Tutorial MLR

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1 Machine Learning in R

In [31]:
```
# Preliminaries
library(mlr)      # ML librabry
library(OpenML)   # ML datasets, models, sharing

# Plotting
library(ggplot2)
library(cowplot)
library(parallelMap)
library(gridExtra)

# Data manipulation
library(plyr)

# mlr configs
options(width = 70)
configureMlr(show.info = FALSE)
configureMlr(show.learner.output = FALSE)

# OpenML config to set your API key (only do this once)
# Find your API key in your profile after registering on OpenML.org
# setOMLConfig(apikey = qwertyuiop1234567890, verbosity=0)

# If you want all algorithms in mlr, install the dependencies
# install.packages(c("party","RWeka","e1071","rpart","car","ada","bartMachine","kohonen","mboo
#                    "SwarmSVM","LiblineaR","glmnet","deepnet","extraTrees","FNN","gbm","Discri
#                    "kknn","class","kernlab","MASS","lqa","mda","RSNNS","neuralnet","nodeHarve
#                     caret","randomForest","randomForestSRC","ranger","klaR","rFerns","rknn","
#                    "rrlda","sda","sparseLDA","elasticnet","xgboost","tgp","crs","Cubist","ear
#                    "DiceKriging","laGP","pls","penalized","rsm","flare","clue","fpc","CoxBoos
```

1.1 Machine learning packages in R

- The Good: hundreds of ML packages, many comply to an unwritten interface definition

```
model = fit(target ~ ., data = train.data, ...)
predictions = predict(model, newdata = test.data, ...)
```

- The Bad: some have different API, many others have package-dependent functionality for general procedures
- The Ugly: meta-information and hyperparameters buried in docs (if documented at all), large experiments lead to tedious error-prone code

2 mlr package (machine learning in R)

- Domain-specific language for machine learning concepts
- Unified interface:
  - Tasks: data and meta-info (e.g. target features)
  - Learners: fit a model, make predictions
  - Resampling: evaluate a model, optimize hyperparameters
- Reflections: all objects are queryable, you can program on them
- OO structure: generic algorithms (Bagging, Stacking, Feature Selection,. . .)
- Guide: https://mlr-org.github.io/mlr-tutorial/
- Reference: http://rpackages.ianhowson.com/cran/mlr/

2.1 mlr tasks

- Encapsulate data and meta-data about it (e.g. target features)
- Define precisely what you want to do with the data
- Types: regression, classification, clustering,. . .

Create regression task on the 'BostonHousing' dataset from the mlbench package

```
In [32]: data(BostonHousing, package = "mlbench")
         task = makeRegrTask(data = BostonHousing, target = "medv")
         print(task)
```

```
Supervised task: BostonHousing
Type: regr
Target: medv
Observations: 506
Features:
numerics  factors  ordered
      12        1        0
Missings: FALSE
Has weights: FALSE
Has blocking: FALSE
```

2.1.1 Task introspection: what's in a task?

```
In [33]: names(task)               # objects in a task
         names(task$task.desc)     # objects in the task description
         str(getTaskId(task))      # a unique ID that we can track
         getTaskSize(task)         # number of data points
         getTaskFeatureNames(task) # feature names
         getTaskTargetNames(task)  # name of target feature
         summary(getTaskTargets(task)) # distribution of target values
```

1. 'type' 2. 'env' 3. 'weights' 4. 'blocking' 5. 'task.desc'
1. 'id' 2. 'type' 3. 'target' 4. 'size' 5. 'n.feat' 6. 'has.missings' 7. 'has.weights' 8. 'has.blocking'

```
chr "BostonHousing"
```

506
1. 'crim' 2. 'zn' 3. 'indus' 4. 'chas' 5. 'nox' 6. 'rm' 7. 'age' 8. 'dis' 9. 'rad' 10. 'tax' 11. 'ptratio' 12. 'b' 13. 'lstat'
'medv'

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
   5.00   17.02   21.20   22.53   25.00   50.00
```

Get the actual data set from a task

```
In [34]: data = getTaskData(task)
         str(data)
```

```
'data.frame':        506 obs. of  14 variables:
 $ crim   : num  0.00632 0.02731 0.02729 0.03237 0.06905 ...
 $ zn     : num  18 0 0 0 0 0 12.5 12.5 12.5 12.5 ...
 $ indus  : num  2.31 7.07 7.07 2.18 2.18 2.18 7.87 7.87 7.87 7.87 ...
 $ chas   : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
 $ nox    : num  0.538 0.469 0.469 0.458 0.458 0.458 0.524 0.524 0.524 0.524 ...
 $ rm     : num  6.58 6.42 7.18 7 7.15 ...
 $ age    : num  65.2 78.9 61.1 45.8 54.2 58.7 66.6 96.1 100 85.9 ...
 $ dis    : num  4.09 4.97 4.97 6.06 6.06 ...
 $ rad    : num  1 2 2 3 3 3 5 5 5 5 ...
 $ tax    : num  296 242 242 222 222 222 311 311 311 311 ...
 $ ptratio: num  15.3 17.8 17.8 18.7 18.7 18.7 15.2 15.2 15.2 15.2 ...
 $ b      : num  397 397 393 395 397 ...
 $ lstat  : num  4.98 9.14 4.03 2.94 5.33 ...
 $ medv   : num  24 21.6 34.7 33.4 36.2 28.7 22.9 27.1 16.5 18.9 ...
```

2.2 OpenML integration

- There are many datasets available, but often hard to find, different formats,...
- Often no view on what are current state-of-the-art models for a dataset
- To compare, we need to rerun all other algorithms ourselves

OpenML.org: Collaboration platform for machine learning

- Datasets, models, evaluations shared by anyone (reproducible and reusable)
- Predefined tasks with train/test splits so that results are comparable
- Run large-scale experiments effortlessly, automatically share results
- Overview of state-of-the-art, leaderboards,...

2.2.1 Load any dataset from OpenML

```
In [35]: datasets = listOMLDataSets()  # fetches all data sets
         nrow(datasets) # number of available datasets
         datasets[1:20, c("did", "name", "NumberOfInstances", "NumberOfFeatures")]
         # You can also view them online on www.openml.org/d/<did>
```

2420

	did	name	NumberOfInstances	NumberOfFeatures
1	1	anneal	898	39
2	2	anneal	898	39
3	3	kr-vs-kp	3196	37
4	4	labor	57	17
5	5	arrhythmia	452	280
6	6	letter	20000	17
7	7	audiology	226	70
8	8	liver-disorders	345	7
9	9	autos	205	26
10	10	lymph	148	19
11	11	balance-scale	625	5
12	12	mfeat-factors	2000	217
13	13	breast-cancer	286	10
14	14	mfeat-fourier	2000	77
15	15	breast-w	699	10
16	16	mfeat-karhunen	2000	65
17	18	mfeat-morphological	2000	7
18	20	mfeat-pixel	2000	241
19	21	car	1728	7
20	22	mfeat-zernike	2000	48

2.2.2 Search for specific datasets

In [36]:
```
# Show only a subset of dataset properties here
datacols = c("did", "name", "NumberOfInstances", "NumberOfFeatures", "NumberOfClasses")
subset(datasets, name == "iris")[, datacols]
subset(datasets, NumberOfInstances > 10000)[0:5, datacols]
subset(datasets, NumberOfClasses == 2)[0:5, datacols]
```

	did	name	NumberOfInstances	NumberOfFeatures	NumberOfClasses
55	61	iris	150	5	3
821	969	iris	150	5	2

	did	name	NumberOfInstances	NumberOfFeatures	NumberOfClasses
6	6	letter	20000	17	26
24	26	nursery	12960	9	5
30	32	pendigits	10992	17	10
57	70	BNG(anneal,nominal,1000000)	1000000	39	6
58	71	BNG(anneal.ORIG,nominal,1000000)	1000000	39	6

	did	name	NumberOfInstances	NumberOfFeatures	NumberOfClasses
3	3	kr-vs-kp	3196	37	2
4	4	labor	57	17	2
13	13	breast-cancer	286	10	2
15	15	breast-w	699	10	2
22	24	mushroom	8124	23	2

2.2.3 Create an mlr task on an OpenML dataset

In [37]:
```
ddata = getOMLDataSet(did = 35)$data # Dermatology dataset (id=35), see openml.org/d/35
task = makeClassifTask(data = ddata, target = "class")
print(task)
```

