

# Toolbox for Machine Learning in Julia



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## KEY FEATURES (under development)

### UNIFIED MODELLING INTERFACE DESIGN

access to a wide class of models, unified syntax

### MODEL TUNING, PIPELINING and COMPOSITION

model abstracted tuning & composition interface

### MODEL VALIDATION and MODEL EVALUATION

automated user workflows, benchmarking

**MLJ** leveraging Julia for fast, efficient integration

## JULIA ECOSYSTEM: STATUS QUO

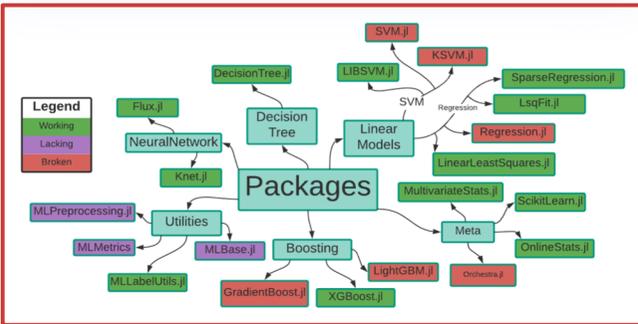


Figure: review of extant machine learning functionality and meta-functionality  
“Meta” category = existing ML toolbox meta-packages in Julia

## MACHINE LEARNING TOOLBOXES



Figure: logos of (the most?) popular open source machine learning toolboxes.  
Left-to-right: Weka, python/sklearn, R/caret, R/mlr, Shogun

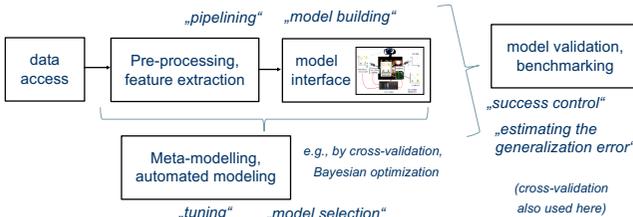
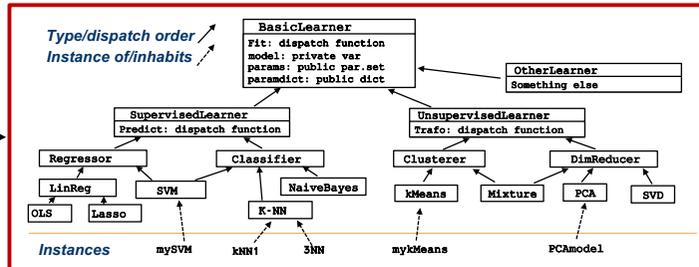
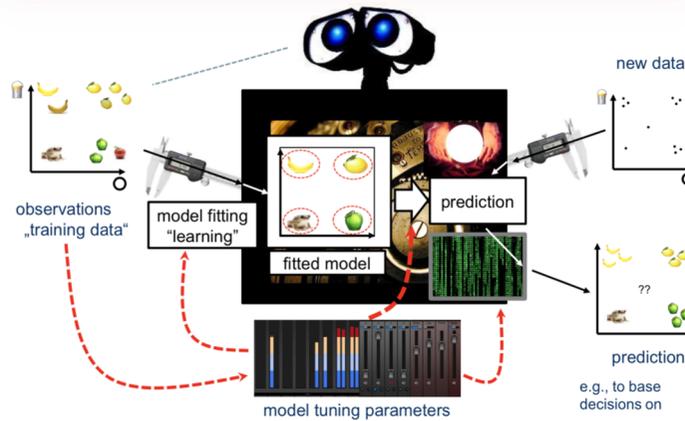


Figure: machine learning toolbox consensus workflow = abstraction layers

## INTERFACE: ABSTRACTION & DISPATCH



Top: the “learner/estimator” abstraction, for supervised learning.  
All strategies must implement fit, predict, model, parameter interfaces  
Bottom: stylized type schema, dispatch functions, and type dispatch order  
for modelling strategies implemented or interfaced by mlj

## USER INTERACTION & SYNTAX: MLR INSPIRED

```
# Simple model fitting
task = Task(task_type="Classification",
  targets=:y, data=data)
lfn = RandomForest( Dict("nsubfeatures"=>2,
  "ntrees"=>10))
lfn_res = fit(lfn, task)
predict!(lfn_res, df_new)
```

```
# Simple benchmarking - rapid trialing
lfn = [ModelLearner(:LDA),
  ModelLearner(:RandomForest)]
tasks = list(IrisTask, SonarTask)
resampling = CV(k=5)
measures = list(Acc(), MMCE())
bmr = benchmark(lfn, tasks, rdsc, measures,
  measures)
```

```
# Tuning an SVM learner over a parameter grid
ps = ParametersSet([
  ContinuousParameter(name = "cost", lower =
  -4,
  upper = 1, transform = x->10^x),
  DiscreteParameter( name = "svmtype",
  values = [SVC()]),
  DiscreteParameter(name = "kernel", values
  = [Kernel.Poly]),
  ContinuousParameter(
  name = "coef0", lower = -4, upper =
  1, transform = x->10^x)
])
svm = LibsvmModel() # we pick a learner
svm_tuned = GridTunedModel(svm, ps ,CV(k=5),
  MMCE())
listLearners(task) # all applicable
Learner
listMetrics(tasks) # all applicable
Metrics
```

## CORE API DESIGN & ABSTRACTIONS

```
immutable Task{T}
  _type::T
  targets::Symbol
  features::Array{Symbol}
  data::DataFrame
end

immutable RegressionTask end
immutable ClassificationTask end

abstract type BaseModel end
abstract type BaseModelFit{T<:BaseModel} end

# model fitting returns modelFit struct type encoding fitted
instance
struct ModelFit{T} <: BaseModelFit{T}
  model :: T
  fit_result
end
model(modelFit::ModelFit) = modelFit.model # Accessor
function, infers type
predict(modelFit::BaseModelFit, Xnew) =
  predict(model(modelFit), modelFit, Xnew)
# to add tuning to the model, this should result in a
composite that inherits
# the initial model, as well as adds a tuning method, metric
and resampling
struct TunedModel{T<:BaseModel} <: BaseModel
  model :: T
  metric
  resampling
  tuning :: BaseTuning
end

# Accessor functions (for compile-time lookup gain)
model(tunedModel::TunedModel) = tunedModel.model
tuning(tunedModel::TunedModel) = tunedModel.tuning
# skeleton of tuning
function simple_tuning(model::BaseModel,
  tuning::SimpleGridTuning, task::Task)
  tuning_result = [fit(typeof(model)(parameters), X, y) for
  parameters in tuning.grid]
end

struct TunedModelFit{T} <: BaseModelFit{T}
  model :: T
  fit_result
  tuning :: BaseTuning
  tuning_result
end
```

## NEXT STEPS: JOIN THE PROJECT!

- We are looking for collaborators @ the Alan Turing Institute!
- Finalizing API design and user interaction patterns!
  - Backend improvement! (Scheduling, Dagger, JuliaDB, Queryverse)
  - Store learner meta info in METADATA.JL fashion (ideally [open.ml](https://openml.org) compatible)
  - Feature Improvement
    - Bootstrapping from Sklearn and mlr by wrapping with task info
    - Pipelining an composition meta-interface
    - Implementation of unsupported learners, e.g., deep learning channel #mlj on [julia.lang.slack.com](https://julia.lang.slack.com)

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<https://github.com/alan-turing-institute/mlj>