
instance = fsi(
  task = tsk("sonar"),
  learner = lrn("classif.svm", type = "C-classification", kernel = "linear"),
  resampling = rsmp("cv", folds = 3),
  measures = msr("classif.ce"),
  terminator = trm("none"),
  callbacks = clbk("mlr3fselect.svm_rfe"),
  store_models = TRUE
)

fselector = fs("rfe", feature_number = 5, n_features = 10)

# Run recursive feature elimination on the Sonar data set
fselector$optimize(instance)

```

---

mlr_fselectors	<i>Dictionary of FSelectors</i>
----------------	---------------------------------

---

## Description

A `mlr3misc::Dictionary` storing objects of class `FSelector`. Each fselector has an associated help page, see `mlr_fselectors_[id]`.

For a more convenient way to retrieve and construct fselectors, see `fs()/fss()`.

## Format

`R6::R6Class` object inheriting from `mlr3misc::Dictionary`.

## Methods

See `mlr3misc::Dictionary`.

## S3 methods

- `as.data.table(dict, ..., objects = FALSE)`  
`mlr3misc::Dictionary` -> `data.table::data.table()`  
Returns a `data.table::data.table()` with fields "key", "label", "properties" and "packages" as columns. If `objects` is set to `TRUE`, the constructed objects are returned in the list column named `object`.

## See Also

Sugar functions: `fs()`, `fss()`

Other `FSelector`: `mlr_fselectors_design_points`, `mlr_fselectors_exhaustive_search`, `mlr_fselectors_genetic_s`, `mlr_fselectors_random_search`, `mlr_fselectors_rfe`, `mlr_fselectors_rfecv`, `mlr_fselectors_sequential`, `mlr_fselectors_shadow_variable_search`

## Examples

```
as.data.table(mlr_fselectors)
mlr_fselectors$get("random_search")
fs("random_search")
```

---

`mlr_fselectors_design_points`*Feature Selection with Design Points*

---

## Description

Feature selection using user-defined feature sets.

## Details

The feature sets are evaluated in order as given.

The feature selection terminates itself when all feature sets are evaluated. It is not necessary to set a termination criterion.

## Dictionary

This `FSelector` can be instantiated with the associated sugar function `fs()`:

```
fs("design_points")
```

## Parameters

`batch_size` `integer(1)`

Maximum number of configurations to try in a batch.

`design` `data.table::data.table`

Design points to try in search, one per row.

## Super classes

```
mlr3fselect::FSelector -> mlr3fselect::FSelectorFromOptimizer -> FSelectorDesignPoints
```

## Methods

### Public methods:

- `FSelectorDesignPoints$new()`
- `FSelectorDesignPoints$clone()`

**Method** `new()`: Creates a new instance of this R6 class.

*Usage:*

```
FSelectorDesignPoints$new()
```

**Method** `clone()`: The objects of this class are cloneable with this method.

*Usage:*

```
FSelectorDesignPoints$clone(deep = FALSE)
```

*Arguments:*

`deep` Whether to make a deep clone.

**See Also**

Other FSelector: [mlr\\_fselectors](#), [mlr\\_fselectors\\_exhaustive\\_search](#), [mlr\\_fselectors\\_genetic\\_search](#), [mlr\\_fselectors\\_random\\_search](#), [mlr\\_fselectors\\_rfe](#), [mlr\\_fselectors\\_rfecv](#), [mlr\\_fselectors\\_sequential](#), [mlr\\_fselectors\\_shadow\\_variable\\_search](#)

**Examples**

```
# Feature Selection

# retrieve task and load learner
task = tsk("pima")
learner = lrn("classif.rpart")

# create design
design = mlr3misc::rowwise_table(
  ~age, ~glucose, ~insulin, ~mass, ~pedigree, ~pregnant, ~pressure, ~triceps,
  TRUE, FALSE, TRUE, TRUE, FALSE, TRUE, FALSE, TRUE,
  TRUE, TRUE, FALSE, TRUE, FALSE, TRUE, FALSE, FALSE,
  TRUE, FALSE, TRUE, TRUE, FALSE, TRUE, FALSE, FALSE,
  TRUE, FALSE, TRUE, TRUE, FALSE, TRUE, TRUE, TRUE
)

