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A review of machine learning commands in Stata

Performance and usability evaluation

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Machine Learning

Definition, relevance, applications

What is Machine Learning ?

Machine Learning

A relatively new approach to **data analytics**, which places itself in the intersection between **statistics**, **computer science**, and **artificial intelligence**

ML objective

Turning **information** into **knowledge** and **value** by "**letting the data speak**"

ML purposes

Limiting **prior assumptions**

Model-free philosophy

Based on **algorithm computation, graphics**

Mostly focused on **prediction** than **inference**

Targeted to **Big Data**

Targeted to **complexity reduction**

ML analyses

Prediction

Feature-importance detection

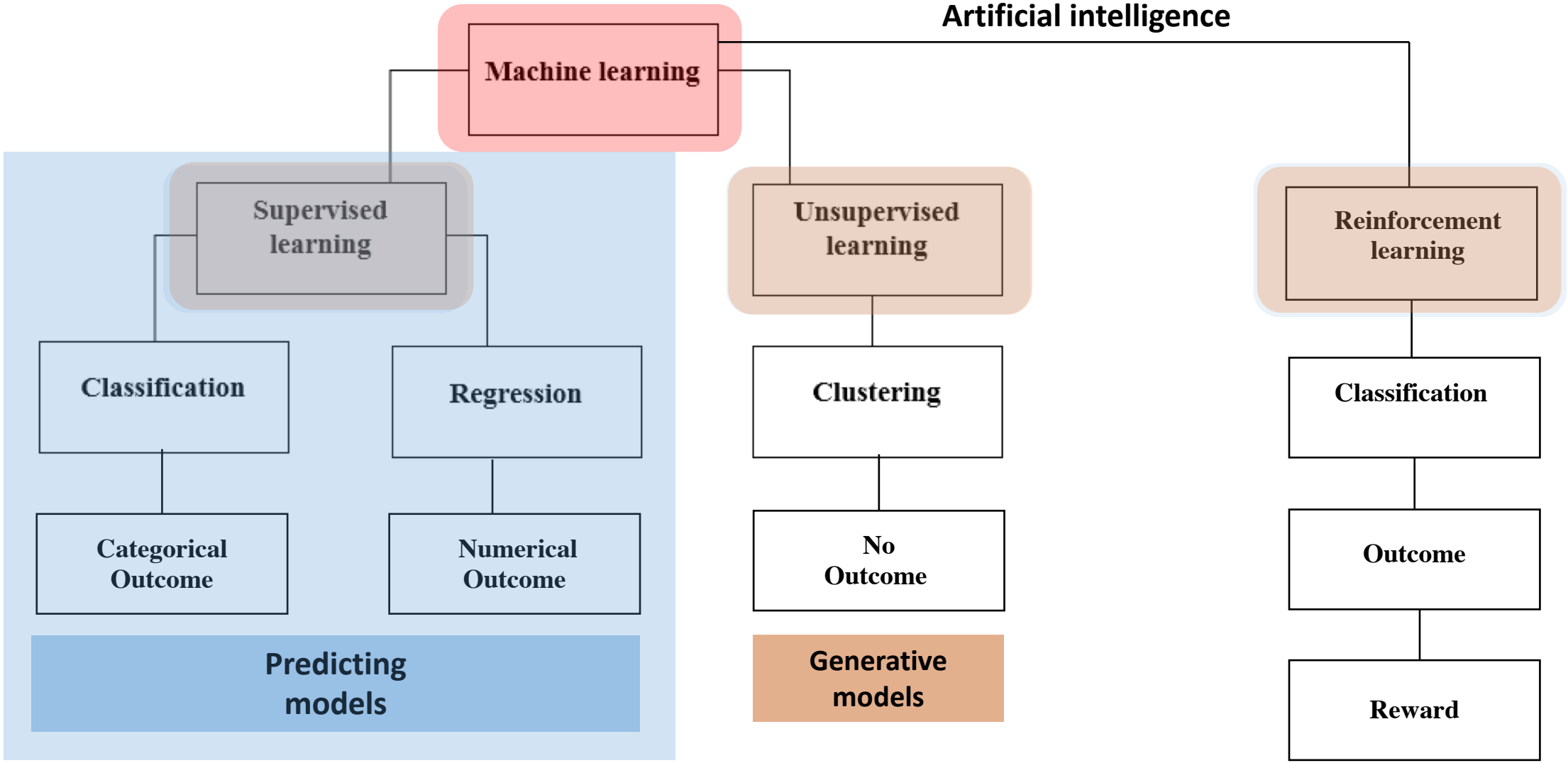
Signal-from-noise extraction

Correct specification via model selection

Model-free classification

Model-free clustering

Supervised, Unsupervised, Reinforcement Learning



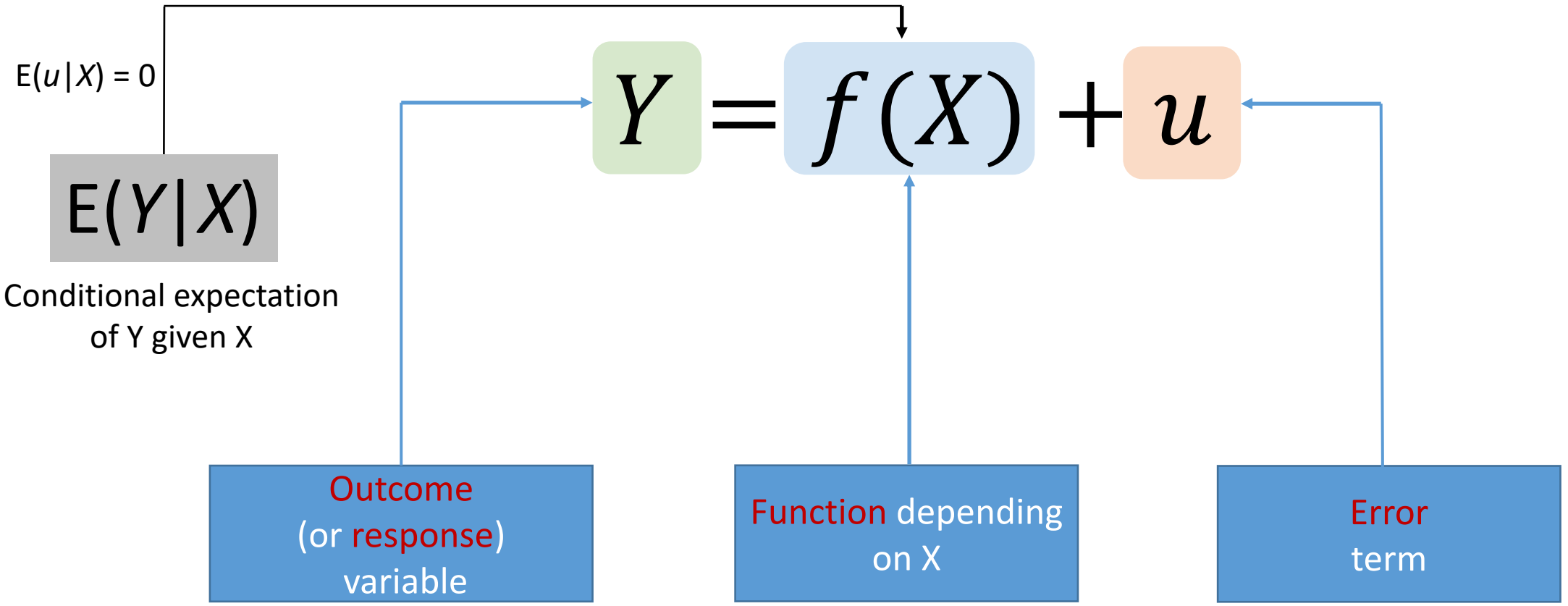
Machine Learning application examples

- Identifying risk factors for prostate cancer
- Predicting heart attack by demographic, diet and clinical measurements
- Customizing email spam detection system
- Predict stock market price variation
- Self-driving cars
- Classifying pixels in a land-satellite images
- Establishing the relationship between salary and many of its determinants
- Pattern recognition of handwritten symbols
- Automated languages translators (Google Translate)
- Vocal recognition systems (Amazon Alexa)