```
Supervised task: ddata
Type: classif
Target: class
```

```
Observations: 366
Features:
numerics  factors  ordered
       1       33        0
Missings: TRUE
Has weights: FALSE
Has blocking: FALSE
Classes: 6
  1   2   3   4   5   6
112  61  72  49  52  20
Positive class: NA
```

2.2.4 Load predefined OpenML tasks

So you can use the same train/test samples as everyone else (and compare results)

In [38]:
```
omltask = getOMLTask(task.id = 35) # Classification on breast-cancer dataset (task_id=35), see
print(omltask)
mlrtask = convertOMLTaskToMlr(omltask)$mlr.task # Optional: convert to MLR
```

```
OpenML Task 35 :: (Data ID = 35)
  Task Type            : Supervised Classification
  Data Set             : dermatology :: (Version = 1, OpenML ID = 35)
  Target Feature(s)    : class
  Estimation Procedure : Stratified crossvalidation (1 x 10 folds)
```

2.2.5 List all OpenML tasks

In [39]:
```
tasks = listOMLTasks() # Fetches all tasks
# Only show a subset of task properties
taskcols = c("task.id","task.type","name","target.feature","estimation.procedure")
head(tasks[,taskcols])
```

	task.id	task.type	name	target.feature	estimation.procedure
1	1	Supervised Classification	anneal	class	10-fold Crossvalidation
2	2	Supervised Classification	anneal	class	10-fold Crossvalidation
3	3	Supervised Classification	kr-vs-kp	class	10-fold Crossvalidation
4	4	Supervised Classification	labor	class	10-fold Crossvalidation
5	5	Supervised Classification	arrhythmia	class	10-fold Crossvalidation
6	6	Supervised Classification	letter	class	10-fold Crossvalidation

2.2.6 Search for specific tasks

In [40]:
```
subset(tasks, name == "breast-cancer")[, taskcols]
```

	task.id	task.type	name	target.feature	estimation.procedure
13	13	Supervised Classification	breast-cancer	Class	10-fold Crossvalidation
66	72	Learning Curve	breast-cancer	Class	10 times 10-fold Learning Cu
231	243	Supervised Classification	breast-cancer	Class	33% Holdout set
341	1712	Learning Curve	breast-cancer	Class	10-fold Learning Curve
402	1777	Supervised Classification	breast-cancer	Class	5 times 2-fold Crossvalidatio
511	1893	Supervised Classification	breast-cancer	Class	10 times 10-fold Crossvalidat
566	1954	Supervised Classification	breast-cancer	Class	Leave one out
698	2181	Supervised Data Stream Classification	breast-cancer	Class	Interleaved Test then Train
2865	5533	Clustering	breast-cancer	NA	50 times Clustering
4881	10125	Clustering	breast-cancer	NA	50 times Clustering

2.3 mlr learners

- Wrappers around `fit()` and `predict()` functions
- Learners: 73 Classification, 54 Regression, 8 Clustering,...
- Descriptions of parameter sets
- Annotations (e.g. handles missing values)
- Naming convention `<tasktype>.<functionname>`

```
makeLearner("classif.rpart")
makeLearner("regr.rpart")
```

2.3.1 Create learner

Initializes a learner with default hyperparameters, not trained yet. Naming convention: `<task>.<algorithm>`

```
In [41]: lrn = makeLearner("classif.rpart")
         print(lrn)
```

```
Learner classif.rpart from package rpart
Type: classif
Name: Decision Tree; Short name: rpart
Class: classif.rpart
Properties: twoclass,multiclass,missings,numerics,factors,ordered,prob,weights
Predict-Type: response
Hyperparameters: xval=0
```

Search for available learners via the help page `?learners` or `listLearners()`

```
In [43]: listLearners()[0:10,c(1,2,5,20)]
```

	class	type	name	note
1	classif.ada	classif	ada Boosting	'xval' has been set to '0' by d
2	classif.avNNet	classif	Neural Network	'size' has been set to '3' by de
3	classif.bartMachine	classif	Bayesian Additive Regression Trees	'use_missing_data' has been se
4	classif.bdk	classif	Bi-Directional Kohonen map	
5	classif.binomial	classif	Binomial Regression	Delegates to 'glm' with freely
6	classif.blackboost	classif	Gradient Boosting With Regression Trees	See '?ctree_control' for possib
7	classif.boosting	classif	Adabag Boosting	'xval' has been set to '0' by d
8	classif.bst	classif	Gradient Boosting	Renamed parameter 'learner'
9	classif.cforest	classif	Random forest based on conditional inference trees	See '?ctree_control' for possib
10	classif.clusterSVM	classif	Clustered Support Vector Machines	'centers' set to '2' by default.

```
In [44]: # list all classification learners which can handle missing values
         listLearners("classif", properties = c("missings"))[, 1:4]
```

	class	type	package	short.name
1	classif.bartMachine	classif	bartMachine	bartmachine
2	classif.blackboost	classif	mboost,party	blackbst
3	classif.boosting	classif	adabag,rpart	adabag
4	classif.cforest	classif	party	cforest
5	classif.ctree	classif	party	ctree
6	classif.gbm	classif	gbm	gbm
7	classif.J48	classif	RWeka	j48
8	classif.JRip	classif	RWeka	jrip
9	classif.naiveBayes	classif	e1071	nbayes
10	classif.OneR	classif	RWeka	oner
11	classif.PART	classif	RWeka	part
12	classif.randomForestSRC	classif	randomForestSRC	rfsrc
13	classif.rpart	classif	rpart	rpart

```
In [45]: # list all classification learners that can handle the current task
         listLearners(task)[, 1:4]
```

	class	type	package	short.name
1	classif.boosting	classif	adabag,rpart	adabag
2	classif.cforest	classif	party	cforest
3	classif.ctree	classif	party	ctree
4	classif.gbm	classif	gbm	gbm
5	classif.J48	classif	RWeka	j48
6	classif.JRip	classif	RWeka	jrip
7	classif.naiveBayes	classif	e1071	nbayes
8	classif.OneR	classif	RWeka	oner
9	classif.PART	classif	RWeka	part
10	classif.randomForestSRC	classif	randomForestSRC	rfsrc
11	classif.rpart	classif	rpart	rpart

2.3.2 Hyperparameters

List all hyperparameters

```
In [46]: lrn = makeLearner("classif.rpart")
         getParamSet(lrn)
```

```
                    Type len  Def   Constr Req Tunable Trafo
minsplit         integer   -   20 1 to Inf   -    TRUE     -
minbucket        integer   -    - 1 to Inf   -    TRUE     -
cp               numeric   - 0.01   0 to 1   -    TRUE     -
maxcompete       integer   -    4 0 to Inf   -    TRUE     -
maxsurrogate     integer   -    5 0 to Inf   -    TRUE     -
usesurrogate    discrete   -    2    0,1,2   -    TRUE     -
surrogatestyle discrete   -    0      0,1   -    TRUE     -
maxdepth         integer   -   30  1 to 30   -    TRUE     -
xval             integer   -   10 0 to Inf   -   FALSE     -
parms            untyped   -    -        -   -   FALSE     -
```

Setting hyperparameters at creation time

```
In [47]: cluster.lrn = makeLearner("cluster.SimpleKMeans", N = 5)
         lrn = makeLearner("classif.rpart", par.vals = list(maxdepth = 10, cp = 0.1))
         lrn
```

```
Learner classif.rpart from package rpart
Type: classif
Name: Decision Tree; Short name: rpart
Class: classif.rpart
Properties: twoclass,multiclass,missings,numerics,factors,ordered,prob,weights
Predict-Type: response
Hyperparameters: xval=0,maxdepth=10,cp=0.1
```

You can change parameter values at any time, or go back to default values

```
In [48]: # Afterwards
         setHyperPars(lrn,maxdepth=20)
         # Go back to defaults
         removeHyperPars(lrn,c("maxdepth","cp"))
```

```
Learner classif.rpart from package rpart
Type: classif
Name: Decision Tree; Short name: rpart
Class: classif.rpart
Properties: twoclass,multiclass,missings,numerics,factors,ordered,prob,weights
Predict-Type: response
Hyperparameters: xval=0,maxdepth=20,cp=0.1
```

```
Learner classif.rpart from package rpart
Type: classif
Name: Decision Tree; Short name: rpart
Class: classif.rpart
Properties: twoclass,multiclass,missings,numerics,factors,ordered,prob,weights
Predict-Type: response
Hyperparameters: xval=0
```

2.3.3 Learner properties

- numerics, factors, ordered: Handles numeric, factors (categories), ordered features
- missings: Handles missing values in the data
- weights: Training examples can be weighted
- oneclass, twoclass, multiclass: Handles 1,2, multi-class classification problems
- class.weights: Handles class weights
- prob: Can predict probabilities
- se: Can predict standard errors (for regression)

Querying and setting learner properties