# run feature selection on the Pima Indians diabetes data set
instance = fselect(
  fselector = fs("design_points", design = design),
  task = task,
  learner = learner,
  resampling = rsmpl("holdout"),
  measure = msr("classif.ce")
)

# best performing feature set
instance$result

# all evaluated feature sets
as.data.table(instance$archive)

# subset the task and fit the final model
task$select(instance$result_feature_set)
learner$train(task)
```

---

```
mlr_fselectors_exhaustive_search
```

*Feature Selection with Exhaustive Search*

---

**Description**

Feature Selection using the Exhaustive Search Algorithm. Exhaustive Search generates all possible feature sets.

## Details

The feature selection terminates itself when all feature sets are evaluated. It is not necessary to set a termination criterion.

## Dictionary

This `FSelector` can be instantiated with the associated sugar function `fs()`:

```
fs("exhaustive_search")
```

## Control Parameters

`max_features` integer(1)

Maximum number of features. By default, number of features in `mlr3::Task`.

## Super class

```
mlr3fselect::FSelector -> FSelectorExhaustiveSearch
```

## Methods

### Public methods:

- `FSelectorExhaustiveSearch$new()`
- `FSelectorExhaustiveSearch$clone()`

**Method** `new()`: Creates a new instance of this R6 class.

*Usage:*

```
FSelectorExhaustiveSearch$new()
```

**Method** `clone()`: The objects of this class are cloneable with this method.

*Usage:*

```
FSelectorExhaustiveSearch$clone(deep = FALSE)
```

*Arguments:*

`deep` Whether to make a deep clone.

## See Also

Other `FSelector`: `mlr_fselectors`, `mlr_fselectors_design_points`, `mlr_fselectors_genetic_search`, `mlr_fselectors_random_search`, `mlr_fselectors_rfe`, `mlr_fselectors_rfecv`, `mlr_fselectors_sequential`, `mlr_fselectors_shadow_variable_search`

**Examples**

```

# Feature Selection

# retrieve task and load learner
task = tsk("penguins")
learner = lrn("classif.rpart")

# run feature selection on the Palmer Penguins data set
instance = fselect(
  fselector = fs("exhaustive_search"),
  task = task,
  learner = learner,
  resampling = rsmpl("holdout"),
  measure = msr("classif.ce"),
  term_evals = 10
)

# best performing feature set
instance$result

# all evaluated feature sets
as.data.table(instance$archive)

# subset the task and fit the final model
task$select(instance$result_feature_set)
learner$train(task)

```

---

mlr\_fselectors\_genetic\_search

*Feature Selection with Genetic Search*


---

**Description**

Feature selection using the Genetic Algorithm from the package **genalg**.

**Dictionary**

This **FSelector** can be instantiated with the associated sugar function **fs()**:

```
fs("genetic_search")
```

**Control Parameters**

For the meaning of the control parameters, see **genalg::rbga.bin()**. **genalg::rbga.bin()** internally terminates after `iters` iteration. We set `iters = 100000` to allow the termination via our terminators. If more iterations are needed, set `iters` to a higher value in the parameter set.

**Super class**

`mlr3fselect::FSelector` -> `FSelectorGeneticSearch`

**Methods****Public methods:**

- `FSelectorGeneticSearch$new()`
- `FSelectorGeneticSearch$clone()`

**Method** `new()`: Creates a new instance of this R6 class.

*Usage:*

```
FSelectorGeneticSearch$new()
```

**Method** `clone()`: The objects of this class are cloneable with this method.

*Usage:*

