XVII Conferenza Italiana degli Utenti di Stata 19th-20th of May, 2022

Machine Learning using Stata/Python

Giovanni Cerulli



What is Machine Learning?

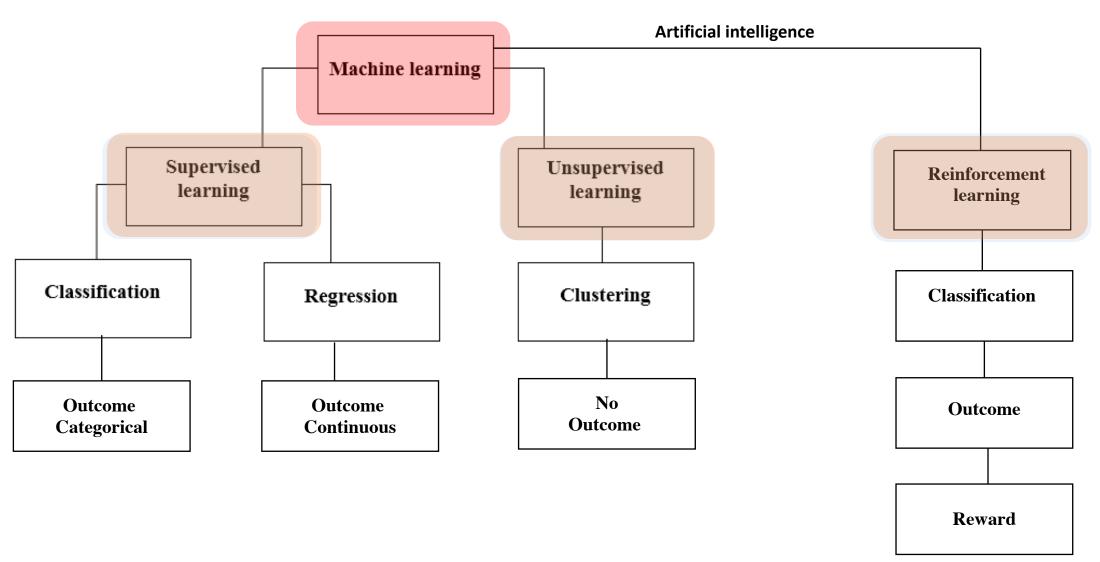
Machine Learning

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

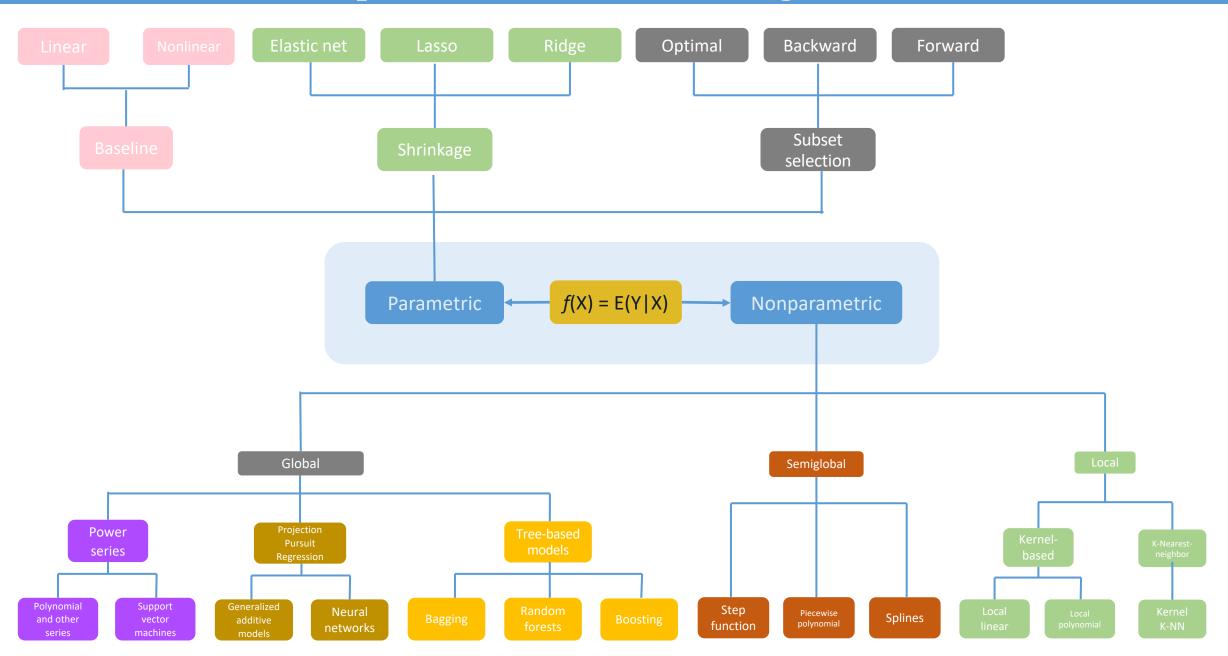
ML objective

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

Supervised, Unsupervised, Reinforcement Learning



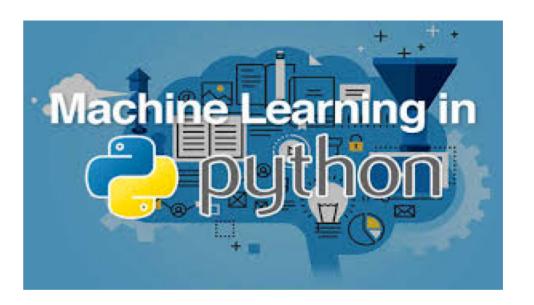
Supervised Machine Learning Methods



Hyper-parameter tuning

ML method	Parameter 1	Parameter 2	Parameter 3
Linear Models and GLM	N of covariates		
Lasso	Penalization coefficient		
$Elastic ext{-}Net$	Penalization coefficient	Elastic parameter	
$Nearest\mbox{-}Neighbor$	N of neighbors		
$Neural\ Network$	N of hidden layers	N of neurons	L2 penalization
Trees	N of leaves/depth		_
Boosting	Learning parameter	N of sequential trees	N of leaves/depth
Random Forest	N of features for splitting	N of bootstraps	N of leaves/depth
Bagging	Tree-depth	N of bootstraps	, -
Support Vector Machine	\mathbf{C}	Γ	
Kernel regression	Bandwidth	Kernel function	
Piecewise regression	N of knots		
Series regression	N of series terms		

Software for ML



Software

General purpose ML platform

Deep Learning platform

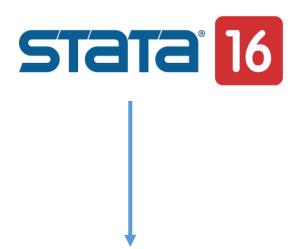
Deep Learning platform







Software







Python/Stata fully integrated platform via the SFI environment

Various ML packages but poor deep learning libraries

Statistics and Machine Learning Toolbox
Deep Learning Toolbox

Python Scikit-learn platform

c_ml_stata_cv & r_ml_stata_cv (Cerulli, 2022)

scikit-learn

Machine Learning in Python

Getting Started