```
In [49]: class_tree = makeLearner("classif.rpart")
         regr_forest = makeLearner("regr.randomForest")
         class_tree$properties
         setPredictType(class_tree, "prob")
         setPredictType(regr_forest, "se")
```

1. 'twoclass' 2. 'multiclass' 3. 'missings' 4. 'numerics' 5. 'factors' 6. 'ordered' 7. 'prob' 8. 'weights'

```
Learner classif.rpart from package rpart
Type: classif
Name: Decision Tree; Short name: rpart
Class: classif.rpart
Properties: twoclass,multiclass,missings,numerics,factors,ordered,prob,weights
Predict-Type: prob
Hyperparameters: xval=0



Learner regr.randomForest from package randomForest
Type: regr
Name: Random Forest; Short name: rf
Class: regr.randomForest
Properties: numerics,factors,ordered,se
Predict-Type: se
Hyperparameters: se.method=bootstrap,se.boot=50,ntree.for.se=100
```

2.3.4 Training a learner

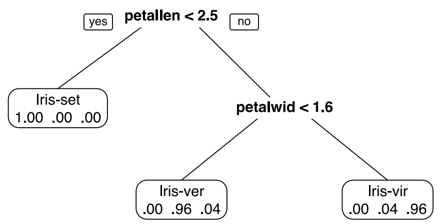
- Training: fitting a model to the given data (as defined in a task)

```
In [50]: iristask = convertOMLTaskToMlr(getOMLTask(task.id=59))$mlr.task
         lrn = makeLearner("classif.rpart")
         model = train(lrn,iristask)
         names(model)
         model$learner.model
```

1. 'learner' 2. 'learner.model' 3. 'task.desc' 4. 'subset' 5. 'features' 6. 'factor.levels' 7. 'time'

```
n= 150

node), split, n, loss, yval, (yprob)
      * denotes terminal node

1) root 150 100 Iris-setosa (0.33333333 0.33333333 0.33333333)
  2) petallength< 2.45 50   0 Iris-setosa (1.00000000 0.00000000 0.00000000) *
  3) petallength>=2.45 100  50 Iris-versicolor (0.00000000 0.50000000 0.50000000)
    6) petalwidth< 1.75 54   5 Iris-versicolor (0.00000000 0.90740741 0.09259259) *
    7) petalwidth>=1.75 46   1 Iris-virginica (0.00000000 0.02173913 0.97826087) *
```

```
In [92]: library(rpart.plot) # For plotting rpart trees
         rpart.plot(model$learner.model, extra = 4)
```



2.3.5 Making predictions

- Given a trained model, make predictions for a test set

```
In [52]: n = getTaskSize(iristask)
         train.set = seq(1, n, by = 2) # odd rows for training
         test.set = seq(2, n, by = 2)  # even rows for testing
         model = train(lrn, iristask, subset = train.set) # train with subbset
         pred = predict(model, task = iristask, subset = test.set) # predict the rest
         pred
```

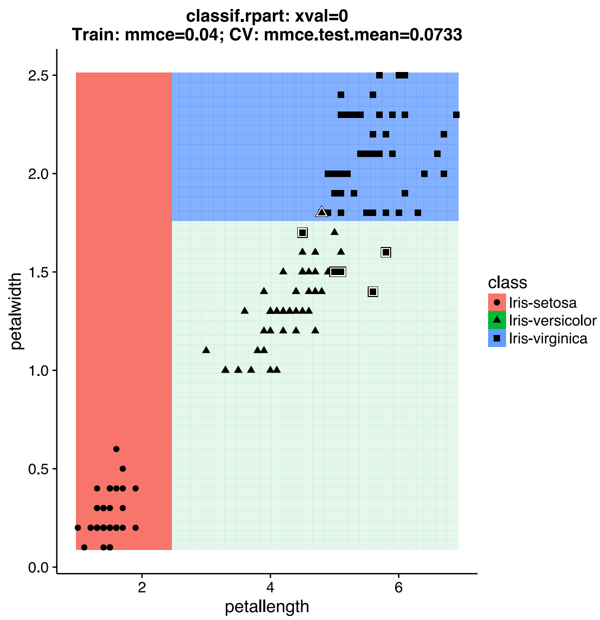
```
Prediction: 75 observations
predict.type: response
threshold:
time: 0.00
   id       truth    response
1   2 Iris-setosa Iris-setosa
3   4 Iris-setosa Iris-setosa
5   6 Iris-setosa Iris-setosa
7   8 Iris-setosa Iris-setosa
9  10 Iris-setosa Iris-setosa
11 12 Iris-setosa Iris-setosa
```

2.3.6 Visualizing predictions

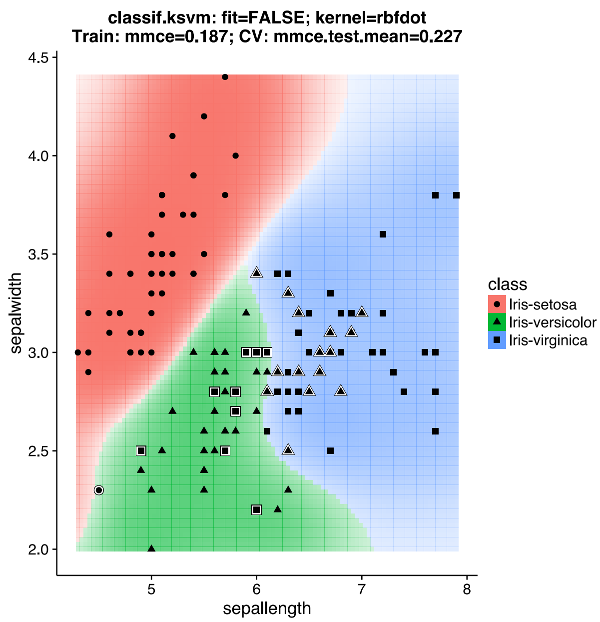
- mlr includes several functions to visualize learning performance
- returns a ggplot object which you can manipulate as usual

Classification: only 2D visualizations

```
In [53]: lrn = makeLearner("classif.rpart")
         plotLearnerPrediction(lrn, iristask, features = c("petallength", "petalwidth")) + theme_cowplo
```

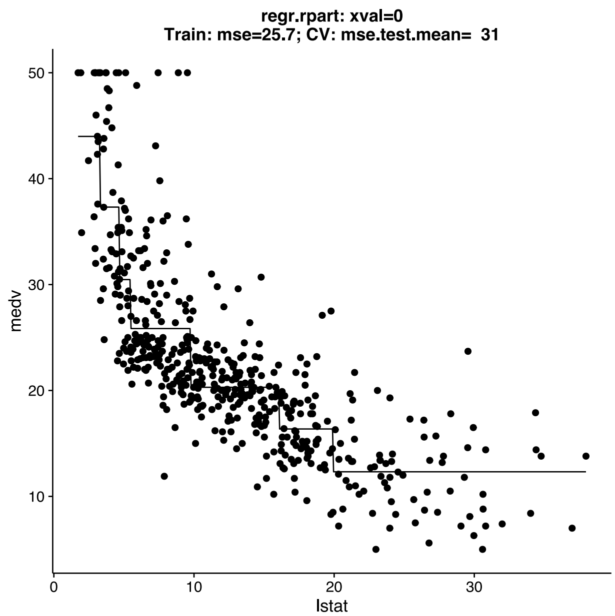



```
In [54]: # Learner parameters can be passed in the plotting function
         lrn = makeLearner("classif.ksvm")
         plotLearnerPrediction(lrn, iristask, kernel = "rbfdot", features = c("sepallength", "sepalwidt
```

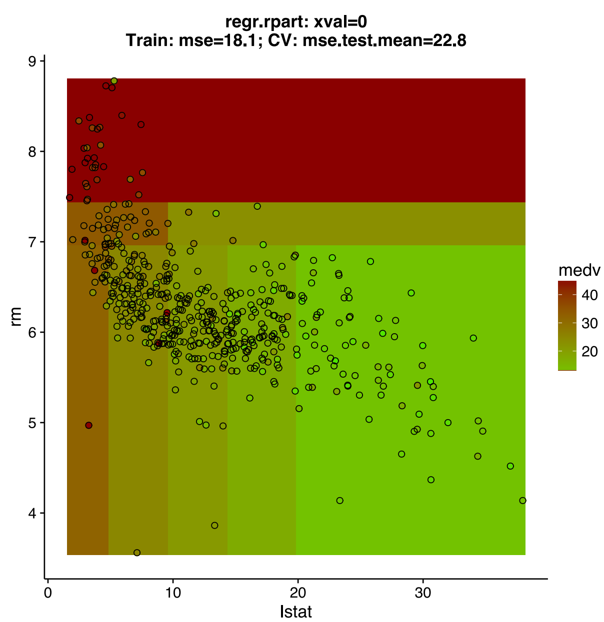


Regression: 1D and 2D visualizations