The basics of Machine Learning

Modelling as "learning"

More generally, suppose that we observe a quantitative response Y and p different predictors, $X_1, X_2, \ldots, X_p$. We assume that there is some relationship between Y and $X = (X_1, X_2, \ldots, X_p)$, which can be written in the very general form



Reducible and irreducible prediction errors

Consider a given estimate $\hat{f}$ and a set of predictors X, which yields the prediction $\hat{Y} = \hat{f}(X)$. Assume for a moment that both $\hat{f}$ and X are fixed. Then, it is easy to show that

$$
\begin{aligned}
E(Y - \hat{Y})^2 &= E[f(X) + \epsilon - \hat{f}(X)]^2 \\
&= \underbrace{[f(X) - \hat{f}(X)]^2}_{\text{Reducible}} + \underbrace{\text{Var}(\epsilon)}_{\text{Irreducible}} ,
\end{aligned}
$$

where $E(Y - \hat{Y})^2$ represents the average, or *expected value*, of the squared difference between the predicted and actual value of Y, and $\text{Var}(\epsilon)$ represents the *variance* associated with the error term ϵ.

Machine Learning

Techniques for estimating f with the aim of **minimizing** the **reducible error**

$f(X) = E(Y|X)$

The ML jargon

STATISTICS	MACHINE LEARNING
Statistical model	*Learner*
Estimation sample	*Training dataset*
Out-of-sample observations	*Test dataset*
Estimation method	*Algorithm*
Observation	*Instance*
Predictor	*Feature*
Dependent variable	*Target*

Assessing model predictive accuracy

Evaluating the **performance** of a **statistical learning method** on a given dataset

Quantifying whether the **predicted response** value for a given observation is close to the **true response** value for that observation

Commonly-used measure is the **Mean Squared Error** (**MSE**), given by:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{f}(x_i))^2,$$

Training error vs. Test error

- The *test error* is the average error that results from using a statistical learning method to predict the response on a new observation, one that was not used in training the method.

- In contrast, the *training error* can be easily calculated by applying the statistical learning method to the observations used in its training.

- But the training error rate often is quite different from the test error rate, and in particular the former can *dramatically underestimate* the latter.

Train-MSE vs Test-MSE

Training dataset

N **in-sample** available observations

$$\mathsf{Tr} = \{x_i, y_i\}_1^N$$

$$\mathrm{MSE}_{\mathsf{Tr}} = \mathrm{Ave}_{i \in \mathsf{Tr}}[y_i - \hat{f}(x_i)]^2$$

Overfitting as flexibility increases

Testing dataset

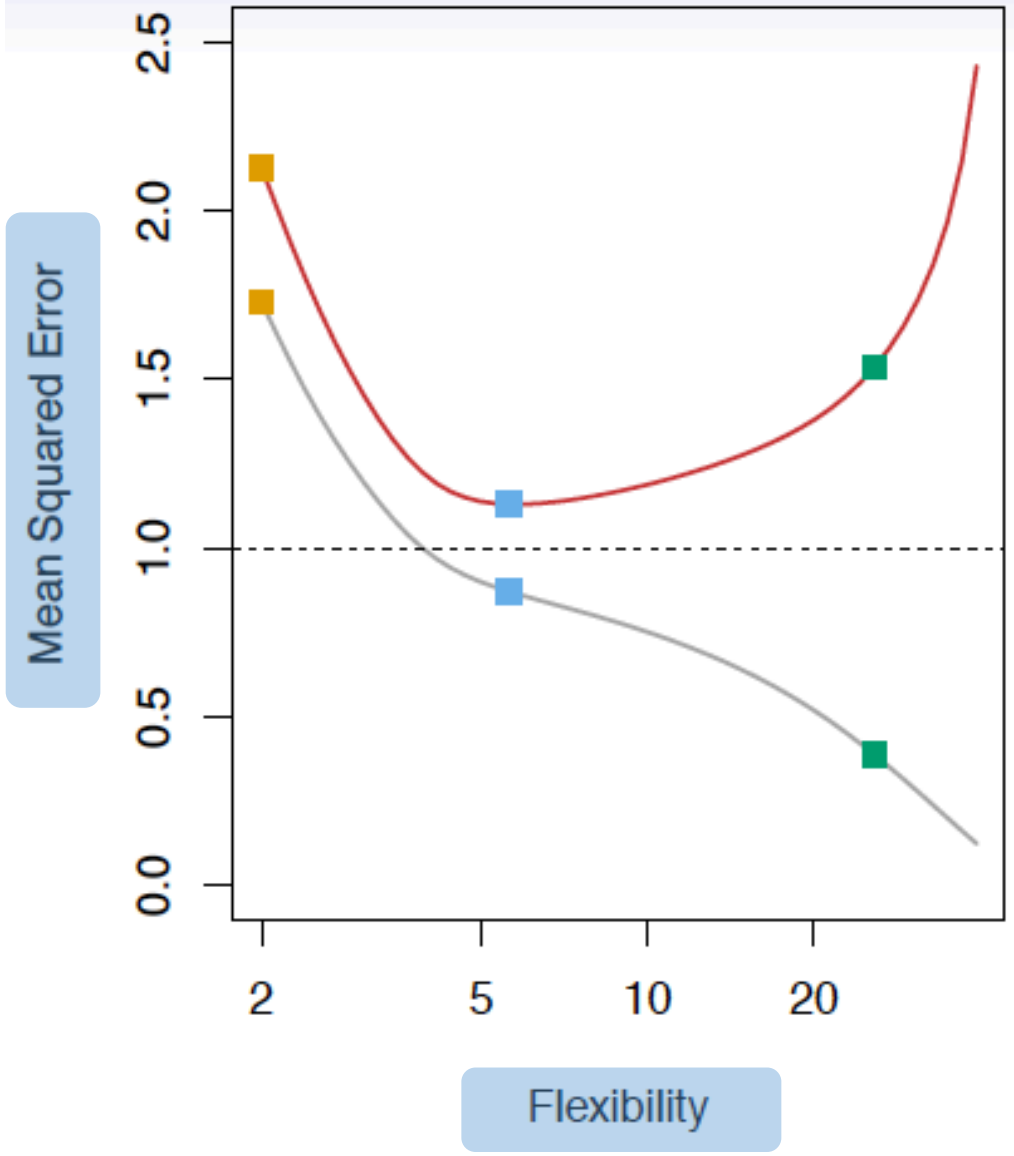
M **out-of-sample** observations

$$\mathsf{Te} = \{x_i, y_i\}_1^M$$

$$\mathrm{MSE}_{\mathsf{Te}} = \mathrm{Ave}_{i \in \mathsf{Te}}[y_i - \hat{f}(x_i)]^2$$

True fitting accuracy

Train-MSE overfitting



Test-MSE

Train-MSE

- As long as model **flexibility** (i.e., degree-of-freedom) increases, the **train-MSE decreases** monotonically.
  - This phenomenon is called **overfitting**
- On the contrary, the **test-MSE** first decreases, and then increases, thus showing a **minimum**

Decomposition of the Test-MSE

Suppose we have fit a model $\hat{f}(x)$ to some training data Tr, and let (x_0, y_0) be a test observation drawn from the population. If the true model is $Y = f(X) + \epsilon$ (with $f(x) = E(Y|X = x)$), then

$$E\left(y_0 - \hat{f}(x_0)\right)^2 = \mathrm{Var}(\hat{f}(x_0)) + [\mathrm{Bias}(\hat{f}(x_0))]^2 + \mathrm{Var}(\epsilon)$$

