R's `mlr` package as common modeling interface

And maybe some R/Python discussions

On Kaggle bike sharing and weather data

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Background and Overview

- Based on work for edX-Course Python for Data Science
- Course project: investigates **to what extent** and **how weather and time of day** influence **bike rentals** in a public bike sharing system in Montreal.
- Analysis in Python for edX course (data prep, some ML models, interpretation)
- Redone using some new cool stuff in the R ecosystem:
    - `mlr` package as a common interface for machine learning in R
    - `iml` package for model interpretation (Pointed out by Andreas/Slack)

Note: Only parts of each package can be covered here! No model interpretation due to time constraints (in preparing the presentation).

The full analysis is available in multiple python files on github: kgl-cycle-share-main-file.py.
A synopsis is available as an ipython notebook cycle-share-analysis-synopsis.ipynb, or as html to download.

Dataset(s)

Two datasets were used: **Bike sharing data**…

- **BIXI Montreal public bicycle sharing system**, North America's first large-scale bike sharing system
- Available via Kaggle from https://www.kaggle.com/aubertsigouin/biximtl/home
- For years 2014 to 2017
- Contains **individual records of bike trips**: timestamp and station code for start and end of trip, duration
- $n = 14598961$ records (individual bike trips)
- Station codes, names, and position (latitude, longitude) available in separate files, but only of secondary interest for this analysis

…and **weather data** from the Canadian government:

- Canadian government's past weather and climate service, available from http://climate.weather.gc.ca/ historical_data/ search_historic_data_e.html
- API for **bulk data download**: http://climate.weather.gc.ca/climate_data/ bulk_data_e.html
- Data can be downloaded per weather station per month and contains **hourly measurements** of different metrics (e.g., timestamp, temperature, relative humidity, atmospheric pressure, wind speed; different measures available for different stations)
- $n = 35064$ hourly weather records in total (between 672 and 744 per monthly file)

Data Preparation and Cleaning

- First, **data download** was performed manually for the bike share data from Kaggle (as only available after login), and via a Python script for the weather data (bulk download).
- For the weather data, the **weather station** that was most central to the locations of the bike rides was picked (see data exploration).
- Next, the **data was loaded** and contatenated into a pandas `DataFrame` each for individual bike rides and hourly weather data.
- The next step was **calculating the variable of interest: Hourly bike rides**. This was done by aggregating individual bike trips to hourly counts of trips (number of trips in each hour), using the starting time of the trip.
- Then, the **weather data was joined to the hourly bike ride data**, using the common timestamp as join key.
- One feature **(wind chill) was dropped**, as it had too many missing values (77.9% missing).
- Finally, **additional features were added** for the analysis: hour of the day (0-23), day of the week (0-6, zero corresponding to Monday, six corresponding to Sunday), month (1-12).
- These features, despite being categorical in nature, were kept as **continuous features**, as this proved to have more predictive power in the models.
- For modeling, **rows with missing values were dropped**, as the goal is not having the most complete prediction coverage, but rather an indication of the prediction quality that is possible with complete data. In total, 1284 rows (0.04%) of the original data were dropped.
- The remaining rows were **split into training and testing set** (90% of the data, $n = 26168$ rows for training, the remaining 10%, $n = 2908$ for testing).

Research Question(s)

The research questions that I wanted to answer with my analysis were:

- **To what extent do** the number of **bike rides depend on the current weather conditions**? That is, how well can the number of bike rides be predicted from weather data (and time of year, time of day)?
- What are the **most important factors** that influence the number of bike rides?
- **How do these factors influence** the number of bike rides? What are the main effects of these factors, and what are the interactions between them?