Release Highlights for 0.24

GitHub

- Simple and efficient tools for predictive data analysis
- Accessible to everybody, and reusable in various contexts
- Built on NumPy, SciPy, and matplotlib
- Open source, commercially usable BSD license

Classification

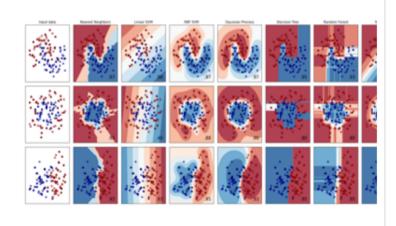
Identifying which category an object belongs to.

Applications: Spam detection, image recogni-

tion.

Algorithms: SVM, nearest neighbors, random

forest, and more...



Examples

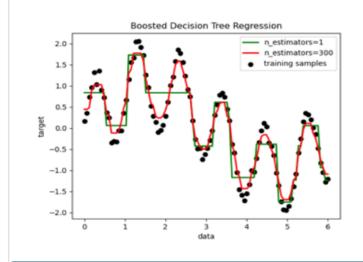
Regression

Predicting a continuous-valued attribute associated with an object.

Applications: Drug response, Stock prices.

Algorithms: SVR, nearest neighbors, random

forest, and more...



Examples

Clustering

Automatic grouping of similar objects into sets.

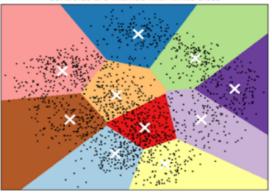
Applications: Customer segmentation, Grouping

experiment outcomes

Algorithms: k-Means, spectral clustering, mean-

shift, and more...

K-means clustering on the digits dataset (PCA-reduced data)
Centroids are marked with white cross



Examples

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Stata's Python API documentation Indices and tables

Next topic

Characteristic (sfi.Characteristic)

Quick search

Go

Stata's Python API documentation

The **Stata Function Interface (sfi)** module allows users to interact Python's capabilities with core features of Stata. The module can be used interactively or in do-files and ado-files.

Within the module, classes are defined to provide access to Stata's characteristics, current dataset, frames, date and time, macros, scalars, matrices, value labels, global Mata matrices, missing values, etc.