```
In [55]: data(BostonHousing, package = "mlbench")
         bh.task = makeRegrTask(data = BostonHousing, target = "medv")
         lrn = makeLearner("regr.rpart")
         plotLearnerPrediction(lrn, bh.task, features = c("lstat"))
```




```
In [56]: lrn = makeLearner("regr.rpart")
         plotLearnerPrediction(lrn, bh.task, features = c("lstat","rm"))
```



2.4 mlr resampling (evaluation)

- Estimate generalization error of our models
- Repeatedly fit models on training sets
- Evaluate performance on independent test sets and average performance results

2.4.1 Evaluation measures

- Default measure for classification: Mean misclassification error (mmce)

$$\frac{1}{n}\sum_{i=1}^{n}\not\Vdash(y_i \neq \hat{y}_i)$$

- Default measure for regression: Mean squared error (mse)

$$\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

```
In [57]: listMeasures("classif") # All available classification measures
         print(mmce)
         listMeasures("regr") # All available regression measures
         print(mse)
```

1. 'timepredict' 2. 'gmean' 3. 'acc' 4. 'auc' 5. 'ber' 6. 'fn' 7. 'fp' 8. 'fnr' 9. 'gpr' 10. 'featperc' 11. 'ppv' 12. 'fpr' 13. 'mmce' 14. 'timeboth' 15. 'npv' 16. 'timetrain' 17. 'fdr' 18. 'tnr' 19. 'mcc' 20. 'bac' 21. 'tpr' 22. 'tn' 23. 'f1' 24. 'tp' 25. 'multiclass.auc' 26. 'brier'

```
Name: Mean misclassification error
Performance measure: mmce
Properties: classif,classif.multi,req.pred,req.truth
Minimize: TRUE
Best: 0; Worst: 1
Aggregated by: test.mean
Note:
```

1. 'timepredict' 2. 'sae' 3. 'sse' 4. 'rmse' 5. 'expvar' 6. 'rsq' 7. 'featperc' 8. 'arsq' 9. 'timeboth' 10. 'timetrain' 11. 'mae' 12. 'mse' 13. 'medae' 14. 'medse'

```
Name: Mean of squared errors
Performance measure: mse
Properties: regr,req.pred,req.truth
Minimize: TRUE
Best: 0; Worst: Inf
Aggregated by: test.mean
Note:
```

Evaluations are included in the predictions object

```
In [58]: lrn = makeLearner("classif.rpart")
         lrn = setPredictType(lrn, "prob") # We need probabilities
         model = train(lrn, iristask, subset = train.set) # train with subbset
         pred = predict(model, task = iristask, subset = test.set) # predict the rest
         performance(pred)
         performance(pred, measures = list(mlr::multiclass.auc, mlr::acc))
         # timetrain also needs the model
         performance(pred, measures = mlr::timetrain, model = model)
```

mmce: 0.0533333333333333

multiclass.auc 0.833333333333333 **acc** 0.946666666666667

timetrain: 0.00500000000465661

2.4.2 Resampling strategies

- Cross-validation (`CV`): Split data in k roughly equal parts (folds), iteratively use one as the test set and the remainder as the training set, then average the performance estimates. k typically 5..10.
- Repeated Cross-validation (`RepCV`): Repeat CV i times (randomly shuffling the data points), and average the CV results
- Leave-one-out Cross-validation (`LOO`): Cross-Validation with $k = n =$ the number of data points
- Holdout, training/test (`Holdout`): Randomly split the data in a train and test set. Typically 70/30 split.
- Subsampling, a.k.a Monte-Carlo Cross-Validation (`Subsample`). Draw k random holdouts, and average the results. k typically 30..100
- Out-of-bag bootstrap (`Bootstrap`): Randomly draw B training sets of size n with replacement (points can be drawn more than once). These are expected to contain 63,2% of the original data points. The non-drawn (out-of-bag, OOB) points form the test sets. B typically 30..100
- Bootstrapping with the 632-rule (`B632`): Variant of OOB bootstrapping that takes a weighted average of the OOB bootstrap estimate and the training set error on the whole dataset. Less pessimistic than the OOB bootstrap.
- Stratified resampling: Option for all strategies, creates splits so that class labels occur in equal proportions as in the original data

First create resample description, then execute with learner and task. Returned resample object contains all performance estimates.

```
In [59]: rdesc = makeResampleDesc("CV", iters = 3)
         lrn = makeLearner("classif.rpart")
         r = resample(lrn, iristask, resampling = rdesc)
         print(r)
         # Shorthand
         r = crossval("classif.rpart", iristask, iters = 3)
```

```
Resample Result
Task: OpenML-Task-59
Learner: classif.rpart
mmce.aggr: 0.07
mmce.mean: 0.07
mmce.sd: 0.01
Runtime: 0.0511
```

```
In [60]: names(r)
         head(r$measures.test) # Results per CV fold
         head(as.data.frame(r$pred)) # Final predictions
```

1. 'learner.id' 2. 'task.id' 3. 'measures.train' 4. 'measures.test' 5. 'aggr' 6. 'pred' 7. 'models' 8. 'err.msgs' 9. 'extract' 10. 'runtime'

	iter	mmce
1	1	0.06
2	2	0.02
3	3	0.1

	id	truth	response	iter	set
1	1	Iris-setosa	Iris-setosa	1	test
2	3	Iris-setosa	Iris-setosa	1	test
3	9	Iris-setosa	Iris-setosa	1	test
4	14	Iris-setosa	Iris-setosa	1	test
5	15	Iris-setosa	Iris-setosa	1	test
6	16	Iris-setosa	Iris-setosa	1	test

To retrieve the models, set `model=TRUE` and extract it from the resample object

```
In [61]: r = resample(lrn, iristask, resampling = rdesc, model = TRUE)
         names(r)
         print(r$models[]) # 3 models are returned (one for each fold)
```

1. 'learner.id' 2. 'task.id' 3. 'measures.train' 4. 'measures.test' 5. 'aggr' 6. 'pred' 7. 'models' 8. 'err.msgs' 9. 'extract' 10. 'runtime'

```
[[1]]
Model for learner.id=classif.rpart; learner.class=classif.rpart
Trained on: task.id = OpenML-Task-59; obs = 100; features = 4
Hyperparameters: xval=0

[[2]]
Model for learner.id=classif.rpart; learner.class=classif.rpart
Trained on: task.id = OpenML-Task-59; obs = 100; features = 4
Hyperparameters: xval=0

[[3]]
Model for learner.id=classif.rpart; learner.class=classif.rpart
Trained on: task.id = OpenML-Task-59; obs = 100; features = 4
Hyperparameters: xval=0
```

To compare multiple learners, reuse the same train/test sets for all by saving an instance of the resampling

```
In [62]: rin = makeResampleInstance(rdesc, iristask)
         model1 = resample("classif.rpart", iristask, resampling = rin)
         model2 = resample("classif.knn", iristask, resampling = rin)
         print(model1$aggr)
         print(model2$aggr)
```

```
mmce.test.mean
    0.04666667
mmce.test.mean
    0.04666667
```

2.4.3 Benchmarking

- Comparing algorithms over many datasets
- Train and test sets need to be synchronized: learners see the same data splits
- Can be combined with feature selection, hyperparameter tuning: mlr wrappers
- Results stored in well-defined container object

A regression benchmark

```
In [63]: data("BostonHousing", "mtcars", "swiss", package = c("mlbench", "datasets"))
         cv10f = makeResampleDesc("CV", iters = 10)
         tasks = list(
             makeRegrTask(data = BostonHousing, target = "medv"),
             makeRegrTask(data = swiss, target = "Fertility"),
             makeRegrTask(data = mtcars, target = "mpg")
             )
         learners = list(
             makeLearner("regr.rpart"),
             makeLearner("regr.randomForest"),
             makeLearner("regr.lm")
             )
         bmr = benchmark(learners, tasks, cv10f, mlr::mse)
         bmr
```