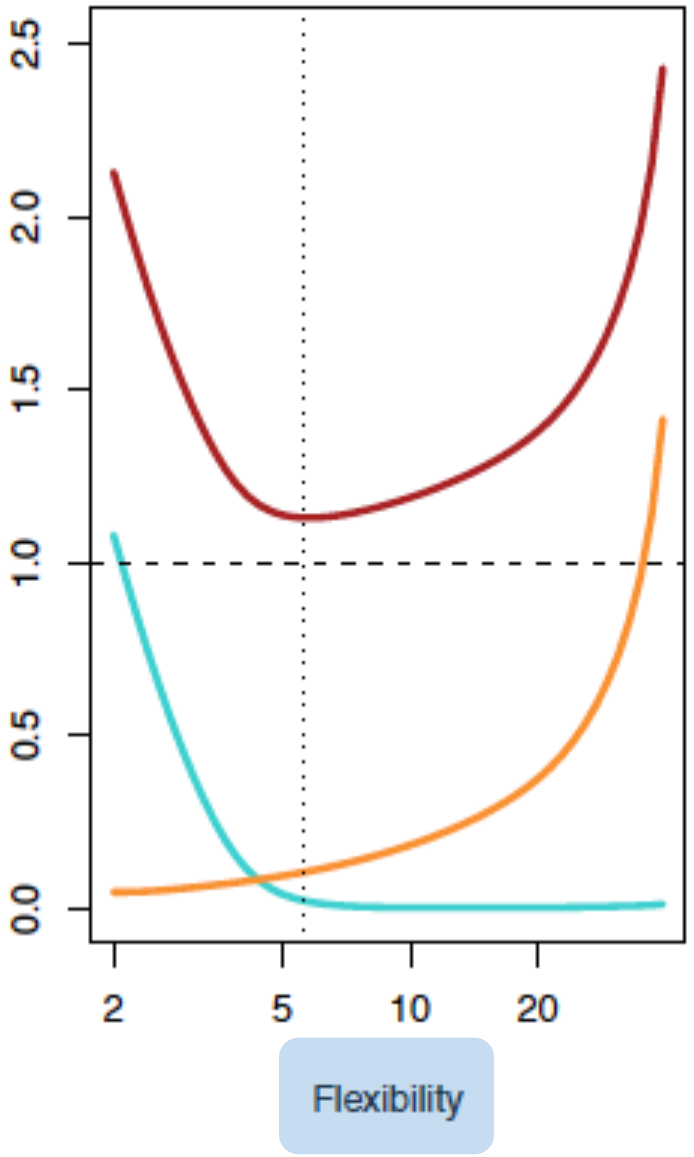
Test-MSE

Variance of the specific ML method

Bias square of the specific ML method

Variance of the Irreducible error term

The variance-bias trade-off



Typically as the *flexibility* of $\hat{f}$ increases, its variance increases, and its bias decreases. So choosing the flexibility based on average test error amounts to a *bias-variance trade-off.*

MSE
Bias
Var
------ Error variance

Observe that the error variance represents a **lower bound** for the **Test-MSE**

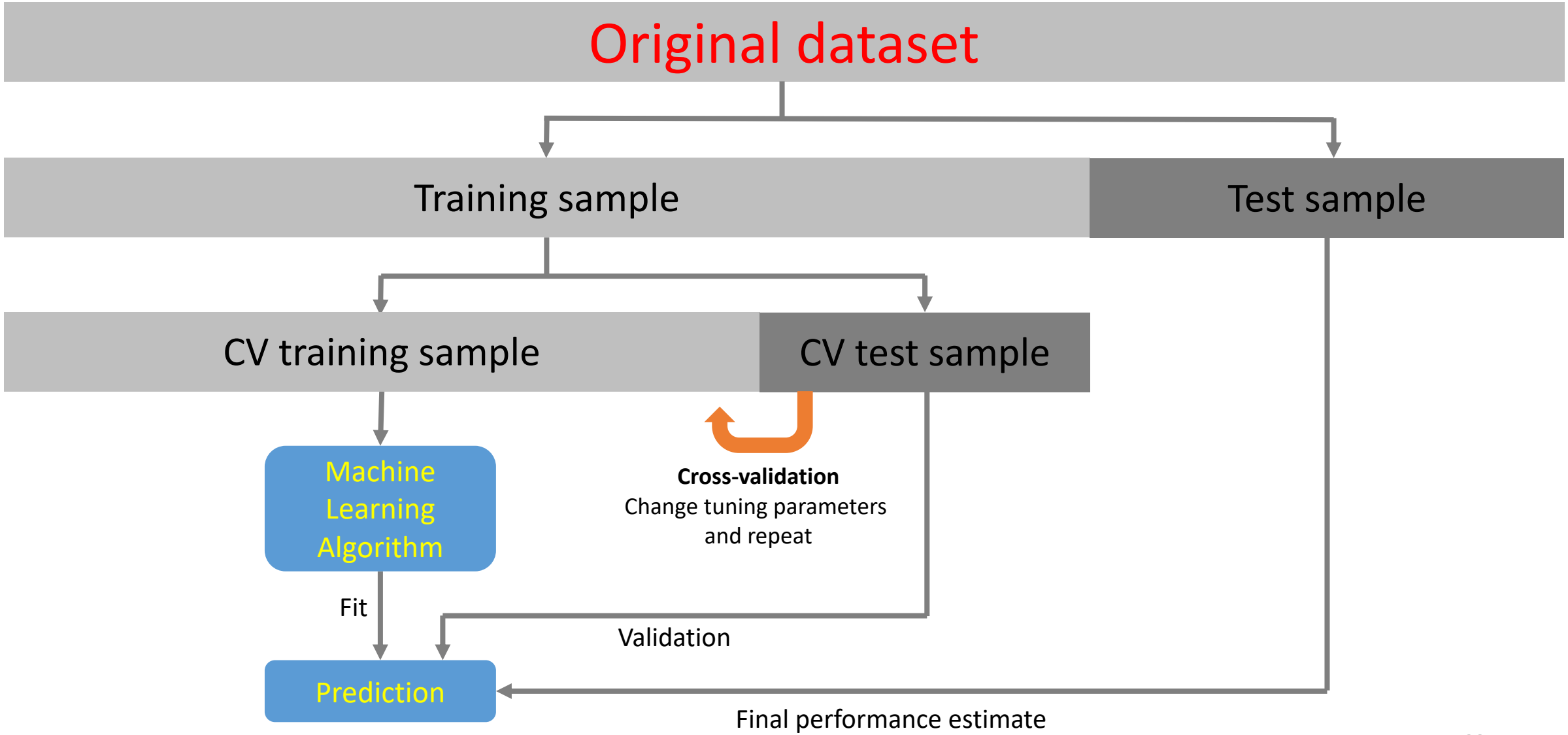
What is optimal tuning?