Findings: Data Exploration

- Context: **number of hourly bike trips** visualized for the time span between 2014 and 2017.
- Baseline model:
  - **Moving average** (red line)
  - 38.8% variance explained ($r^2 = 0.388$)
  - Mean absolute error of $MAE = 316.2$

Note:

- All data prep and exploration done in Python
- Data stored in `feather` format (fast data exchange between R and Python)

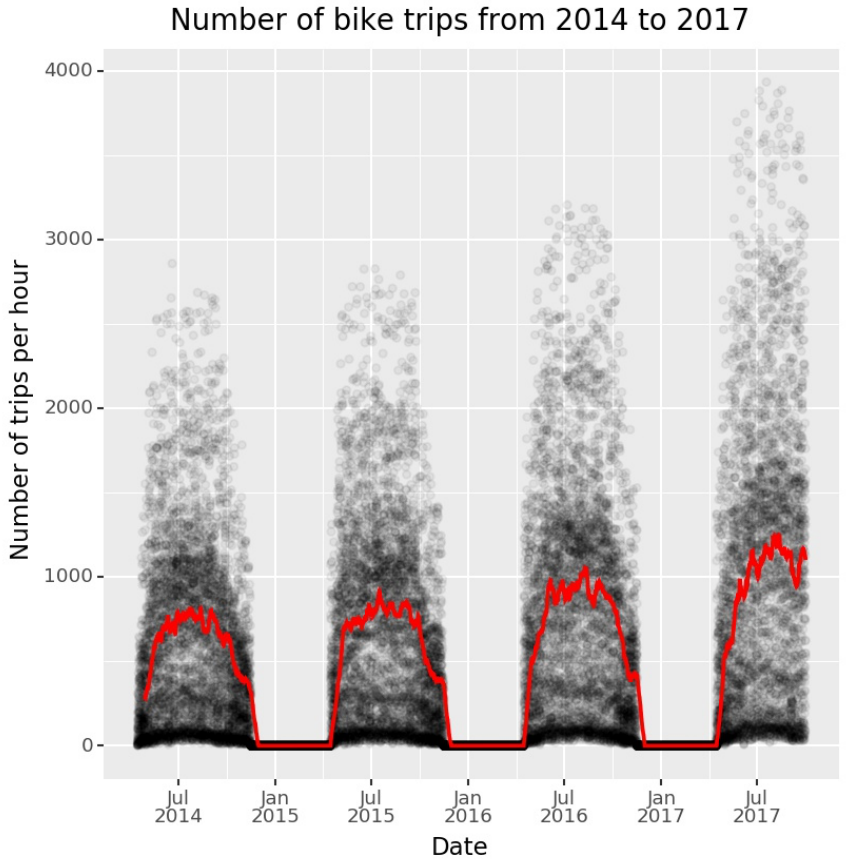


Figure: Number of hourly rides from 2014 to 2017. Each dot represents the number of trips in one specifc hour. Red line represents a moving average using a window of 14 days.

Methods

- 90% training and 10% test set
- **Different machine learning models** (predicting hourly number of bike rides):
  - Random forest regression (`scikit-learn` / `randomForest`, `ranger`)
  - gradient boosting regression (`scikit-learn` / `gbm`)
  - gradient boosting regression via `xgboost` (Python and R)
- Hyperparameter tuning: randomized search with 4-fold CV (40 iterations)
- Interpretation not part of this presentation

R package `mlr`: Overview

- **Standardized interface** for R's machine learning algorithms
- Infrastructure to:
  - **Resample** your models (cross validation, etc.)
  - **Select features**
  - Cope with **pre- and post-processing** of data
  - **Optimize hyperparameters** (of models and also preprocessing)
  - **Compare models** in a statistically meaningful way
- Classification (including multilabel), regression, clustering, survival analysis
- Offers **parallelization** out of the box

Note: Only some parts of regression with hyperparameter tuning covered here.

Building blocks

- **Task**: Data + meta data (target, positive class)
- **Learners**: Machine learning algorithms
  - `train()` → trained model: `predict()`, `performance()`, etc.
- **Resampling** strategy descriptions
  - `resample()` → trained model instances with performance metrics
- **Parameter tuners**: `tuneParams()` → trained and tuned model
- **Benchmark experiments**
  - `benchmark()` → multiple trained models and their instances
- **Wrappers** for Data preprocessing, Imputation, Over- and undersampling, Feature selection, Bagging, Parameter Tuning (return a **learner**)
- **Plots**

Tasks

```
## load mlr package:
library(mlr)

## load housing data from package `mlbench`:
data(BostonHousing, package = "mlbench")

## define task
regr.task = makeRegrTask(id = "bh",
                         data = BostonHousing,
                         target = "medv")
regr.task
```