```
FSelectorGeneticSearch$clone(deep = FALSE)
```

*Arguments:*

`deep` Whether to make a deep clone.

**See Also**

Other `FSelector`: `mlr_fselectors`, `mlr_fselectors_design_points`, `mlr_fselectors_exhaustive_search`, `mlr_fselectors_random_search`, `mlr_fselectors_rfe`, `mlr_fselectors_rfecv`, `mlr_fselectors_sequential`, `mlr_fselectors_shadow_variable_search`

**Examples**

```
# Feature Selection

# retrieve task and load learner
task = tsk("penguins")
learner = lrn("classif.rpart")

# run feature selection on the Palmer Penguins data set
instance = fselect(
  fselector = fs("genetic_search"),
  task = task,
  learner = learner,
  resampling = rsmpl("holdout"),
  measure = msr("classif.ce"),
  term_evals = 10
)

# best performing feature set
instance$result

# all evaluated feature sets
as.data.table(instance$archive)
```

```
# subset the task and fit the final model
task$select(instance$result_feature_set)
learner$train(task)
```

---

```
mlr_fselectors_random_search
```

*Feature Selection with Random Search*

---

## Description

Feature selection using Random Search Algorithm.

## Details

The feature sets are randomly drawn. The sets are evaluated in batches of size `batch_size`. Larger batches mean we can parallelize more, smaller batches imply a more fine-grained checking of termination criteria.

## Dictionary

This [FSelector](#) can be instantiated with the associated sugar function `fs()`:

```
fs("random_search")
```

## Control Parameters

`max_features` integer(1)

Maximum number of features. By default, number of features in [mlr3::Task](#).

`batch_size` integer(1)

Maximum number of feature sets to try in a batch.

## Super class

```
mlr3fselect::FSelector -> FSelectorRandomSearch
```

## Methods

### Public methods:

- [FSelectorRandomSearch\\$new\(\)](#)
- [FSelectorRandomSearch\\$clone\(\)](#)

**Method** `new()`: Creates a new instance of this [R6](#) class.

*Usage:*

```
FSelectorRandomSearch$new()
```



**Method** clone(): The objects of this class are cloneable with this method.

*Usage:*

```
FSelectorRandomSearch$clone(deep = FALSE)
```

*Arguments:*

deep Whether to make a deep clone.

## Source

Bergstra J, Bengio Y (2012). “Random Search for Hyper-Parameter Optimization.” *Journal of Machine Learning Research*, **13**(10), 281–305. <https://jmlr.csail.mit.edu/papers/v13/bergstra12a.html>.

## See Also

Other FSelector: [mlr\\_fselectors](#), [mlr\\_fselectors\\_design\\_points](#), [mlr\\_fselectors\\_exhaustive\\_search](#), [mlr\\_fselectors\\_genetic\\_search](#), [mlr\\_fselectors\\_rfe](#), [mlr\\_fselectors\\_rfecv](#), [mlr\\_fselectors\\_sequential](#), [mlr\\_fselectors\\_shadow\\_variable\\_search](#)

## Examples

```
# Feature Selection

# retrieve task and load learner
task = tsk("penguins")
learner = lrn("classif.rpart")

# run feature selection on the Palmer Penguins data set
instance = fselect(
  fselector = fs("random_search"),
  task = task,
  learner = learner,
  resampling = rsmpl("holdout"),
  measure = msr("classif.ce"),
  term_evals = 10
)