Any learner is characterized by one or more **hyper-parameters** λ controlling for model **flexibility** :

$$Y = f(X, \lambda)$$

Optimal tuning means to find the λ^* that **minimizes the test error** among all possible λ

Model optimal tuning for prediction



Tuning parameters of ML methods

ML method	Tuning parameter 1	Tuning parameter 2	Tuning parameter 3
Linear Models and GLS	*N. of covariates*		
Lasso	*Penalization coefficient*		
Elastic-Net	*Penalization coefficient*	*Elastic parameter*	
Nearest-Neighbor	*N. of neighbors*		
Neural Network	*N. of hidden layers*	*N. of neurons*	
Trees	*N. of leaves (or tree-depth)*		
Boosting	*Learning parameter*	*N. of sequential trees*	*Tree-depth*
Random Forest	*N. of features for splitting*	*N. of bootstrapped trees*	*Tree-depth*
Bagging	*Tree-depth*	*N. of bootstrapped trees*	
Support Vector Machine	*C*	*Gamma*	
Kernel regression	*Bandwidth*	*Kernel type*	
Piecewise regression	*N. of knots*		
Series regression	*N. of series terms*		

Software

Software

General purpose ML platform

Deep Learning platform

Deep Learning platform

scikit learn

TensorFlow

Keras

Software

Python/Stata fully integrated platform via the SFI environment

Various ML packages but poor deep learning libraries (CARET library)

Statistics and Machine Learning Toolbox
Deep Learning Toolbox

Supervised Machine learning in Stata

First-generation stand-alone commands

- `rforest`
- `boost` (only for Windows)
- `svm`
- `sctree, srtree`
- `subset`
- `mlp2`

Regularized regression/classification in Stata

- Stata Corp LASSO package
- LASSOPACK

Second-generation general purpose ML commands (based on *Python's Scikit-learn*)

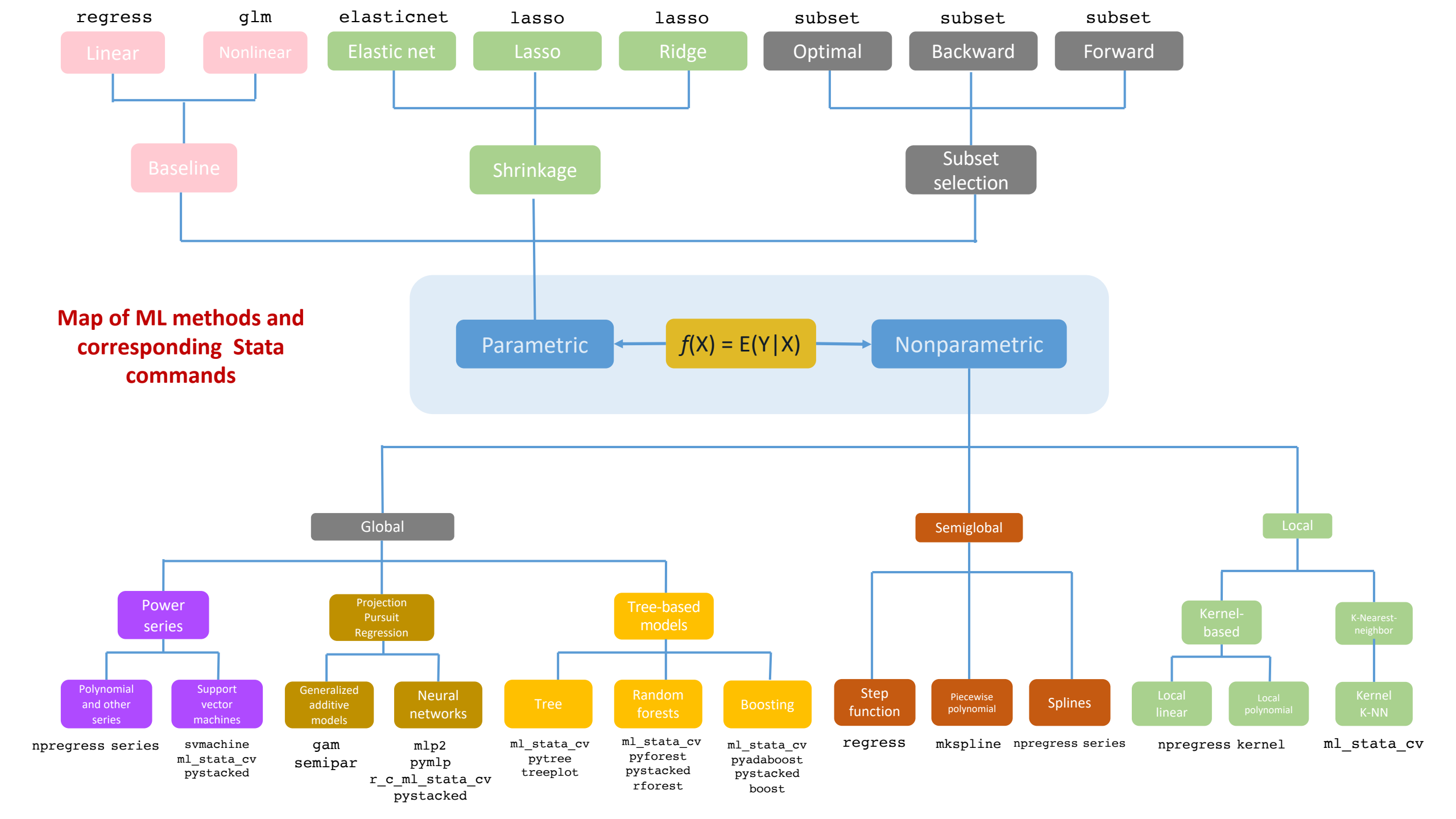
- `pylearn`
- `pystacked`
- `r_ml_stata_cv` and `c_ml_stata_cv`

ML for causal inference

- Lasso-based causal inference
- General ML causal inference (double-debiased ML)

ML hyperparameters' tuning

- `gridsearch`
- `r_ml_stata_cv` and `c_ml_stata_cv`


regress
glm
elasticnet
lasso
lasso
subset
subset
subset
Linear
Nonlinear
Elastic net
Lasso
Ridge
Optimal
Backward
Forward
Baseline
Shrinkage
Subset selection
Map of ML methods and corresponding Stata commands
Parametric
f(X) = E(Y|X)
Nonparametric
Global
Semiglobal
Local
Power series
Projection Pursuit Regression
Tree-based models
Kernel-based
K-Nearest-neighbor
Polynomial and other series
Support vector machines
Generalized additive models
Neural networks
Tree
Random forests
Boosting
Step function
Piecewise polynomial
Splines
Local linear
Local polynomial
Kernel K-NN
npregress series
svmachine
ml_stata_cv
pystacked
gam
semipar
mlp2
pymlp
r_c_ml_stata_cv
pystacked
ml_stata_cv
pytree
treeplot
ml_stata_cv
pyforest
pystacked
rforest
ml_stata_cv
pyadaboost
pystacked
boost
regress
mkspline
npregress series
npregress kernel
ml_stata_cv

First-generation stand-alone commands

- `rforest`
- `svm`
- `boost` (only for Windows)
- `sctree`, `srtree`
- `subset`
- `mlp2`

rforest (Schonlau and Zou, 2020)

The syntax to fit a random forest model is

```
rforest depvar indepvars [if] [in] [, type(string) iterations(int)
    numvars(int) depth(int) lsize(int) variance(real) seed(int)
    numdecimalplaces(int)]
```

with the following postestimation command:

```
predict newvar|varlist|stub* [if] [in] [, pr]
```

`type(str)`
The type of decision tree. Must be one of "`class`" (classification) or "`reg`" (regression).

`iterations(int)`
Set the number of iterations (trees), default to 100 if not specified.

`numvars(int)`
Set the number of variables to randomly investigate, default to sqrt(number of indepvars).

`depth(int)`
Set the maximum depth of the random forest, default to 0 for unlimited, if not specified.

The software development in Stata was built on top of the Weka Java implementation, which was developed by the University of Waikato.

svmachines (Schonlau and Guenther, 2016)

The full syntax of the command to fit a SVM model is as follows:

```
svmachines depvar indepvars [if] [in] [, type(type) kernel(kernel) c(#)
    epsilon(#) nu(#) gamma(#) coef0(#) degree(#) shrinking probability
    sv(newvar) tolerance(#) verbose cache_size(#)]
```

The most interesting thing a fitted machine-learning model can do is predict response values. To that end, the standard `predict` command may be used during postestimation as follows:

```
predict newvar [if] [in] [, probability scores verbose]
```

This command is a wrapper for Python's `libsvm`

boost (Schonlau, 2005)

boost *varlist* [*if*] [*in*], distribution(*string*) maxiter(#) [influence predict(*varname*) shrink(#) bag(#) trainfraction(#) interaction(#) seed(#)]

boost is implemented as a Windows C++ plugin.

sctree and srtree (Cerulli, 2019)

sctree— Implementing classification trees via optimal pruning, bagging, random forests, and boosting methods

Syntax

sctree *outcome* [*varlist*] [*if*] [*in*] **model(***modeltype***) rversion(***R_version***)** [**prune(***integer***) cv_tree prediction(***new_data_filename***)**
in_samp_data(*filename***) out_samp_data(***filename***) ntree(***integer***) mtry(***integer***) inter_depth(***integer***) shrinkage(***number***)**
pdp(*string***) seed(***integer***)**]

Description

sctree is a Stata wrapper for the R functions "tree()", "randomForest()", and "gbm()". It allows to implement the following classification tree models: (1) classification tree with optimal pruning, (2) bagging, (3) random forests, and (4) boosting.