```
        task.id        learner.id mse.test.mean
1 BostonHousing        regr.rpart     23.196284
2 BostonHousing regr.randomForest     10.877412
3 BostonHousing           regr.lm     23.654804
4        mtcars        regr.rpart     16.844322
5        mtcars regr.randomForest      5.016773
6        mtcars           regr.lm     12.279907
7         swiss        regr.rpart    134.075749
8         swiss regr.randomForest     65.037044
9         swiss           regr.lm     57.770478
```

Accessing benchmark results

```
In [64]: head(getBMRAggrPerformances(bmr, as.df = TRUE), 3) # Aggregated results
         head(getBMRPerformances(bmr, as.df = TRUE), 3) # Per-fold results
         head(getBMRPredictions(bmr, as.df = TRUE), 3)  # Predictions
```

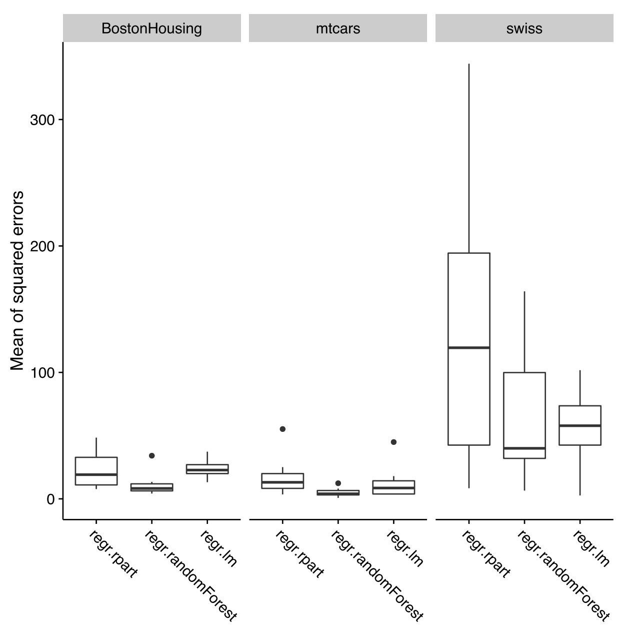
	task.id	learner.id	mse.test.mean
1	BostonHousing	regr.rpart	23.19628
2	BostonHousing	regr.randomForest	10.87741
3	BostonHousing	regr.lm	23.6548

	task.id	learner.id	iter	mse
1	BostonHousing	regr.rpart	1	48.42943
2	BostonHousing	regr.rpart	2	9.563561
3	BostonHousing	regr.rpart	3	21.84305

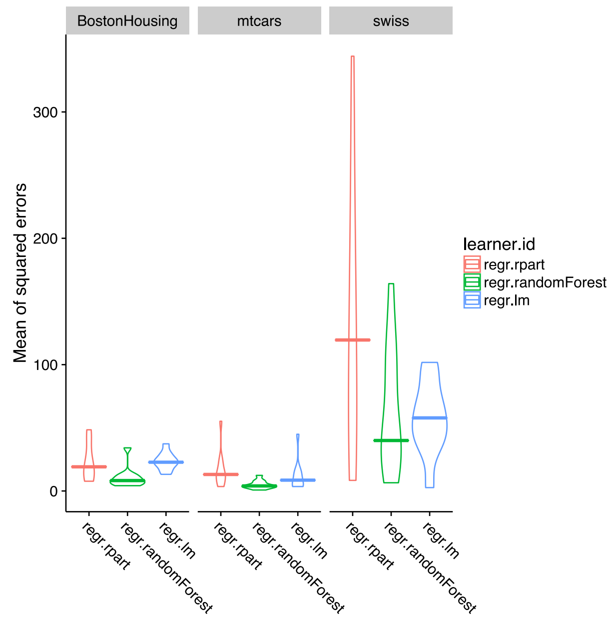
	task.id	learner.id	id	truth	response	iter	set
1	BostonHousing	regr.rpart	19	20.2	21.32925	1	test
2	BostonHousing	regr.rpart	45	21.2	21.32925	1	test
3	BostonHousing	regr.rpart	46	19.3	21.32925	1	test

Visualizing performance

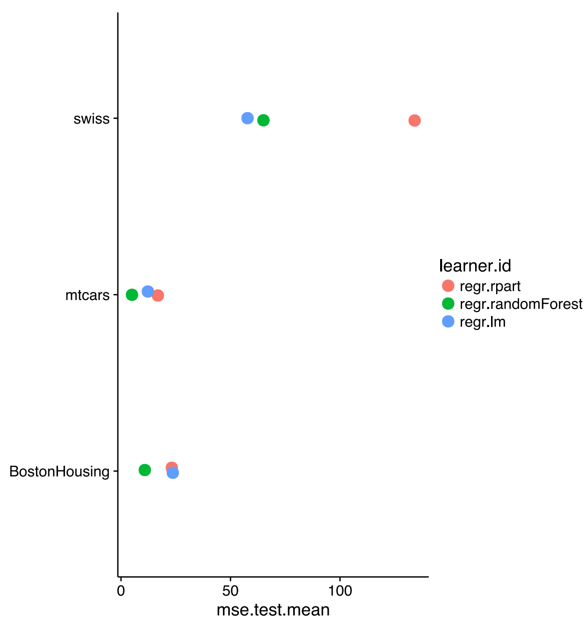
```
In [65]: plotBMRBoxplots(bmr, measure = mlr::mse)
```



```
In [66]: # Some ggplot2 customizations
         plotBMRBoxplots(bmr, measure = mlr::mse, style = "violin") + aes(color = learner.id)
```




```
In [67]: # Summary plot
         plotBMRSummary(bmr)
```



A classification benchmark

```
In [68]: # Classification benchmark with OpenML
         cv10f = makeResampleDesc("CV", iters = 10)
         tasks = list(
             convertOMLTaskToMlr(getOMLTask(task.id=59))$mlr.task,  # iris
             convertOMLTaskToMlr(getOMLTask(task.id=57))$mlr.task,  # ionosphere
             convertOMLTaskToMlr(getOMLTask(task.id=2382))$mlr.task # wine
             )
         learners = list(
             makeLearner("classif.rpart"),
             makeLearner("classif.knn"),
             makeLearner("classif.randomForest")
             )
         bmr = benchmark(learners, tasks, cv10f, mlr::mmce)
         bmr
```

```
           task.id           learner.id mmce.test.mean
1 OpenML-Task-2382        classif.rpart     0.11143791
2 OpenML-Task-2382          classif.knn     0.26928105
3 OpenML-Task-2382 classif.randomForest     0.01666667
4   OpenML-Task-57        classif.rpart     0.13912698
5   OpenML-Task-57          classif.knn     0.13920635
6   OpenML-Task-57 classif.randomForest     0.07111111
7   OpenML-Task-59        classif.rpart     0.06000000
8   OpenML-Task-59          classif.knn     0.04000000
9   OpenML-Task-59 classif.randomForest     0.04000000
```

Benchmark + share automatically on OpenML - After running this, check your runs on http://www.openml.org/search?type=run

```
In [69]: task.ids = c(59,57,2382)
         for (lrn in learners) {
           for (id in task.ids) {
             task = getOMLTask(id)
             res = runTaskMlr(task, lrn) # shorthand to run OpenML tasks
             run.id = uploadOMLRun(res)  # upload results
           }
         }
```

2.5 Hyperparameter tuning

- Find the 'best' hyperparameters for a given dataset
- Tuners iteratively evaluate hyperparameters and move to next setting
- `mlr` offers many tuners through the same interface
- All info logged in `OptPath` object

2.5.1 Tuning strategies

- Grid search: exhaustively try all combinations on finite grid
- Random search: draw parameters randomly (scales better)
- Iterated F-Racing: all candidatea are trained in parallel, on increasing amount of data (steps). At each step, models that perform statistically worse than others are dropped
- Model-based (Bayesian) optimization: while evaluating parameter settings, a surrogate model learns the hyperparameter space and predicts interesting parameter settings to try next
- ...

A simple grid search