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

Tasks

```
## create a task: (= data + meta-information)
task_full <- makeRegrTask(id = "trip_cnt_mod",
                      data = dat_hr_mod[varnames_model],
                      target = varnames_target)

task <- subsetTask(task = task_full, subset = idx_train)

task_small <- subsetTask(task = task_full,
                         subset = sample(idx_test, size = 1000))
```

Cycling trip data example:

- One full task (for final model estimation with evaluation on a fixed test set)
- Subtask for CV within the training set
- Subtask with small sample size for plotting

Learners

```
## Classification tree, set it up for predicting probabilities:
classif_lrn <- makeLearner("classif.randomForest",
                           predict.type = "prob",
                           fix.factors.prediction = TRUE)

## Regression gradient boosting machine, specify hyperparameters via a list
regr_lrn = makeLearner("regr.gbm",
                       par.vals = list(
                         n.trees = 500,
                         interaction.depth = 3)
                       )
```

- Parameters like `predict.type` are standardized for all learners
- Model-specific parameters passed in `par.vals` list

Learners: Parameters

```
## define learner without basic parameters:
learner_rf <- makeLearner("regr.randomForest",
                          par.vals = list(ntree = 500))
getParamSet(learner_rf)  ## or: getParamSet("regr.randomForest")
```

```
##                     Type  len   Def                 Constr Req Tunable Trafo
## ntree            integer    -   500               1 to Inf   -    TRUE     -
## se.ntree         integer    -   100               1 to Inf   Y    TRUE     -
## se.method       discrete    -    sd bootstrap,jackknife,sd   Y    TRUE     -
## se.boot          integer    -    50               1 to Inf   -    TRUE     -
## mtry             integer    -     -               1 to Inf   -    TRUE     -
## replace          logical    -  TRUE                      -   -    TRUE     -
## strata           untyped    -     -                      -   -   FALSE     -
## sampsize    integervector <NA>     -               1 to Inf   -    TRUE     -
## nodesize         integer    -     5               1 to Inf   -    TRUE     -
## maxnodes         integer    -     -               1 to Inf   -    TRUE     -
## importance       logical    - FALSE                      -   -    TRUE     -
## localImp         logical    - FALSE                      -   -    TRUE     -
## nPerm            integer    -     1            -Inf to Inf   -    TRUE     -
## proximity        logical    - FALSE                      -   -   FALSE     -
## oob.prox         logical    -     -                      -   Y   FALSE     -
## do.trace         logical    - FALSE                      -   -   FALSE     -
## keep.forest      logical    -  TRUE                      -   -   FALSE     -
## keep.inbag       logical    - FALSE                      -   -   FALSE     -
```

List of Learners

```
## get list of learners:
listLearners(warn.missing.packages = FALSE)
```

```
##                class                                 name  short.name      package    type installed numerics factors
## 1         classif.ada                         ada Boosting         ada    ada,rpart classif      TRUE     TRUE    TRUE
## 2  classif.adaboostm1                       ada Boosting M1  adaboostm1        RWeka classif     FALSE     TRUE    TRUE
## 3 classif.bartMachine Bayesian Additive Regression Trees bartmachine  bartMachine classif     FALSE     TRUE    TRUE
## 4    classif.binomial                  Binomial Regression    binomial        stats classif      TRUE     TRUE    TRUE
## 5    classif.boosting                      Adabag Boosting      adabag adabag,rpart classif      TRUE     TRUE    TRUE
## 6         classif.bst                    Gradient Boosting         bst    bst,rpart classif      TRUE     TRUE   FALSE
##   ordered missings weights  prob oneclass twoclass multiclass class.weights featimp oobpreds functionals
## 1   FALSE    FALSE   FALSE  TRUE    FALSE     TRUE      FALSE         FALSE   FALSE    FALSE       FALSE
## 2   FALSE    FALSE   FALSE  TRUE    FALSE     TRUE       TRUE         FALSE   FALSE    FALSE       FALSE
## 3   FALSE     TRUE   FALSE  TRUE    FALSE     TRUE      FALSE         FALSE   FALSE    FALSE       FALSE
## 4   FALSE    FALSE    TRUE  TRUE    FALSE     TRUE      FALSE         FALSE   FALSE    FALSE       FALSE
## 5   FALSE     TRUE   FALSE  TRUE    FALSE     TRUE       TRUE         FALSE    TRUE    FALSE       FALSE
## 6   FALSE    FALSE   FALSE FALSE    FALSE     TRUE      FALSE         FALSE   FALSE    FALSE       FALSE
##   single.functional    se lcens rcens icens
## 1             FALSE FALSE FALSE FALSE FALSE
## 2             FALSE FALSE FALSE FALSE FALSE
## 3             FALSE FALSE FALSE FALSE FALSE
## 4             FALSE FALSE FALSE FALSE FALSE
## 5             FALSE FALSE FALSE FALSE FALSE
## 6             FALSE FALSE FALSE FALSE FALSE
## ... (#rows: 167, #cols: 24)
```