Based on R

modeltype_options	Description
Model	
tree	Simple classification tree model
randomforests	bagging and random forest models
boosting1	Boosting model with a binary outcome (i.e, y=0,1)
boosting2	Boosting model with a multinomial outcome (e.g., y=A,B,C)

subset (Cerulli, 2019)

subset— Implementing covariates best and stepwise subset selection

Syntax

subset *outcome* [*varlist*] [*if*] [*in*], **model(***modeltype***) rversion(***R_version***)** [**nvmax(***number***) index_values(***filename***)**
matrix_results(*filename***) optimal_vars(***filename***)**]

Description

subset is a Stata wrapper for the R function "regsubsets()", providing "best", "backward", and "forward" stepwise subset covariates selection, a Machine Learning approach to select the optimal number of features (covariates) in a supervised linear learning approach (i.e. a linear regression model) with many covariates. The "forward" model can be also used when *p* (the number of covariates) is larger than *N* (the sample size). This method provides both the optimal subset of covariates for each specific size of the model (i.e., size=1 covariates, size=2 covariates, etc.), and the overall optimal size. The latter one is found using three criteria as validation approaches: Adjusted R2, CP, and BIC.

Based on R

modeltype_options	Description
Model	
best_subset	Best subset selection
backward	Backward stepwise selection
forward	Forward stepwise selection

mlp2 (Balov, 2018)

2-layer neural network algorithm

Programmed in Mata

mlp2 —— Multilayer perceptron with 2 hidden layers

mlp2 fit *depvar indepvars* [*if*] [*in*] [, *fit_options*]

depvar is a categorical or continuous variable. The list *indepvars* cannot be empty.

options	Description
layer1(#)	numbers of neurons in the 1-st hidden layer; default is the number of levels of *depvar*
layer2(#)	numbers of neurons in the 2-nd hidden layer; default is **level1**
nobias	no bias terms are used
optimizer(*string***)**	optimizer; default is **optimizer(gd)**
loss(*string***)**	loss function; default depends on *depvar*
initvar(#)	initializing variance factor; default is **initvar(1)**
restarts(#)	maximum number of restarts; default is **restarts(10)**
lrate(#)	learning rate of the optimizer; default is **lrate(0.1)**
friction(#)	target friction for momentum optimizers; default is **friction(0.9)**
fricrate(#)	friction rate for momentum optimizers; default is **fricrate(0.5)**
epsilon(#)	gradient smoothing term; default is **epsilon(1e-8)**
decay(#)	decay parameter of RMSProp optimizer; default is **decay(0.9)**
losstol(#)	stopping loss tolerance; default is **losstol(1e-4)**
drop1out1(#)	1st hidden layer dropout probability; default is **dropout1(0)**
drop1out2(#)	2nd hidden layer dropout probability; default is **dropout2(0)**
batch(#)	training batch size; default is **batch(50)** or entire sample
epochs(#)	maximum number of iterations; default is **epochs(100)**
echo(#)	report loss values at every # number of iterations; defailt is **echo(0)**

Account

PROS

- All these commands are valuable commands for implementing in Stata specific ML methods
- **`rforest`** and **`boost`** allow also for *factor importance*
- **`sctree`** and **`srtree`** produce a tree plot (also with optimal pruning)
- **`mlp2`** is the directly programmed in Mata

CONS

- Mainly wrappers for R, Java, C++, and Python (not SFI)
- All these commands are not very well suited for the optimal tuning of the hyper-parameters
- For optimal tuning, **`rforest`** and **`boost`** can use **`gridsearch`** which has however limitations
- **`Boost`** runs only under Windows
- **`Subset`** only consider linear models (no GLM implemented)
- **`mlp2`** considers only 2 layers and is not suited for the optimal tuning of the hyper-parameters

Regularized regression/classification in Stata

- LASSOPACK
- Stata Corp LASSO package

Stata implementation via LASSOPACK (Ahrens, Hansen, and Schaffer, 2020)

`LASSOPACK` includes three commands: `lasso2` implements LASSO and related estimators. `cvlasso` supports cross-validation, and `rlasso` offers the 'rigorous' (theory-driven) approach to penalization.

Basic syntax

`lasso2` *depvar indepvars* [*if*] [*in*] [, ...]

`cvlasso` *depvar indepvars* [*if*] [*in*] [, ...]

`rlasso` *depvar indepvars* [*if*] [*in*] [, ...]

Stata 18 built-in commands `lasso/elasticnet`

Basic regularized regression commands			
Model	Lasso	Elasticnet	Square-root Lasso
Linear	`lasso linear`	`elasticnet linear`	`sqrtlasso`
Probit	`lasso probit`	`elasticnet probit`	
Logit	`lasso logit`	`elasticnet logit`	
Poisson	`lasso poisson`	`elasticnet poisson`	

Lasso for Cox proportional hazards models

`lasso cox` and **`elasticnet cox`** expand the existing LASSO suite for prediction and model selection to include a high-dimensional semiparametric Cox proportional hazards model.

Stata 18 built-in command `lasso`

`lasso` *model depvar* [(*alwaysvars*)] *othervars* [*if*] [*in*] [*weight*] [, *options*]

model is one of `linear`, `logit`, `probit`, or `poisson`.

alwaysvars are variables that are always included in the model.

othervars are variables that `lasso` will choose to include in or exclude from the model.

Examples

```
lasso linear y1 (x1 x2) x3-x100
lasso logit y2 x1-x100 rseed(1234)
```

Lasso in Stata (post-estimation commands)

Command	Description
`bicplot`	plot Bayesian information criterion function
`coefpath`	plot path of coefficients
`cvplot`	plot cross-validation function
`lassocoef`	display selected coefficients
`lassogof`	goodness of fit after lasso for prediction
`lassoinfo`	information about lasso estimation results
`lassoknots`	knot table of coefficient selection and measures of fit
`lassoselect`	select alternative λ^* (and α^* for `elasticnet`)

Account

PROS

- Both LASSOPACK and LASSO are flexible packages to implement regularized regression
- Both use three optimal-tuning strategies:
  - Information criteria
  - Plug-in
  - Cross-validation
- Both have useful post-estimation commands (including `predict`)
- Both have useful graphical representations of results
  - Lasso coefficient-path plot
  - Cross-validation optimal tuning plot

CONS

- Both do not estimate multinomial lasso/elasticnet
- Absent or not flexible time-series cross-validation for optimal tuning
  - LASSOPACK has time-series/panel-data cross-validation available, but it is poorly flexible and computationally *slow*

Second-generation general-purpose ML commands

- `pylearn`
- `pystacked`
- `r_ml_stata_cv` and `c_ml_stata_cv`

pylearn (Doste, 2022)

pylearn - Supervised learning algorithms in Stata based on the **Scikit-learn** library of Python.

pylearn is a set of Stata commands to perform supervised learning in Stata. These commands all exhibit a common Stata-like syntax for model estimation and post-estimation (i.e., they look very similar to regress). **pylearn** currently includes these models:

```
[R] pytree estimates decision trees.

[R] pyforest estimates random forests.

[R] pymlp estimates multi-layer perceptrons (feed-forward neural networks).

[R] pyadaboost estimates adaptive boosted trees/regressions (AdaBoost).

[R] pygradboost estimates gradient boosted trees.
```

pytree - example

pytree — Decision tree regression and classification with Python and scikit-learn