```
In [118]: task = convertOMLTaskToMlr(getOMLTask(task.id=2073))$mlr.task #yeast
          lrn = makeLearner("classif.rpart")
          rdesc = makeResampleDesc("CV", iters = 3)
          ps = makeParamSet( # Define the grid
              makeIntegerParam("maxdepth", lower = 2, upper = 30),
              makeNumericParam("cp", lower = 0, upper = 0.5)
              )
          ctrl = makeTuneControlGrid() # Use a grid search
          res = tuneParams(lrn,task, rdesc, par.set = ps, control = ctrl,
                          measures = list(acc, setAggregation(acc, test.sd)))
          res
```

```
Tune result:
Op. pars: maxdepth=5; cp=0
acc.test.mean=0.567,acc.test.sd=0.0136
```

Replace the controller to try other tuning strategies - http://mlr-org.github.io/mlr-tutorial/devel/html/tune/index.html#tuning-hyperparameters

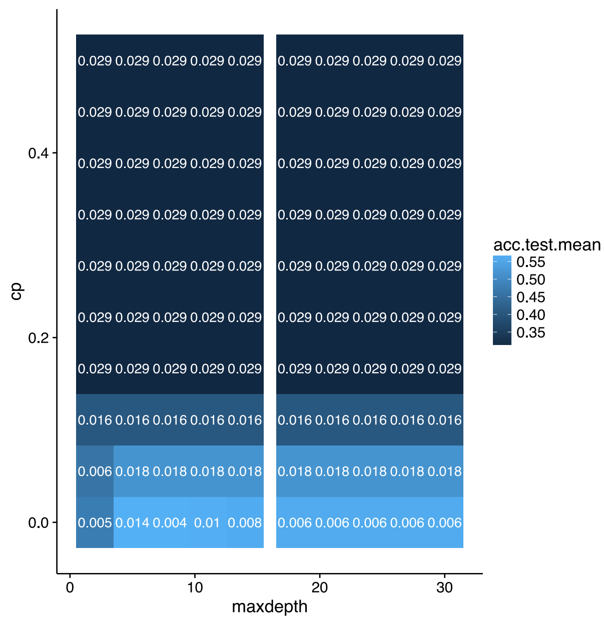
```
In [105]: ctrl = makeTuneControlIrace(maxExperiments = 200) # Iterative F-Racing
          ctrl = makeTuneControlRandom(maxit = 200) # Random Search
```

```
In [119]: res$opt.path
          opt.grid = as.data.frame(res$opt.path)
          head(opt.grid)
```

```
Optimization path
  Dimensions: x = 2/2, y = 2
  Length: 100
  Add x values transformed: FALSE
  Error messages: TRUE. Errors: 0 / 100.
  Exec times: TRUE. Range: 0.055 - 0.126. 0 NAs.
```

	maxdepth	cp	acc.test.mean	acc.test.sd	dob	eol	error.message	exec.time
1	2	0	0.477088	0.005189885	1	NA	NA	0.063
2	5	0	0.5667144	0.01361103	2	NA	NA	0.07
3	8	0	0.566713	0.004435438	3	NA	NA	0.083
4	11	0	0.561991	0.01018816	4	NA	NA	0.084
5	14	0	0.5586213	0.007977376	5	NA	NA	0.082
6	18	0	0.5566011	0.006109453	6	NA	NA	0.083

```
In [121]: myg = ggplot(opt.grid, aes(x = maxdepth, y = cp, fill = acc.test.mean, label = round(acc.test
          myg + geom_tile() + geom_text(color = "white")
```



2.5.2 Nested resampling

- Never optimize parameters over the same test data as used for estimating the final performance of the model
- Nested resampling: embed the whole model selection process into an outer resampling loop
- In mlr you can wrap the learner in a tuning procedure with `makeTuneWrapper`

Nested subsampling with 2 iterations in the inner loop (for selecting hyperparameters) and 3-fold cross-validation in the outer loop (for final evaluation)

```
In [74]: ## Inner tuning loop
         ctrl = makeTuneControlGrid()
         inner = makeResampleDesc("Subsample", iters = 2)
         lrn = makeTuneWrapper("classif.rpart", resampling = inner, par.set = ps, control = ctrl, show.i

         ## Outer resampling loop
         outer = makeResampleDesc("CV", iters = 3)
         r = resample(lrn, iristask, resampling = outer, extract = getTuneResult, show.info = FALSE)
         print(r)
```

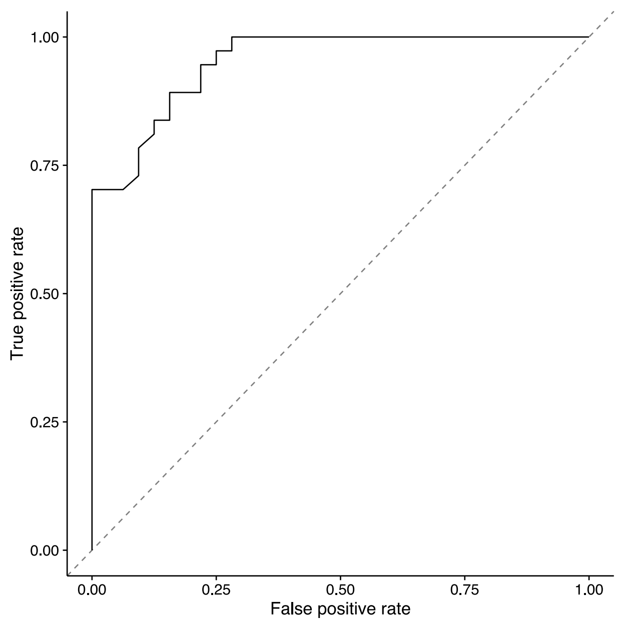
```
Resample Result
Task: OpenML-Task-59
Learner: classif.rpart.tuned
mmce.aggr: 0.05
mmce.mean: 0.05
mmce.sd: 0.02
Runtime: 58.4672
```

2.6 ROC analysis

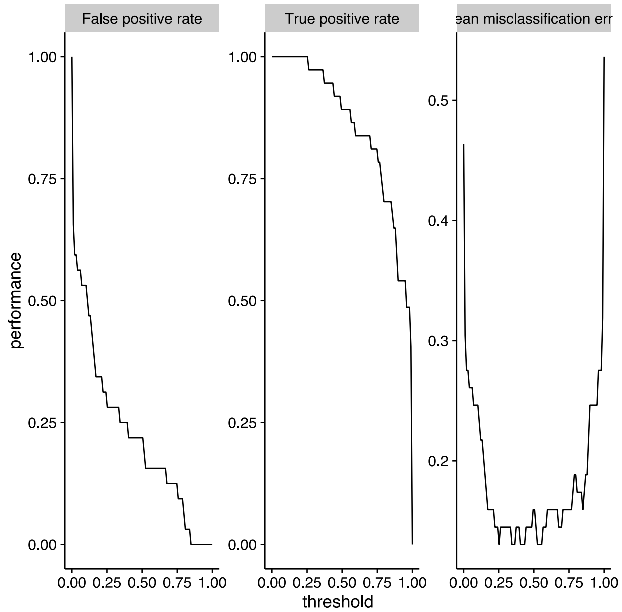
- mlr has support for plotting ROC curves and doing ROC analysis
- http://mlr-org.github.io/mlr-tutorial/devel/html/roc_analysis/index.html

```
In [122]: data(Sonar, package = "mlbench")
          sonar.task = makeClassifTask(data=Sonar,target="Class")

          n = getTaskSize(sonar.task) # make a 2/3 split
          train.set = sample(n, size = round(2/3 * n))
          test.set = setdiff(seq_len(n), train.set)

          lrn1 = makeLearner("classif.kknn", predict.type = "prob") # output probabilities
          mod1 = train(lrn1, sonar.task, subset = train.set)
          pred1 = predict(mod1, task = sonar.task, subset = test.set)

          # Evaluate performance over different thresholds
          df = generateThreshVsPerfData(pred1, measures = list(fpr, tpr, mmce))
```