List of Learners with properties

```
## get list of learners wich certain properties::
listLearners("regr", properties = c("missings", "weights"), warn.missing.packages = FALSE)
```

```
##                  class                                                name short.name         package type installed
## 1          regr.cforest Random Forest Based on Conditional Inference Trees    cforest           party regr      TRUE
## 2            regr.ctree                          Conditional Inference Trees      ctree           party regr      TRUE
## 3              regr.gbm                            Gradient Boosting Machine        gbm             gbm regr      TRUE
## 4 regr.h2o.deeplearning                                    h2o.deeplearning     h2o.dl             h2o regr      TRUE
## 5          regr.h2o.glm                                            h2o.glm    h2o.glm             h2o regr      TRUE
## 6  regr.randomForestSRC                                      Random Forest      rfsrc randomForestSRC regr      TRUE
##   numerics factors ordered missings weights  prob oneclass twoclass multiclass class.weights featimp oobpreds
## 1     TRUE    TRUE    TRUE     TRUE    TRUE FALSE    FALSE    FALSE      FALSE         FALSE    TRUE    FALSE
## 2     TRUE    TRUE    TRUE     TRUE    TRUE FALSE    FALSE    FALSE      FALSE         FALSE   FALSE    FALSE
## 3     TRUE    TRUE   FALSE     TRUE    TRUE FALSE    FALSE    FALSE      FALSE         FALSE    TRUE    FALSE
## 4     TRUE    TRUE   FALSE     TRUE    TRUE FALSE    FALSE    FALSE      FALSE         FALSE   FALSE    FALSE
## 5     TRUE    TRUE   FALSE     TRUE    TRUE FALSE    FALSE    FALSE      FALSE         FALSE   FALSE    FALSE
## 6     TRUE    TRUE    TRUE     TRUE    TRUE FALSE    FALSE    FALSE      FALSE         FALSE    TRUE     TRUE
##   functionals single.functional    se lcens rcens icens
## 1       FALSE             FALSE FALSE FALSE FALSE FALSE
## 2       FALSE             FALSE FALSE FALSE FALSE FALSE
## 3       FALSE             FALSE FALSE FALSE FALSE FALSE
## 4       FALSE             FALSE FALSE FALSE FALSE FALSE
## 5       FALSE             FALSE FALSE FALSE FALSE FALSE
## 6       FALSE             FALSE FALSE FALSE FALSE FALSE
## ... (#rows: 8, #cols: 24)
```

Unified Interface

```
## train learner:
model <- train(learner = learner_rf, task = task_full, subset = idx_train)
model
```

```
Model for learner.id=regr.randomForest; learner.class=regr.randomForest
Trained on: task.id = trip_cnt_mod; obs = 26168; features = 8
Hyperparameters: ntree=500
```

```
## access model:
getLearnerModel(model) %>% class()
```

```
[1] "randomForest"
```

```
getLearnerModel(model)
```

```
Call:
 randomForest(x = data[["data"]], y = data[["target"]], ntree = 500,
              keep.inbag = if (is.null(keep.inbag)) TRUE else keep.inbag)
               Type of random forest: regression
                     Number of trees: 500
No. of variables tried at each split: 2

          Mean of squared residuals: 41190.02
                    % Var explained: 90.01
```

Unified Interface

```
## predict with learner:
pred <- predict(model, newdata = dat_hr_mod, subset = idx_test)
pred
```