Syntax

pytree *depvar indepvars* [*if*] [*in*], type(string) [*options*]

options	Description
Main	
type(*string***)**	*string* may be **regress** or **classify.**
Pre-processing	
training(*varname***)**	varname is an indicator for the training sample
Decision tree options	
criterion(*string***)**	Criterion for splitting nodes (see details below)
max_depth(#)	Maximum tree depth
min_samples_split(#)	Minimum observations per node
min_weight_fraction_leaf(#)	Min fraction at leaf
max_features(*numeric***)**	Maximum number of features to consider per tree
max_leaf_nodes(#)	Maximum leaf nodes
min_impurity_decrease(#)	Propensity to split

pystacked (Ahrens,Hansen, and Schaffer, 2022)

pystacked -- Stata program for Stacking Regression

- pystacked implements stacking regression (Wolpert, 1992) via Scikit-learn's modules:
  `sklearn.ensemble.StackingRegressor`
  `sklearn.ensemble.StackingClassifier`

- Stacking is a way of combining multiple supervised machine learners (the "base" or "level-0 learners) into a meta learner.

- The currently supported base learners are: *linear regression*, *logit*, *lasso*, *ridge*, *elastic-net*, (linear) *support vector machines*, *gradient boosting*, and *neural-nets* (MLP)

- **pystacked** can also be used with a single base learner and, thus, provides an easy-to-use API for Scikit-learn's machine learning algorithms

pystacked - syntax

```
pystacked depvar predictors [if] [in] [, methods(string)
cmdopt1(string) cmdopt2(string) ... cmdopt10(string)
pipe1(string) pipe2(string) ... pipe10(string)
xvars1(predictors) xvars2(predictors) ... xvars10(predictors)
general_options ]
```

Notes:

- `methods(string)` is used to select base learners, where *string* is a list of base learners.
- Options are passed on to base learners via `cmdopt1(string)`, `cmdopt2(string)` to `cmdopt10(string)`.
- `pipe*(string)` are for pipelines; `xvars*(predictors)` allows to specify a learner-specific variable lists of predictors.
- *Limitation:* only 10 base learners supported.

pystacked - learners

method()	type()	*Machine learner description*
ols	*regress*	Linear regression
logit	*class*	Logistic regression
lassoic	*regress*	Lasso with AIC/BIC penalty
lassocv	*regress*	Lasso with CV penalty
	class	Logistic lasso with CV penalt
ridgecv	*regress*	Ridge with CV penalty
	class	Logistic ridge with CV penalty
elasticcv	*regress*	Elastic net with CV penalty
	class	Logistic elastic net with CV
svm	*regress*	Support vector regression
	class	Support vector classification
gradboost	*regress*	Gradient boosting regressor
	class	Gradient boosting classifier
rf	*regress*	Random forest regressor
	class	Random forest classifier
linsvm	*class*	Linear SVC
nnet	*regress*	Neural net
	class	Neural net

r_ml_stata_cv and c_ml_stata_cv (Cerulli, 2022)

r_ml_stata_cv and **c_ml_stata_cv** are two commands for implementing machine learning regression and classification algorithms respectively in Stata 16

- They use the Stata/Python integration (sfi) capability of Stata 16 and allows to implement the following ML algorithms:

  r_ml_stata_cv

  ordinary least squares, elastic-net, tree, boosting, random forest, neural network, nearest neighbor, support vector machine.

  c_ml_stata_cv

  tree, boosting, random forest, regularized multinomial, neural network, naive Bayes, nearest neighbor, support vector machine, standard (unregularized) multinomial.

- They provides **hyper-parameters' optimal tuning via K-fold cross-validation using greed search**

- These commands make use of the Python **Scikit-learn** API to carry out both cross-validation and prediction

r_ml_stata_cv

```
r_ml_stata_cv depvar varlist , mlmodel(modeltype) data_test(filename)
    seed(integer) [ learner_options cv_options other_options ]
```

modeltype_options	Description
Model	
ols	Ordinary least squares
elasticnet	Elastic net
tree	Tree regression
randomforest	Bagging and random forests
boost	Boosting
nearestneighbor	Nearest neighbor
neuralnet	Neural network
svm	Support vector machine

Regression

c_ml_stata_cv

```
c_ml_stata_cv depvar varlist , mlmodel(modeltype) data_test(filename)
    seed(integer) [ learner_options cv_options other_options ]
```

modeltype_options	Description
Model	
tree	Classification tree
randomforest	Bagging and random forests
boost	Boosting
regmult	Regularized multinomial
nearestneighbor	Nearest Neighbor
neuralnet	Neural network
naivebayes	Naive Bayes
svm	Support vector machine
multinomial	Standard multinomial

Classification

Account

PROS

- All three commands are valuable and flexible commands for implementing in Stata many ML methods
- **`pylearn`** is very flexible, as it is a perfect duplication in Stata of the Scikit-learn API of Python
- **`pystacked`** is also very flexible as pretty all the Scikit-learn's modules options are implemented. Also, it allows for stacking regression and classification
- **`r_ml_stata_cv`** and **`c_ml_stata_cv`** allow for a larger set of learners to implement (for example, the *nearest-neighbor* and the *regularized multinomial*!). Also, they allow for *grid-search* for optimal tuning using *cross-validation* using **`sklearn.model_selection.GridSearchCV`**. This is not carried out by neither **`pylearn`**, nor **`pystacked`**

CONS

- **`pylearn`** implements only a few learners and does not provide for grid-search for optimal tuning using cross-validation
- **`pystacked`** does not provide for grid-search for optimal tuning using cross-validation and does not provide stacking for classification when the outcome is multinomial
- **`r_ml_stata_cv`** and **`c_ml_stata_cv`** are a little less flexible - as only the most important options (main hyperparameters) of the Scikit-learn's modules are implemented. Also, it does not have a **`predict`** post-estimation command (as predictions are automatically generated)

ML and Causal Inference with Stata

Introduction

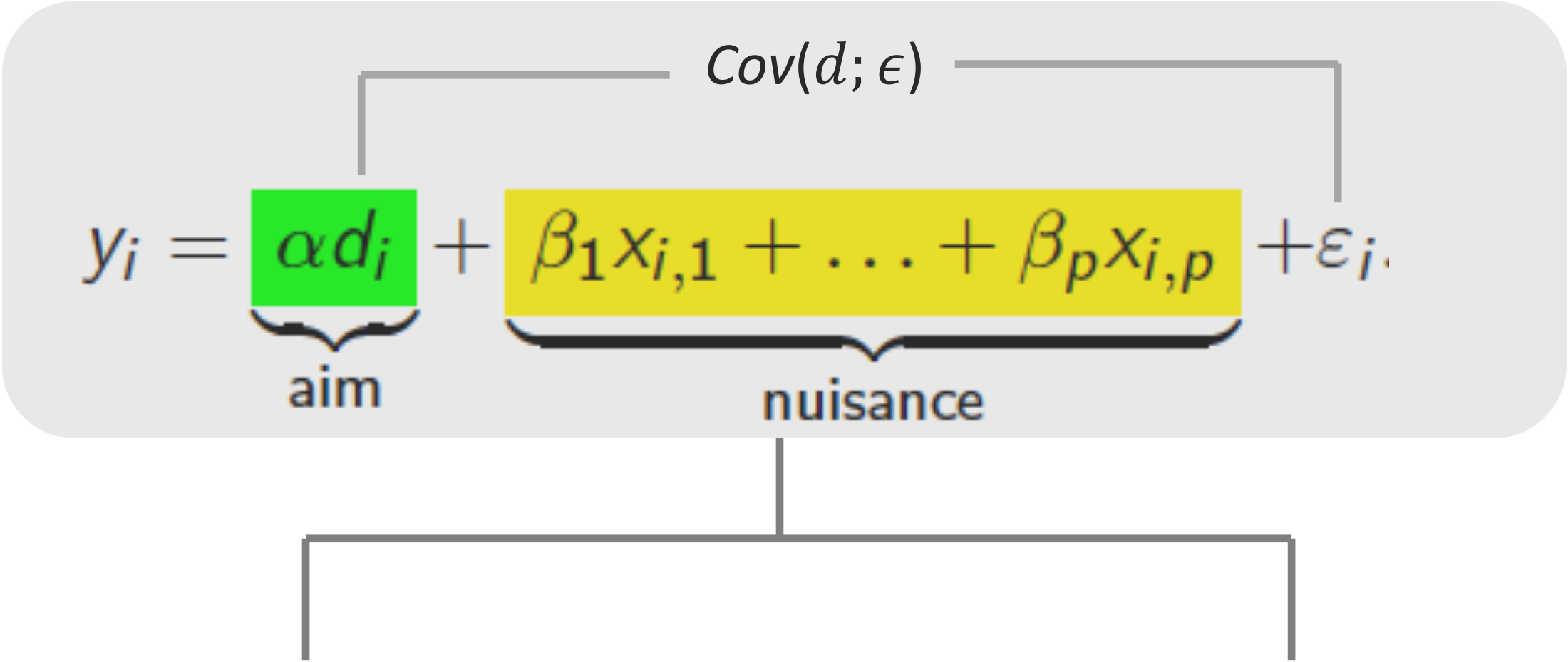
- Growing literature exploits machine learning (ML) to improve causal inference (CI)
- In applications, we may have high-dimensional controls and/or instruments
- Also, controls and/or instruments can enter through an unknown functions
- Two approaches for integrating ML and CI:

    1. **Lasso-based** approach
       (Belloni, Chernozhukov, and Hansen, 2014; Belloni et al., 2012)

    2. **Double-debiased ML** (**DDML**)
       (Chernozhukov et al., 2018; Chernozhukov et al., 2021).

Lasso causal inference with Stata

Lasso HD for treatment effects



LASSO for TE: **exogeneity** case [$Cov(d; \epsilon) = 0$]

Our model is

$$y_i = \underbrace{\alpha d_i}_{\text{aim}} + \underbrace{\beta_1 x_{i,1} + \ldots + \beta_p x_{i,p}}_{\text{nuisance}} + \varepsilon_i.$$

The causal variable of interest or "treatment" is d_i. The xs are the set of potential controls and not directly of interest. We want to obtain an estimate of the parameter α.

- How to infer correctly on α?
- Which controls to select?
- What if $p >> N$

Strategies to estimate α

- **Naïve approach**
- **Partialing-out**
- **Double-selection**

Lasso in Stata

Lasso commands for causal inference

Model	Partialing-out	Double-selection	Cross-fit partialing-out
Linear	`poregress`	`dsregress`	`xporegress`
Logit	`pologit`	`dslogit`	`xpologit`
Poisson	`popoisson`	`dspoisson`	`xpopoisson`
Linear IV	`poivregress`		`xpoivregress`

Stata implementation via `pdslasso`

Basic syntax

`pdslasso` *depvar d_varlist (hd_controls_varlist)* [*if*] [*in*] [, ...]

with many options and features, including:

- heteroskedastic- and cluster-robust penalty loadings.
- LASSO or Sqrt-LASSO
- support for Stata time-series and factor-variables
- pweights and aweights
- fixed effects and partialling-out unpenalized regressors

IMPORTANT: `pdslasso` provides 3 estimates of the effect:

Partialling-out (PO) approach:

- OLS using CHS lasso-orthogonalized vars
- OLS using CHS post-lasso-orthogonalized vars

Double-selection (DS) approach:

- OLS with PDS-selected variables and full regressor set

Stata implementation via `ivlasso`

Basic syntax

`ivlasso` *depvar d_varlist (hd_controls_varlist) (endog_d_varlist = high_dimensional_IVs) [if] [in] [, ...]*

IMPORTANT: `ivlasso` provides 3 estimates of the effect:

Partialling-out (PO) approach:
- *IV using CHS lasso-orthogonalized vars*
- *IV using CHS post-lasso-orthogonalized vars*

Double-selection (DS) approach:
- *IV with PDS-selected variables and full regressor set*

IMPORTANT: Compared to the Stata built-in `poivregress`, the user-written command `ivlasso` performs two additional effect estimates:
- *IV using CHS lasso-orthogonalized vars*
- *IV with PDS-selected variables and full regressor set*

The IV procedure used is however the same, that is: **Lasso IV-2**. The difference is in the last step, where `ivlasso` uses the DS approach or the PO with lasso coefficients as alternatives.

In sum, `poivregress` uses the `ivlasso` PO type:
- *IV using CHS post-lasso-orthogonalized vars*

Double-debiased ML

Why relaying on DDML?

- The **Lasso** learner might not be the best-performing machine learner in specific settings (parametric model)
- The Lasso relies on the **approximate sparsity** assumption, which might not be appropriate in some settings
- **Double-Debiased Machine Learning (DDML)** allows to exploit various machine learners other than the Lasso. So, it is a more general approach for integrating ML and CI

Three sources of bias when estimating ATEs by ML

1. Bias due to absence of orthogonalization

   Easily solved using the Frisch-Waugh-Lovell orthogonalization
   (equivalent to the Robinson's partially linear model)

2. Bias due to learner's low rate of convergence

   Fortunately, most ML methods have sufficiently fast rate of convergence,
   including neural nets, random forests, lasso and boosting

3. Bias due to learner's over-fitting

   Easily solved by cross-fitting estimation

Treatment models to estimate

A. Model with **homogenous** treatment effect (ATE = ATET = ATENT)

$$y = \theta \cdot d + g(\mathbf{x}) + \epsilon$$

`[partial]`

Model 1: $(d \perp \varepsilon)|\,\mathbf{x}$

`[interactive]`

Model 3: $(d\ correlated\ to\ \varepsilon)|\,\mathbf{x}$

B. Model with **heterogenous** treatment effect (ATE ≠ ATET ≠ ATENT)

$$y = g(d, \mathbf{x}) + \epsilon$$

`[iv]`

Model 2: $(d \perp \varepsilon)|\,\mathbf{x}$

`[interactiveiv]`

Model 4: $(d\ correlated\ to\ \varepsilon)|\,\mathbf{x}$

The **ddml** command

ddml -- *Stata package for Double Debiased Machine Learning*

ddml implements algorithms for causal inference aided by supervised machine learning as proposed in **Double/debiased machine learning** for treatment and structural parameters (Econometrics Journal, 2018).

Five different models are supported, allowing for binary or continuous treatment variables and endogeneity, high-dimensional controls and/or instrumental variables. **ddml** supports a variety of different ML programs, including but not limited to **lassopack** and **pystacked**.

ddml - syntax

Estimation with **ddml** proceeds in four steps.

Step 1. Initialize **ddml** and select model:

ddml init *model* [if] [in] [, **mname(***name***) kfolds(***integer***) fcluster(***varname***) foldvar(***varlist***) reps(***integer***) norandom tabfold vars(***varlist***)**]

where *model* is either *partial*, *iv*, *interactive*, *fiv*, *interactiveiv*; see **model descriptions**.

Step 2. Add supervised ML programs for estimating conditional expectations:

ddml *eq* [, **mname(***name***) vname(***varname***) learner(***varname***) vtype(***string***) predopt(***string***)**] : *command depvar vars* [, *cmdopt*]

where, depending on model chosen in Step 1, *eq* is either *E[Y|X] E[Y|D,X] E[Y|X,Z] E[D|X] E[D|X,Z] E[Z|X]*. *command* is a supported supervised ML program (e.g. **pystacked** or **cvlasso**). See **supported programs**.