```
In [76]: plotROCCurves(df)
```

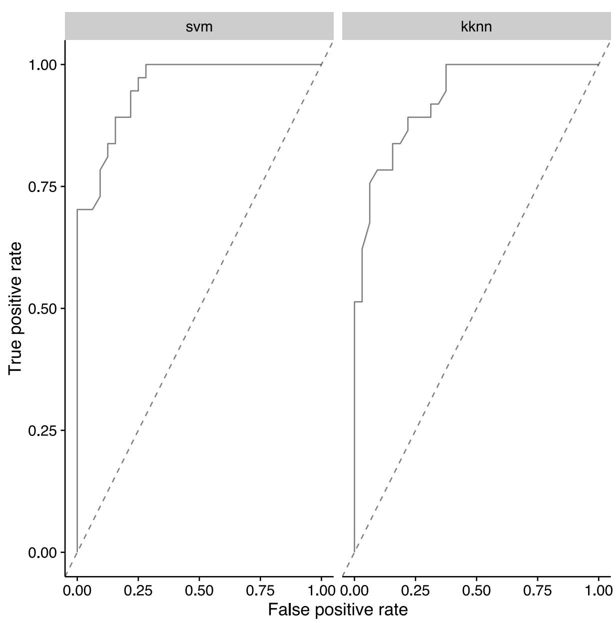



```
In [77]: plotThreshVsPerf(df)
```

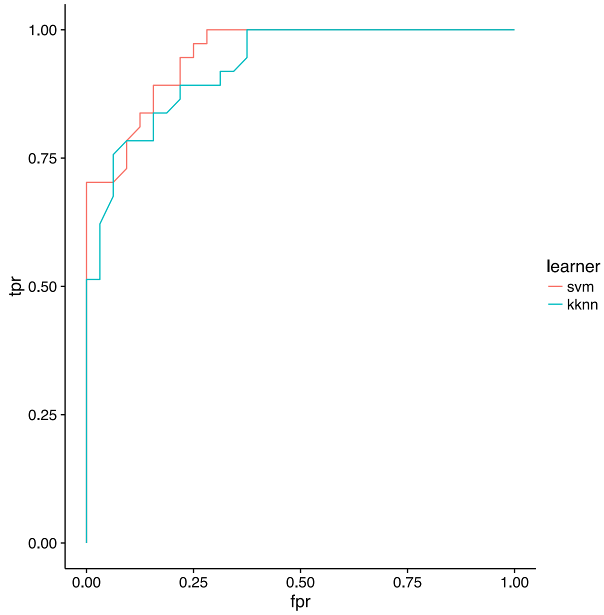


Compare learners

```
In [78]: lrn2 = makeLearner("classif.ksvm", predict.type = "prob")
         mod2 = train(lrn2, sonar.task, subset = train.set)
         pred2 = predict(mod2, task = sonar.task, subset = test.set)
         df = generateThreshVsPerfData(list(svm = pred1, kknn = pred2), measures = list(fpr, tpr))
         plotROCCurves(df)
```




```
In [79]: qplot(x = fpr, y = tpr, color = learner, data = df$data, geom = "path")
```



2.7 Extra: Handling datasets in R

- In R, datasets are represented as R Data Frames
- Here, we show some useful methods. Skip it if you know them.

Also see: - R Cookbook: http://www.cookbook-r.com/ - DataCamp tutorial: https://www.datacamp.com/community/tutorials/15-easy-solutions-data-frame-problems-r

2.7.1 Basics

```
In [80]: data(iris, package = "datasets") # Loads dataset iris
         str(iris) # Returns a description
```

```
'data.frame':        150 obs. of  5 variables:
 $ Sepal.Length: num  5.1 4.9 4.7 4.6 5 5.4 4.6 5 4.4 4.9 ...
 $ Sepal.Width : num  3.5 3 3.2 3.1 3.6 3.9 3.4 3.4 2.9 3.1 ...
 $ Petal.Length: num  1.4 1.4 1.3 1.5 1.4 1.7 1.4 1.5 1.4 1.5 ...
 $ Petal.Width : num  0.2 0.2 0.2 0.2 0.2 0.4 0.3 0.2 0.2 0.1 ...
 $ Species     : Factor w/ 3 levels "setosa","versicolor",..: 1 1 1 1 1 1 1 1 1 1 ...
```

```
In [81]: head(iris) # First few rows
         summary(iris) # Summary statistics
```

	Sepal.Length	Sepal.Width	Petal.Length	Petal.Width	Species
1	5.1	3.5	1.4	0.2	setosa
2	4.9	3	1.4	0.2	setosa
3	4.7	3.2	1.3	0.2	setosa
4	4.6	3.1	1.5	0.2	setosa
5	5	3.6	1.4	0.2	setosa
6	5.4	3.9	1.7	0.4	setosa

```
  Sepal.Length    Sepal.Width     Petal.Length    Petal.Width   
 Min.   :4.300   Min.   :2.000   Min.   :1.000   Min.   :0.100  
 1st Qu.:5.100   1st Qu.:2.800   1st Qu.:1.600   1st Qu.:0.300  
 Median :5.800   Median :3.000   Median :4.350   Median :1.300  
 Mean   :5.843   Mean   :3.057   Mean   :3.758   Mean   :1.199  
 3rd Qu.:6.400   3rd Qu.:3.300   3rd Qu.:5.100   3rd Qu.:1.800  
 Max.   :7.900   Max.   :4.400   Max.   :6.900   Max.   :2.500  
       Species  
 setosa    :50  
 versicolor:50  
 virginica :50  
```

```
In [82]: names(iris) # All feature names
         dim(iris)   # Dimensions
         nrow(iris)  # Number of rows / examples
         ncol(iris)  # Number of columns / features
```

1. 'Sepal.Length' 2. 'Sepal.Width' 3. 'Petal.Length' 4. 'Petal.Width' 5. 'Species'
1. 150 2. 5
150
5

2.7.2 Slicing

```
In [83]: head(iris$Petal.Length) # Select specific feature
         iris[1:5,3]      # Select values in row 1:5, column 3
         head(iris[,c("Petal.Length","Petal.Width")]) # Select columns by name
         iris[3,]         # Select row 3
```

1. 1.4 2. 1.4 3. 1.3 4. 1.5 5. 1.4 6. 1.7
1. 1.4 2. 1.4 3. 1.3 4. 1.5 5. 1.4

	Petal.Length	Petal.Width
1	1.4	0.2
2	1.4	0.2
3	1.3	0.2
4	1.5	0.2
5	1.4	0.2
6	1.7	0.4

	Sepal.Length	Sepal.Width	Petal.Length	Petal.Width	Species
3	4.7	3.2	1.3	0.2	setosa

```
In [84]: # R will convert a single column to a vector, use drop=FALSE to avoid
         head(iris[,c("Petal.Length")])
         head(iris[,c("Petal.Length"), drop=FALSE])
```

1. 1.4 2. 1.4 3. 1.3 4. 1.5 5. 1.4 6. 1.7

	Petal.Length
1	1.4
2	1.4
3	1.3
4	1.5
5	1.4
6	1.7

2.7.3 Applying functions

```
In [85]: dat = iris[1:8,3:4] # select rows 1-8, columns 3-4
         apply(dat, 1, mean)       # computes mean per ROW (=1)
         apply(dat, 2, median)     # computes median per COLUMN (=2)
```

1 0.8 **2** 0.8 **3** 0.75 **4** 0.85 **5** 0.8 **6** 1.05 **7** 0.85 **8** 0.85
Petal.Length 1.4 **Petal.Width** 0.2

2.7.4 Subsetting

```
In [86]: head(subset(iris, Petal.Length <= 4 & Petal.Width > 1.2))
         head(subset(iris, Species == "setosa"))
         head(subset(iris, Species %in% c("setosa", "versicolor")))
```

	Sepal.Length	Sepal.Width	Petal.Length	Petal.Width	Species
54	5.5	2.3	4	1.3	versicolor
60	5.2	2.7	3.9	1.4	versicolor
65	5.6	2.9	3.6	1.3	versicolor
72	6.1	2.8	4	1.3	versicolor
90	5.5	2.5	4	1.3	versicolor

	Sepal.Length	Sepal.Width	Petal.Length	Petal.Width	Species
1	5.1	3.5	1.4	0.2	setosa
2	4.9	3	1.4	0.2	setosa
3	4.7	3.2	1.3	0.2	setosa
4	4.6	3.1	1.5	0.2	setosa
5	5	3.6	1.4	0.2	setosa
6	5.4	3.9	1.7	0.4	setosa

	Sepal.Length	Sepal.Width	Petal.Length	Petal.Width	Species
1	5.1	3.5	1.4	0.2	setosa
2	4.9	3	1.4	0.2	setosa
3	4.7	3.2	1.3	0.2	setosa
4	4.6	3.1	1.5	0.2	setosa
5	5	3.6	1.4	0.2	setosa
6	5.4	3.9	1.7	0.4	setosa

```
In [87]: # Use droplevels to actually remove unused feature values (levels) from the dataset
         onlysetosa = subset(iris, Species == "setosa")
         str(onlysetosa)
         str(droplevels(onlysetosa))
```