# best performing feature subset
instance$result

# all evaluated feature subsets
as.data.table(instance$archive)

# subset the task and fit the final model
task$select(instance$result_feature_set)
learner$train(task)
```

## Description

Feature selection using the Recursive Feature Elimination (RFE) algorithm. Recursive feature elimination iteratively removes features with a low importance score. Only works with `mlr3::Learners` that can calculate importance scores (see the section on optional extractors in `mlr3::Learner`).

## Details

The learner is trained on all features at the start and importance scores are calculated for each feature. Then the least important feature is removed and the learner is trained on the reduced feature set. The importance scores are calculated again and the procedure is repeated until the desired number of features is reached. The non-recursive option (`recursive = FALSE`) only uses the importance scores calculated in the first iteration.

The feature selection terminates itself when `n_features` is reached. It is not necessary to set a termination criterion.

When using a cross-validation resampling strategy, the importance scores of the resampling iterations are aggregated. The parameter `aggregation` determines how the importance scores are aggregated. By default (`"rank"`), the importance score vector of each fold is ranked and the feature with the lowest average rank is removed. The option `"mean"` averages the score of each feature across the resampling iterations and removes the feature with the lowest average score. Averaging the scores is not appropriate for most importance measures.

## Archive

The `ArchiveFSelect` holds the following additional columns:

- `"importance"` (`numeric()`)  
The importance score vector of the feature subset.

## Resources

The [gallery](#) features a collection of case studies and demos about optimization.

- Utilize the built-in feature importance of models with [Recursive Feature Elimination](#).

## Dictionary

This `FSelector` can be instantiated with the associated sugar function `fs()`:

```
fs("rfe")
```

**Control Parameters**

- `n_features` integer(1)  
The minimum number of features to select, by default half of the features.
- `feature_fraction` double(1)  
Fraction of features to retain in each iteration. The default of 0.5 retains half of the features.
- `feature_number` integer(1)  
Number of features to remove in each iteration.
- `subset_sizes` integer()  
Vector of the number of features to retain in each iteration. Must be sorted in decreasing order.
- `recursive` logical(1)  
If TRUE (default), the feature importance is calculated in each iteration.
- `aggregation` character(1)  
The aggregation method for the importance scores of the resampling iterations. See details.
- The parameter `feature_fraction`, `feature_number` and `subset_sizes` are mutually exclusive.

**Super class**

`mlr3fselect::FSelector` -> `FSelectorRFE`

**Methods****Public methods:**

- `FSelectorRFE$new()`
- `FSelectorRFE$clone()`

**Method** `new()`: Creates a new instance of this R6 class.

*Usage:*

`FSelectorRFE$new()`

**Method** `clone()`: The objects of this class are cloneable with this method.

*Usage:*

`FSelectorRFE$clone(deep = FALSE)`

*Arguments:*

`deep` Whether to make a deep clone.

**Source**

Guyon I, Weston J, Barnhill S, Vapnik V (2002). “Gene Selection for Cancer Classification using Support Vector Machines.” *Machine Learning*, **46**(1), 389–422. ISSN 1573-0565, doi:10.1023/A:1012487302797.

**See Also**

Other `FSelector`: `mlr_fselectors`, `mlr_fselectors_design_points`, `mlr_fselectors_exhaustive_search`, `mlr_fselectors_genetic_search`, `mlr_fselectors_random_search`, `mlr_fselectors_rfecv`, `mlr_fselectors_sequential`, `mlr_fselectors_shadow_variable_search`

## Examples

```
# Feature Selection

# retrieve task and load learner
task = tsk("penguins")
learner = lrn("classif.rpart")

# run feature selection on the Palmer Penguins data set
instance = fselect(
  fselector = fs("rfe"),
  task = task,
  learner = learner,
  resampling = rsmp("holdout"),
  measure = msr("classif.ce"),
  store_models = TRUE
)