Note: Options before ":" and after the first comma refer to **ddml**. Options that come after the final comma refer to the estimation command.

Step 3. Cross-fitting:

ddml crossfit [, **mname(***name***) shortstack**]

This step implements the cross-fitting algorithm. Each learner is fitted iteratively on training folds and out-of-sample predicted values are obtained.

Step 4. Estimate causal effects:

ddml estimate [, **mname(***name***) robust cluster(***varname***) vce(***type***) atet ateu trim(***real***)**]

The **ddml estimate** command returns treatment effect estimates for all combination of learners added in Step 2.

ML hyperparameters' tuning

- `gridsearch`
- `r_ml_stata_cv` and `c_ml_stata_cv`

gridsearch (Schonlau, 2021)

gridsearch runs a user-specified statistical learning algorithm repeatedly with a **grid of values** corresponding to **one or two tuning parameters**. This facilities the tuning of statistical learning algorithms.

After evaluating all combinations of values according to criterion, **gridsearch** lists the best combination and the corresponding value of the criterion.

Only estimation commands that allow the use of **predict** after the estimation command can be used.

The program does not currently support the prediction of multiple variables as would be needed, for example, for *multinomial logistic regression*

gridsearch - syntax

gridsearch —— Optimizing tuning parameter levels with a grid search

Syntax

gridsearch command *depvar indepvars* [*if*] [*in*] , method(str1 str2) par1name(str) par1list(numlist) criterion(str) [*options*]

gridsearch discrim subcommand *indepvars* [*if*] [*in*] , method(str1 str2) par1name(str) par1list(numlist) criterion(str) group(*depvar*) [*options*]

options	Description
par1name(*string***)**	Name of the a tuning parameter of **command**
par1list(*numlist***)**	Values to explore for tuning parameter
par2name(*string***)**	Name of the an optional second tuning parameter of **command**
par2list(*numlist***)**	Values to explore for the second tuning parameter
criterion(*string***)**	Evaluation criterion
method(*str1 str2***)**	str1 specifies train-validation method; str2 specifies corresponding option.
nogrid	Explore all parameter values as a list (do not form a grid)
options	Additional options are passed to the estimation command
predoptions(*string***)**	Any prediction options are passed to the prediction command

Account

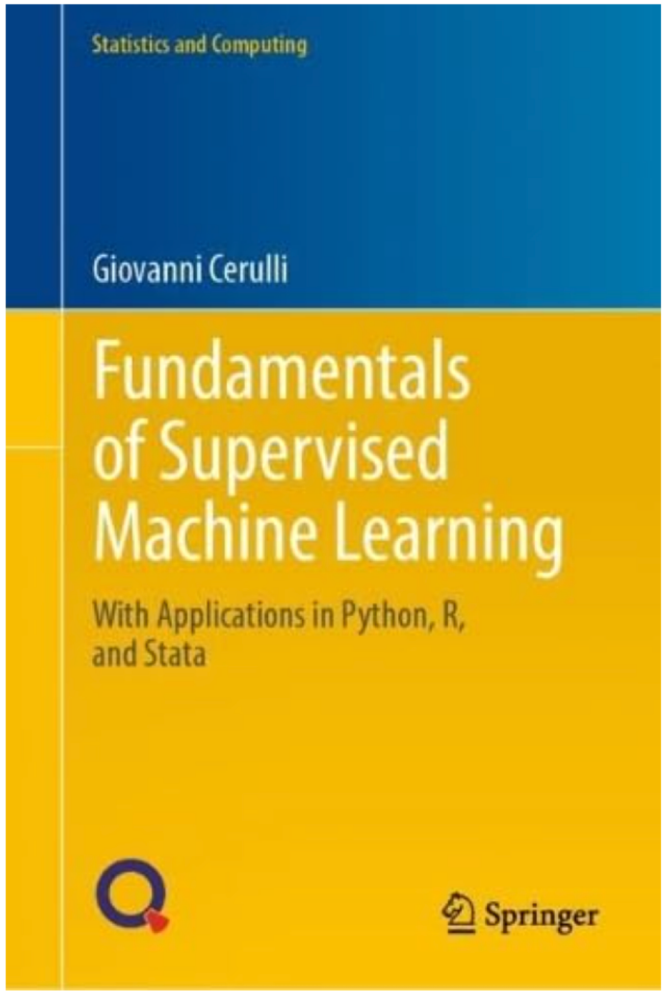
PROS

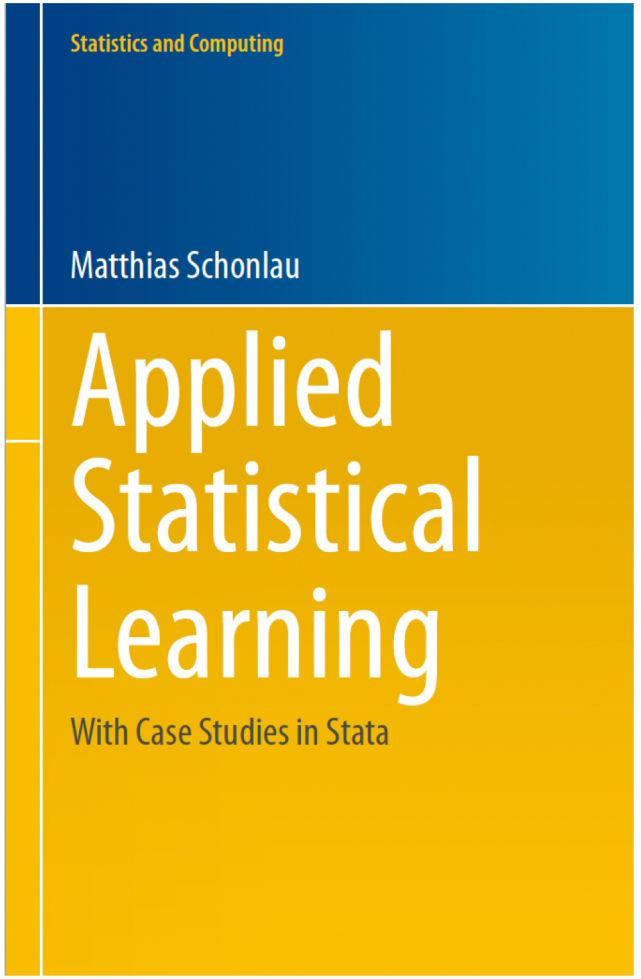
- All commands are valuable commands for hyper-parameter optimal tuning
- **`gridsearch`** allows for hyper-parameter optimal tuning using Stata native code
- **`gridsearch`** allows to use whatever learner having a **`predict`** post-estimation
- **`r_ml_stata_cv`** and **`c_ml_stata_cv`** allow for grid-search for optimal tuning using cross-validation using **`sklearn.model_selection.GridSearchCV`**. Also, they allow for optimal tuning of the *regularized multinomial*

CONS

- **`gridsearch`** allows only for the tuning of only **two hyper-parameters**.
- **`gridsearch`** is rather slow and does not allow for optimal tuning of the *regularized multinomial*
- **`r_ml_stata_cv`** and **`c_ml_stata_cv`** do not have a **`predict`** post-estimation command (as predictions are automatically generated). They allow for only a sunsert of hyper-parameters tuning (the most relevant, though!)

Books on Machine Learning using Stata





Conclusions

- Stata has many **valuable ML commands**, both native and based on other software
- The integration with **Python** is key for ML implementation
- However, there is **poor development for grid-search** for hyper-parameters optimal tuning. I would suggest the Stata Corp to develop an improvement of the **GRIDSEARCH** command using an architecture similar to the **CARET** package in R
- Stata users can provide **deep-learning** implementations by integrating into Stata the **KERAS** package of Python. Useful also for **advanced unsupervised learning**
- Stata has poor implementations of **reinforcement learning** (excluding the **OPL** command for “optimal policy learning” provided by Cerulli (2023) presented in Palo Alto at the US Stata Conference)

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