```
'data.frame':        50 obs. of  5 variables:
 $ Sepal.Length: num  5.1 4.9 4.7 4.6 5 5.4 4.6 5 4.4 4.9 ...
 $ Sepal.Width : num  3.5 3 3.2 3.1 3.6 3.9 3.4 3.4 2.9 3.1 ...
 $ Petal.Length: num  1.4 1.4 1.3 1.5 1.4 1.7 1.4 1.5 1.4 1.5 ...
 $ Petal.Width : num  0.2 0.2 0.2 0.2 0.2 0.4 0.3 0.2 0.2 0.1 ...
 $ Species     : Factor w/ 3 levels "setosa","versicolor",..: 1 1 1 1 1 1 1 1 1 1 ...
'data.frame':        50 obs. of  5 variables:
 $ Sepal.Length: num  5.1 4.9 4.7 4.6 5 5.4 4.6 5 4.4 4.9 ...
 $ Sepal.Width : num  3.5 3 3.2 3.1 3.6 3.9 3.4 3.4 2.9 3.1 ...
 $ Petal.Length: num  1.4 1.4 1.3 1.5 1.4 1.7 1.4 1.5 1.4 1.5 ...
 $ Petal.Width : num  0.2 0.2 0.2 0.2 0.2 0.4 0.3 0.2 0.2 0.1 ...
 $ Species     : Factor w/ 1 level "setosa": 1 1 1 1 1 1 1 1 1 1 ...
```

2.7.5 Removing and adding rows

In [88]:
```
small_iris = iris[iris$Sepal.Length < 4.5,] # Remove rows based on test
head(small_iris)
new_row = c(4.0, 3.0, 1.0, 0.2, "setosa")
small_iris = rbind(small_iris, new_row)
head(small_iris)
```

	Sepal.Length	Sepal.Width	Petal.Length	Petal.Width	Species
9	4.4	2.9	1.4	0.2	setosa
14	4.3	3	1.1	0.1	setosa
39	4.4	3	1.3	0.2	setosa
43	4.4	3.2	1.3	0.2	setosa

	Sepal.Length	Sepal.Width	Petal.Length	Petal.Width	Species
9	4.4	2.9	1.4	0.2	setosa
14	4.3	3	1.1	0.1	setosa
39	4.4	3	1.3	0.2	setosa
43	4.4	3.2	1.3	0.2	setosa
5	4	3	1	0.2	setosa

2.7.6 Removing and adding columns

In [89]:
```
sepalwidth = iris$Sepal.Width
iris$Sepal.Width = NULL # Remove column Sepal.Width
head(iris)
iris$Sepal.Width = sepalwidth # Add it again
head(iris)
iris = iris[c("Sepal.Length","Sepal.Width","Petal.Length","Petal.Width","Species")] #Reorder
head(iris)
```

	Sepal.Length	Petal.Length	Petal.Width	Species
1	5.1	1.4	0.2	setosa
2	4.9	1.4	0.2	setosa
3	4.7	1.3	0.2	setosa
4	4.6	1.5	0.2	setosa
5	5	1.4	0.2	setosa
6	5.4	1.7	0.4	setosa

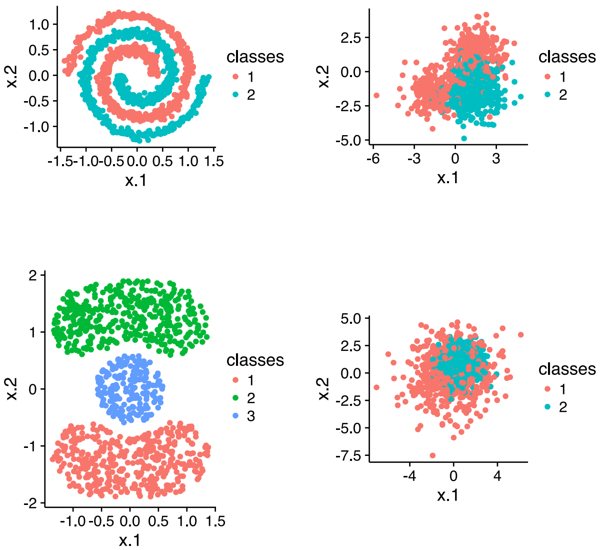
	Sepal.Length	Petal.Length	Petal.Width	Species	Sepal.Width
1	5.1	1.4	0.2	setosa	3.5
2	4.9	1.4	0.2	setosa	3
3	4.7	1.3	0.2	setosa	3.2
4	4.6	1.5	0.2	setosa	3.1
5	5	1.4	0.2	setosa	3.6
6	5.4	1.7	0.4	setosa	3.9

	Sepal.Length	Sepal.Width	Petal.Length	Petal.Width	Species
1	5.1	3.5	1.4	0.2	setosa
2	4.9	3	1.4	0.2	setosa
3	4.7	3.2	1.3	0.2	setosa
4	4.6	3.1	1.5	0.2	setosa
5	5	3.6	1.4	0.2	setosa
6	5.4	3.9	1.7	0.4	setosa

2.7.7 Generating data

Several R packages allow you to generate synthetic data

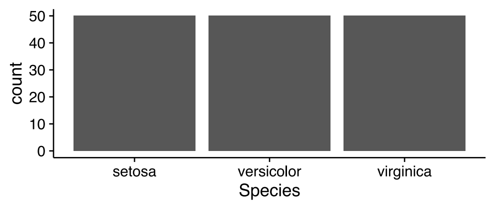
```
In [90]: library(mlbench)
         newdata = as.data.frame(mlbench.spirals(n=1000, cycles=1.5, sd=0.05))
         spirals = ggplot(data=newdata, aes(x=x.1, y=x.2, color=classes)) + geom_point() + coord_fixed(r
         newdata = as.data.frame(mlbench.threenorm(n=1000, d=2))
         blobs = ggplot(data=newdata, aes(x=x.1, y=x.2, color=classes)) + geom_point() + coord_fixed(ra
         newdata = as.data.frame(mlbench.cassini(n=1000, relsize=c(2,2,1)))
         waves = ggplot(data=newdata, aes(x=x.1, y=x.2, color=classes)) + geom_point() + coord_fixed(ra
         newdata = as.data.frame(mlbench.ringnorm(n=1000, d=2))
         shapes = ggplot(data=newdata, aes(x=x.1, y=x.2, color=classes)) + geom_point() + coord_fixed(r
         grid.arrange(spirals, blobs, waves, shapes, ncol=2, nrow =2)
```

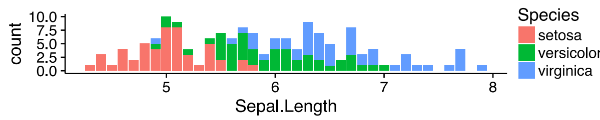


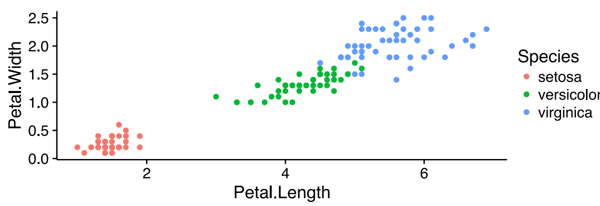
2.7.8 Visualizing data (ggplot)

- http://www.cookbook-r.com/Graphs/index.html
- https://www.rstudio.com/wp-content/uploads/2015/03/ggplot2-cheatsheet.pdf
- http://zevross.com/blog/2014/08/04/beautiful-plotting-in-r-a-ggplot2-cheatsheet-3/

```
In [91]: # Class distribution
         plotclass = ggplot(data=iris, aes(x=Species)) + geom_bar(stat="count") + coord_fixed(ratio=0.0
         #  feature
         plotpetal = ggplot(data=iris, aes(x=Sepal.Length, fill=Species)) + geom_bar(stat="count") + co
         # Plot lym_nodes_dimin against lym_nodes_enlar
         plotdim = ggplot(data=iris, aes(x=Petal.Length, y=Petal.Width, color=Species)) + geom_point()
         grid.arrange(plotclass, plotpetal, plotdim, ncol = 1)
```


50
40
30
20
10
0
count
setosa
versicolor
virginica
Species


10.0
7.5
5.0
2.5
0.0
count
5
6
7
8
Sepal.Length
Species
setosa
versicolor
virginica


2.5
2.0
1.5
1.0
0.5
0.0
Petal.Width
2
4
6
Petal.Length
Species
setosa
versicolor
virginica