# best performing feature subset
instance$result

# all evaluated feature subsets
as.data.table(instance$archive)

# subset the task and fit the final model
task$select(instance$result_feature_set)
learner$train(task)
```

---

mlr\_fselectors\_rfecv *Feature Selection with Recursive Feature Elimination with Cross Validation*

---

## Description

Feature selection using the Recursive Feature Elimination with Cross-Validation (RFE-CV) algorithm. See [FSelectorRFE](#) for a description of the base algorithm. RFE-CV runs a recursive feature elimination in each iteration of a cross-validation to determine the optimal number of features. Then a recursive feature elimination is run again on the complete dataset with the optimal number of features as the final feature set size. The performance of the optimal feature set is calculated on the complete data set and should not be reported as the performance of the final model. Only works with [mlr3::Learners](#) that can calculate importance scores (see the section on optional extractors in [mlr3::Learner](#)).

## Details

The resampling strategy is changed during the feature selection. The resampling strategy passed to the instance (`resampling`) is used to determine the optimal number of features. Usually, a cross-validation strategy is used and a recursive feature elimination is run in each iteration of the cross-validation. Internally, [mlr3::ResamplingCustom](#) is used to emulate this part of the algorithm. In the

final recursive feature elimination run the resampling strategy is changed to [mlr3::ResamplingInsample](#) i.e. the complete data set is used for training and testing.

The feature selection terminates itself when the optimal number of features is reached. It is not necessary to set a termination criterion.

## Archive

The [ArchiveFSelect](#) holds the following additional columns:

- "iteration" (integer(1))  
The resampling iteration in which the feature subset was evaluated.
- "importance" (numeric())  
The importance score vector of the feature subset.

## Resources

The [gallery](#) features a collection of case studies and demos about optimization.

- Utilize the built-in feature importance of models with [Recursive Feature Elimination](#).

## Dictionary

This [FSelector](#) can be instantiated with the associated sugar function `fs()`:

```
fs("rfe")
```

## Control Parameters

`n_features` integer(1)

The number of features to select. By default half of the features are selected.

`feature_fraction` double(1)

Fraction of features to retain in each iteration. The default 0.5 retrains half of the features.

`feature_number` integer(1)

Number of features to remove in each iteration.

`subset_sizes` integer()

Vector of number of features to retain in each iteration. Must be sorted in decreasing order.

`recursive` logical(1)

If TRUE (default), the feature importance is calculated in each iteration.

The parameter `feature_fraction`, `feature_number` and `subset_sizes` are mutually exclusive.

## Super class

[mlr3fselect::FSelector](#) -> [FSelectorRFECV](#)

## Methods

### Public methods:

- [FSelectorRFECV\\$new\(\)](#)
- [FSelectorRFECV\\$clone\(\)](#)

**Method** `new()`: Creates a new instance of this [R6](#) class.

*Usage:*

```
FSelectorRFECV$new()
```

**Method** `clone()`: The objects of this class are cloneable with this method.

*Usage:*

```
FSelectorRFECV$clone(deep = FALSE)
```

*Arguments:*

`deep` Whether to make a deep clone.

## See Also

Other `FSelector`: [mlr\\_fselectors](#), [mlr\\_fselectors\\_design\\_points](#), [mlr\\_fselectors\\_exhaustive\\_search](#), [mlr\\_fselectors\\_genetic\\_search](#), [mlr\\_fselectors\\_random\\_search](#), [mlr\\_fselectors\\_rfe](#), [mlr\\_fselectors\\_sequential\\_search](#), [mlr\\_fselectors\\_shadow\\_variable\\_search](#)

## Examples

```
# Feature Selection

# retrieve task and load learner
task = tsk("penguins")
learner = lrn("classif.rpart")

# run feature selection on the Palmer Penguins data set
instance = fselect(
  fselector = fs("rfecv"),
  task = task,
  learner = learner,
  resampling = rsmpl("cv", folds = 3),
  measure = msr("classif.ce"),
  store_models = TRUE
)

# best performing feature subset
instance$result

# all evaluated feature subsets
as.data.table(instance$archive)

# subset the task and fit the final model
task$select(instance$result_feature_set)
learner$train(task)
```

---

`mlr_fselectors_sequential`*Feature Selection with Sequential Search*

---

## Description

Feature selection using Sequential Search Algorithm.

## Details

Sequential forward selection (`strategy = fsf`) extends the feature set in each iteration with the feature that increases the model's performance the most. Sequential backward selection (`strategy = fsb`) follows the same idea but starts with all features and removes features from the set.

The feature selection terminates itself when `min_features` or `max_features` is reached. It is not necessary to set a termination criterion.

## Dictionary

This [FSelector](#) can be instantiated with the associated sugar function `fs()`:

```
fs("sequential")
```

## Control Parameters

`min_features` integer(1)

Minimum number of features. By default, 1.

`max_features` integer(1)

Maximum number of features. By default, number of features in [mlr3::Task](#).

`strategy` character(1)

Search method `sfs` (forward search) or `sbs` (backward search).

## Super class

```
mlr3fselect::FSelector -> FSelectorSequential
```

## Methods

### Public methods:

- [FSelectorSequential\\$new\(\)](#)
- [FSelectorSequential\\$optimization\\_path\(\)](#)
- [FSelectorSequential\\$clone\(\)](#)

**Method** `new()`: Creates a new instance of this R6 class.‘

*Usage:*

```
FSelectorSequential$new()
```

**Method** `optimization_path()`: Returns the optimization path.

*Usage:*

```
FSelectorSequential$optimization_path(inst, include_uhash = FALSE)
```

*Arguments:*

`inst` ([FSelectInstanceSingleCrit](#))

Instance optimized with [FSelectorSequential](#).

`include_uhash` (`logical(1)`)

Include uhash column?

*Returns:* `data.table::data.table()`

**Method** `clone()`: The objects of this class are cloneable with this method.

*Usage:*

```
FSelectorSequential$clone(deep = FALSE)
```

*Arguments:*

`deep` Whether to make a deep clone.

### See Also

Other [FSelector](#): [mlr\\_fselectors](#), [mlr\\_fselectors\\_design\\_points](#), [mlr\\_fselectors\\_exhaustive\\_search](#), [mlr\\_fselectors\\_genetic\\_search](#), [mlr\\_fselectors\\_random\\_search](#), [mlr\\_fselectors\\_rfe](#), [mlr\\_fselectors\\_rfecv](#), [mlr\\_fselectors\\_shadow\\_variable\\_search](#)

### Examples

```
# Feature Selection

# retrieve task and load learner
task = tsk("penguins")
learner = lrn("classif.rpart")

# run feature selection on the Palmer Penguins data set
instance = fselect(
  fselector = fs("sequential"),
  task = task,
  learner = learner,
  resampling = rsmpl("holdout"),
  measure = msr("classif.ce"),
  term_evals = 10
)

# best performing feature set
instance$result

# all evaluated feature sets
as.data.table(instance$archive)

# subset the task and fit the final model
task$select(instance$result_feature_set)
```



```
learner$train(task)
```

---

```
mlr_fselectors_shadow_variable_search
```

*Feature Selection with Shadow Variable Search*

---

## Description

Feature selection using the Shadow Variable Search Algorithm. Shadow variable search creates for each feature a permuted copy and stops when one of them is selected.

## Details

The feature selection terminates itself when the first shadow variable is selected. It is not necessary to set a termination criterion.

## Resources

The [gallery](#) features a collection of case studies and demos about optimization.

- Run a feature selection with [Shadow Variable Search](#).

## Dictionary

This [FSelector](#) can be instantiated with the associated sugar function [fs\(\)](#):

```
fs("shadow_variable_search")
```

## Super class

```
mlr3fselect::FSelector -> FSelectorShadowVariableSearch
```

## Methods

### Public methods:

- [FSelectorShadowVariableSearch\\$new\(\)](#)
- [FSelectorShadowVariableSearch\\$optimization\\_path\(\)](#)
- [FSelectorShadowVariableSearch\\$clone\(\)](#)

**Method** [new\(\)](#): Creates a new instance of this [R6](#) class.

*Usage:*

```
FSelectorShadowVariableSearch$new()
```

**Method** [optimization\\_path\(\)](#): Returns the optimization path.

*Usage:*

```
FSelectorShadowVariableSearch$optimization_path(inst)
```

*Arguments:*

inst ([FSelectInstanceSingleCrit](#))

Instance optimized with [FSelectorShadowVariableSearch](#).

*Returns:* [data.table::data.table](#)

**Method** clone(): The objects of this class are cloneable with this method.

*Usage:*