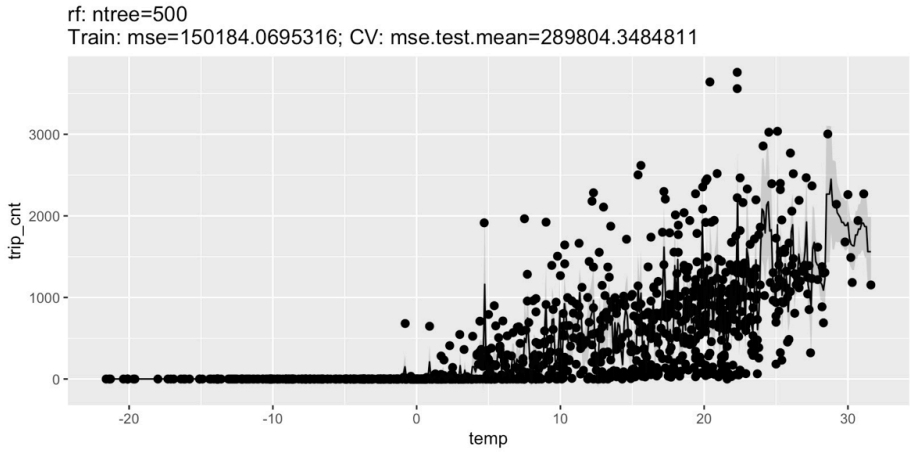
```
Prediction: 2908 observations
predict.type: response
threshold:
time: 1.47
   truth  response
2      5  42.53462
6      5  30.70638
... (#rows: 2912, #cols: 2)
```

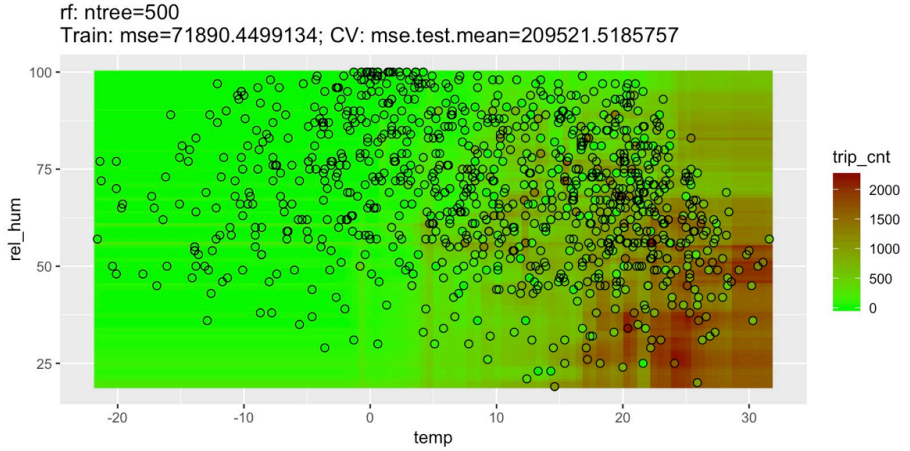
Inspect Learner Predictions

```
## inspect predictions on a small subset
set.seed(1548)
task_small_prelim <- subsetTask(
  task = task_full,
  subset = sample(idx_test, size = 1000)
)

plotLearnerPrediction(
  learner_rf, task = task_small_prelim,
  features = "temp"
)

plotLearnerPrediction(
  learner_rf,
  task = task_small_prelim, features = c("temp", "rel_hum")
)
```





Performance Measures

```
## assess performance of learner:
performance(pred, measures = list(mse, mae, rsq))
```

```
       mse         mae         rsq
42114.37355   110.04546     0.89036
```

```
## list of suitable measures for a task:
listMeasures()
```

```
##  [1] "tnr"                "iauc.uno"           "tpr"                "featperc"           "mae"
##  [6] "multilabel.tpr"     "f1"                 "mmce"               "mape"               "ibrier"
## [11] "multilabel.hamloss" "db"                 "mcc"                "brier.scaled"       "medse"
## [16] "mcp"                "lsr"                "msle"               "rae"                "bac"
## [21] "fn"                 "fp"                 "fnr"                "spearmanrho"        "multilabel.subset01"
## [26] "qsr"                "fpr"                "npv"                "brier"              "auc"
## [31] "meancosts"          "timeboth"           "multiclass.aunp"    "timetrain"          "multiclass.aunu"
## [36] "rmsle"              "ber"                "timepredict"        "medae"              "sse"
## [41] "multiclass.brier"   "ssr"                "ppv"                "multilabel.ppv"     "dunn"
## [46] "expvar"             "acc"                "logloss"            "kendalltau"         "rmse"
## [51] "wkappa"             "cindex.uno"         "multilabel.f1"      "mse"                "tn"
## [56] "tp"                 "rrse"               "multiclass.au1p"    "multiclass.au1u"    "sae"
## [61] "multilabel.acc"     "silhouette"         "fdr"                "G1"                 "kappa"
## [66] "G2"                 "rsq"                "cindex"             "gpr"                "gmean"
## [71] "arsq"
```

Cross Validation

```
## set random seed, also valid for parallel execution:
set.seed(4271, "L'Ecuyer")

## choose resampling strategy for parameter tuning:
rdesc <- makeResampleDesc(predict = "both",
                          method = "CV", iters = 4)

## not needed: estimating performance using resampling:
res <- resample(learner = "regr.ranger", task = task,
                resampling = rdesc,
                measures = list(mse, mae, rsq))
```

```
Resampling: cross-validation
Measures:             mse.test   mae.test   rsq.test
[Resample] iter 1:    113423.0606216188.7838823   0.7348283
[Resample] iter 2:    65289.2298107164.0962026  0.8057397
[Resample] iter 3:    109819.4070038195.5073898   0.7204328
[Resample] iter 4:    102574.8995368195.6119237   0.7466122

Aggregated Result: mse.test.mean=97776.6492433,mae.test.mean=185.9998496,rsq.test.mean=0.7519033
```

Parallelism

Supported backends for parallelism:

- local multicore execution using `parallel`
- socket and MPI clusters using `snow`
- makeshift SSH-clusters using `BatchJobs`
- high performance computing clusters (managed by a scheduler like SLURM, Torque/PBS, SGE or LSF) also using BatchJobs.

```
## enable parallel execution on a multicore machine:
library(parallelMap)
parallelStartMulticore(cpus = n_cpus,
                       level = "mlr.resample")
```

Parallelism can be set to different execution levels:

```
parallelGetRegisteredLevels()
```

```
mlr: mlr.benchmark, mlr.resample, mlr.selectFeatures,
     mlr.tuneParams, mlr.ensemble
```

Parameter tuning

```
## tuning strategy for parameter tuning:
ctrl <- makeTuneControlRandom(maxit = 40)
tune_measures <- list(rmse, mae, rsq, timetrain, timepredict)

## tune standard random forest implementation:
tune_results_rf <- tuneParams(
  "regr.randomForest",
  task = task, resampling = rdesc, measures = tune_measures, control = ctrl,
  par.set = makeParamSet(
    makeIntegerParam("mtry", lower = 2, upper = length(varnames_features)),
    makeIntegerParam("nodesize", lower = 10, upper = 50),
    makeIntegerParam("ntree", lower = 100, upper = 500)
  )
)
tune_results_rf
```

```
Tune result:
Op. pars: mtry=6; nodesize=10; ntree=445
rmse.test.rmse=182.8800473,mae.test.mean=96.1463276,rsq.test.mean=0.9188789,
timetrain.test.mean=168.3022500,timepredict.test.mean=0.5545000
```

```
## access tuned parameters:
tune_results_rf$x
```

```
$mtry
[1] 6

$nodesize
[1] 10

$ntree
[1] 445
```

Benchmark experiments

```
lrns_tuned <- list(
  makeLearner("regr.randomForest",  par.vals = tune_results_rf$x),
  makeLearner("regr.ranger", par.vals = tune_results_ranger$x),
  makeLearner("regr.gbm", par.vals = tune_results_gbm$x),
  makeLearner("regr.xgboost", par.vals = tune_results_xgboost$x)
)

## set resampling strategy for benchmarking:
rdesc_bm <- makeResampleDesc(predict = "both",
                             method = "RepCV", reps = 3, folds = 4)

## refit tuned models on complete training data:
bmr_train <- benchmark(
  lrns_tuned, task, rdesc_bm,
  measures = list(rmse, mae, rsq,
                  timetrain, timepredict)
)
bmr_train
```