```
FSelectorShadowVariableSearch$clone(deep = FALSE)
```

*Arguments:*

deep Whether to make a deep clone.

**Source**

Thomas J, Hepp T, Mayr A, Bischl B (2017). “Probing for Sparse and Fast Variable Selection with Model-Based Boosting.” *Computational and Mathematical Methods in Medicine*, **2017**, 1–8. doi:10.1155/2017/1421409.

Wu Y, Boos DD, Stefanski LA (2007). “Controlling Variable Selection by the Addition of Pseudovariates.” *Journal of the American Statistical Association*, **102**(477), 235–243. doi:10.1198/016214506000000843.

**See Also**

Other [FSelector](#): [mlr\\_fselectors](#), [mlr\\_fselectors\\_design\\_points](#), [mlr\\_fselectors\\_exhaustive\\_search](#), [mlr\\_fselectors\\_genetic\\_search](#), [mlr\\_fselectors\\_random\\_search](#), [mlr\\_fselectors\\_rfe](#), [mlr\\_fselectors\\_rfecv](#), [mlr\\_fselectors\\_sequential](#)

**Examples**

```
# Feature Selection

# retrieve task and load learner
task = tsk("penguins")
learner = lrn("classif.rpart")

# run feature selection on the Palmer Penguins data set
instance = fselect(
  fselector = fs("shadow_variable_search"),
  task = task,
  learner = learner,
  resampling = rsm("holdout"),
  measure = msr("classif.ce"),
)

# best performing feature subset
instance$result

# all evaluated feature subsets
as.data.table(instance$archive)
```

```
# subset the task and fit the final model
task$select(instance$result_feature_set)
learner$train(task)
```

---

ObjectiveFSelect      *Class for Feature Selection Objective*

---

### Description

Stores the objective function that estimates the performance of feature subsets. This class is usually constructed internally by the [FSelectInstanceSingleCrit](#) / [FSelectInstanceMultiCrit](#).

### Super class

[bbotk::Objective](#) -> ObjectiveFSelect

### Public fields

task ([mlr3::Task](#)).

learner ([mlr3::Learner](#)).

resampling ([mlr3::Resampling](#)).

measures (list of [mlr3::Measure](#)).

store\_models (logical(1)).

store\_benchmark\_result (logical(1)).

archive ([ArchiveFSelect](#)).

callbacks (List of [CallbackFSelects](#)).

### Methods

#### Public methods:

- [ObjectiveFSelect\\$new\(\)](#)
- [ObjectiveFSelect\\$clone\(\)](#)

**Method** `new()`: Creates a new instance of this [R6](#) class.

*Usage:*

```
ObjectiveFSelect$new(
  task,
  learner,
  resampling,
  measures,
  check_values = TRUE,
  store_benchmark_result = TRUE,
  store_models = FALSE,
```

```

    archive = NULL,
    callbacks = list()
)

```

*Arguments:*

task ([mlr3::Task](#))

Task to operate on.

learner ([mlr3::Learner](#))

Learner to optimize the feature subset for.

resampling ([mlr3::Resampling](#))

Resampling that is used to evaluate the performance of the feature subsets. Uninstantiated resamplings are instantiated during construction so that all feature subsets are evaluated on the same data splits. Already instantiated resamplings are kept unchanged.

measures (list of [mlr3::Measure](#))

Measures to optimize. If NULL, **mlr3**'s default measure is used.

check\_values (logical(1))

Check the parameters before the evaluation and the results for validity?

store\_benchmark\_result (logical(1))

Store benchmark result in archive?

store\_models (logical(1)). Store models in benchmark result?

archive ([ArchiveFSelect](#))

Reference to the archive of [FSelectInstanceSingleCrit](#) | [FSelectInstanceMultiCrit](#). If NULL (default), benchmark result and models cannot be stored.

callbacks (list of [CallbackFSelect](#))

List of callbacks.

**Method** `clone()`: The objects of this class are cloneable with this method.

*Usage:*

```
ObjectiveFSelect$clone(deep = FALSE)
```

*Arguments:*

deep Whether to make a deep clone.

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