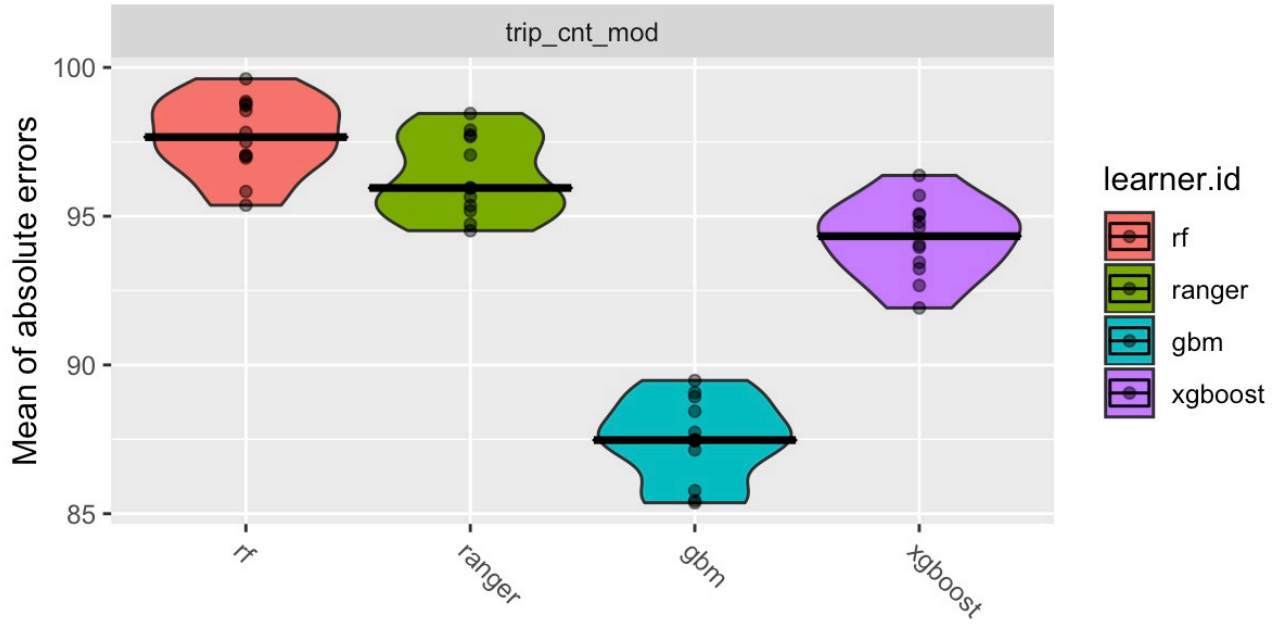
	task.id	learner.id	rmse.test.rmse	mae.test.mean	rsq.test.mean	timetrain.test.mean	timepredict.test.mean
1	trip_cnt_mod	regr.randomForest	185.6066	97.34310	0.9158034	39.06592	0.1747500
2	trip_cnt_mod	regr.ranger	182.8889	95.97002	0.9182493	27.85592	1.3381667
3	trip_cnt_mod	regr.gbm	183.7731	95.91192	0.9174738	105.31608	0.6764167
4	trip_cnt_mod	regr.gbm.ntreeplus	171.5927	87.12461	0.9280451	729.68542	4.3349167
5	trip_cnt_mod	regr.xgboost	169.8597	96.49248	0.9294890	24.11000	1.1610833

Visualizing benchmark experiments

```
bmr_train
```

	task.id	learner.id	rmse.test.rmse	mae.test.mean	rsq.test.mean	timetrain.test.mean	timepredict.test.mean
1	trip_cnt_mod	regr.randomForest	185.6066	97.34310	0.9158034	39.06592	0.1747500
2	trip_cnt_mod	regr.ranger	182.8889	95.97002	0.9182493	27.85592	1.3381667
3	trip_cnt_mod	regr.gbm	183.7731	95.91192	0.9174738	105.31608	0.6764167
4	trip_cnt_mod	regr.gbm.ntreeplus	171.5927	87.12461	0.9280451	729.68542	4.3349167
5	trip_cnt_mod	regr.xgboost	169.8597	96.49248	0.9294890	24.11000	1.1610833

```
plotBMRBoxplots(bmr_train,
                measure = mae,
                style = "violin") +
  aes(fill = learner.id) +
  geom_point(alpha = .5)
```



R and Python Results

Model	MAE_{test}	r^2_{test}	tuning time
Gradient Boosting (R/gbm) (ntree++)	81.1	0.936	$\sim$ 260 min
Gradient Boosting (Python/sklearn)	85.4	0.941	(?)
Gradient Boosting (R/XGBoost)	85.8	0.942	$\sim$ 14 min
Gradient Boosting (R/gbm) (re-tuned)	89.7	0.927	$\sim$ 36 min
Random Forest (R/ranger)	90.0	0.928	$\sim$ 11 min
Random Forest (R/randomForest)	91.9	0.924	$\sim$ 33 min
Gradient Boosting (R/gbm) (LR low)	101.8	0.927	$\sim$ 8 min
Random Forest (Python/sklearn)	111.2	0.894	$\sim$ 20 min
Gradient Boosting (Python/XGBoost)	155.3	0.865	(no tuning)

Notes:

- All models used 40 iterations of random search with 4-fold CV for tuning (except ***Gradient Boosting (Python/XGBoost)***, where no parameter tuning was performed)
- R models **were refitted** on complete training data with parameters from tuning and scored on the same test data set, except ***Gradient Boosting (R/gbm) (re-tuned)***
- Python models **used best model** from tuning and were refitted on the same data set
- R and Python train/test splits were not identical (different test sets for R and Python)

Python Modeling Discussion

Using `patsy` design matrices for formula interface:

```
## formula as text for patsy: without interactions
formula_txt = target + ' ~ ' + \
    ' + '.join(features) + ' - 1'
formula_txt
```

```
"Q('trip_cnt') ~ Q('Month') + Q('Temp (°C)') + Q('Rel Hum (%)') + Q('Wind Dir (10s deg)') +
 Q('Wind Spd (km/h)') + Q('Stn Press (kPa)') + Q('hr_of_day') + Q('day_of_week') - 1"
```

```
## create design matrices using patsy (could directly be used for modeling):
dat_y, dat_x = patsy.dmatrices(formula_txt, dat_hr_all,
                               NA_action = 'drop',
                               return_type = 'dataframe')
```

Python Modeling Discussion (cont'd)

Train/test split and data type issues:

```
## Split the data into training/testing sets (using patsy/dmatrices):
dat_train_x, dat_test_x, dat_train_y, dat_test_y = train_test_split(
    dat_x, dat_y, test_size = 0.1, random_state = 142)

## convert y's to Series (to match data types between patsy and non-patsy data prep:)
dat_train_y = dat_train_y[target]
dat_test_y = dat_test_y[target]
```

Python Modeling Discussion (cont'd)

```
## Instantiate random forest estimator:
mod_gb = GradientBoostingRegressor(
  n_estimators = 100, random_state = 42,
  loss = 'ls', learning_rate = 0.1,
  max_depth = 20,
  min_samples_split = 70,min_samples_leaf = 30
)
# specify parameters and distributions to sample from:
param_distributions = {
    "n_estimators" : stats.randint(50, 201),
    "learning_rate" : [0.2, 0.1, 0.05],
    "max_depth" : stats.randint(4, 21),
    "min_samples_leaf" : stats.randint(30, 61)
}
mod_randsearch = RandomizedSearchCV(
    estimator = mod_gb,
    param_distributions = param_distributions,
    n_iter = 40,
    scoring = "r2",
    cv = 4,
    random_state = 7, n_jobs = -1
)
mod_randsearch.fit(dat_train_x, dat_train_y)

## get best model (estimator):
mod_gb = mod_randsearch.best_estimator_
```

Links

- https://mlr.mlr-org.com/: MLR Homepage
- https://arxiv.org/abs/1609.06146: MLR tutorial
- https://www.inovex.de/blog/machine-learning-interpretability: Blog post on ML interpretability using the `mlr` package