Class Summary

- Characteristic (sfi.Characteristic)
- Data (sfi.Data)
- Datetime (sfi.Datetime)
- Frame (sfi.Frame)
- Macro (sfi.Macro)
- Mata (sfi.Mata)
- Matrix (sfi.Matrix)
- Missing (sfi.Missing)
- Platform (sfi.Platform)
- Preference (sfi.Preference)
- Scalar (sfi.Scalar)
- SFIToolkit (sfi.SFIToolkit)
- StrLConnector (sfi.StrLConnector)
- ValueLabel (sfi.ValueLabel)

ML regression and classification with

r_ml_stata_cv & c_ml_stata_cv

Stata command r ml stata cv

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

Stata command c ml stata cv

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

Practical implementation

Tree regression

Tree regression in "default" mode

```
* Load intial dataset
sysuse boston, clear
* Form the train and test datasets
get_train_test , dataname("boston") split(0.80 0.20) split_var(svar) rseed(101)
* Form the target and the features
global y "medv"
global X "zn indus chas nox rm age dis rad tax ptratio black lstat"
* Run tree regression in default mode
use boston_train, clear
r_ml_stata_cv $y $X , ///
mlmodel("tree") data_test("boston_test") ///
default prediction("pred") seed(10)
```

Results

```
Learner: Tree regression
Dataset information
Target variable = "medv"
                                             Number of features = 12
N. of training units = 405
                                             N_{\bullet} of testing units = 101
N. of used training units = 405
                                             N. of used testing units = 101
Parameters
Tree depth = largest tree possible
Validation results
MSE = mean squared error
                                             MAPE = mean absolute percentage error
Training MSE = 0
                                             Testing MSE = 49.644951
                                             Testing MAPE % = 21.923632
Training MAPE % = 0
```

Tree regression in "non-default" mode

```
* Run tree regression with specific tree depth
cap rm CV.dta
use boston_train, clear
r_ml_stata_cv $y $X , ///
mlmodel("tree") data_test("boston_test") ///
prediction("pred") tree_depth(3) cross_validation("CV") ///
n_folds(5) seed(10)
```

Results

```
Learner: Tree regression
Dataset information
Target variable = "medv"
                                             Number of features = 12
N_{\bullet} of training units = 405
                                             N_{\bullet} of testing units = 101
N. of used training units = 405
                                             N. of used testing units = 101
Cross-validation results
Accuracy measure = explained variance
                                             Number of folds = 5
Best grid index = 0
                                             Optimal tree depth = 3
Training accuracy = .84580618
                                             Testing accuracy = .2984019
Std. err. test accuracy = .65469445
Validation results
                                             MAPE = mean absolute percentage error
MSE = mean squared error
Training MSE = 14.502344
                                             Testing MSE = 40.720762
Training MAPE % = 16.141842
                                             Testing MAPE % = 21.355281
```

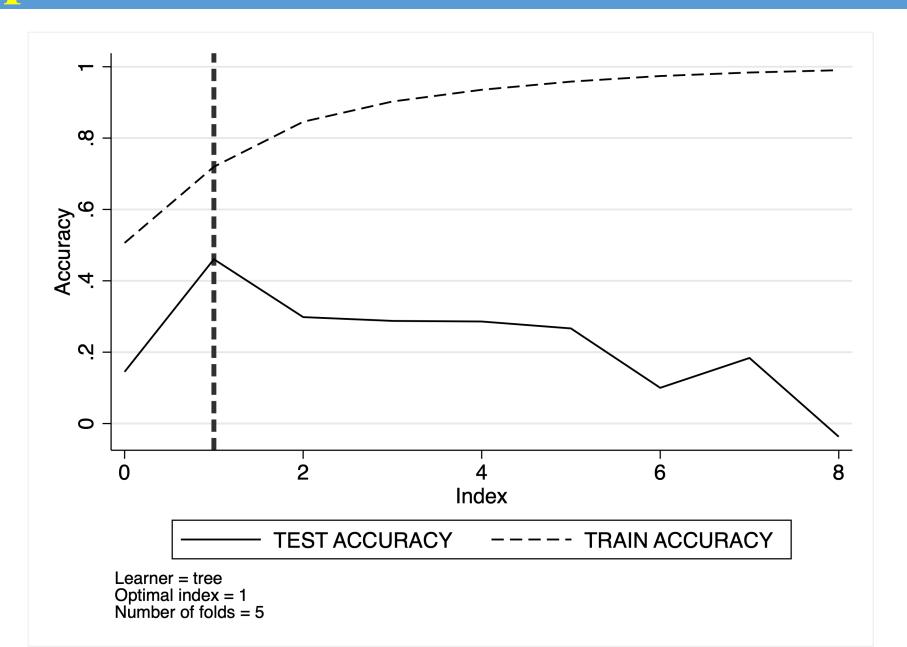
Tree regression in "cross-validation" mode

```
* Run tree regression with cross-validated tree depth
cap rm CV.dta
use boston_train, clear
r_ml_stata_cv $y $X , ///
mlmodel("tree") data_test("boston_test") ///
prediction("pred") tree_depth(1 2 3 4 5 6 7 8 9) cross_validation("CV") ///
n_folds(5) seed(10) graph_cv
```

Results

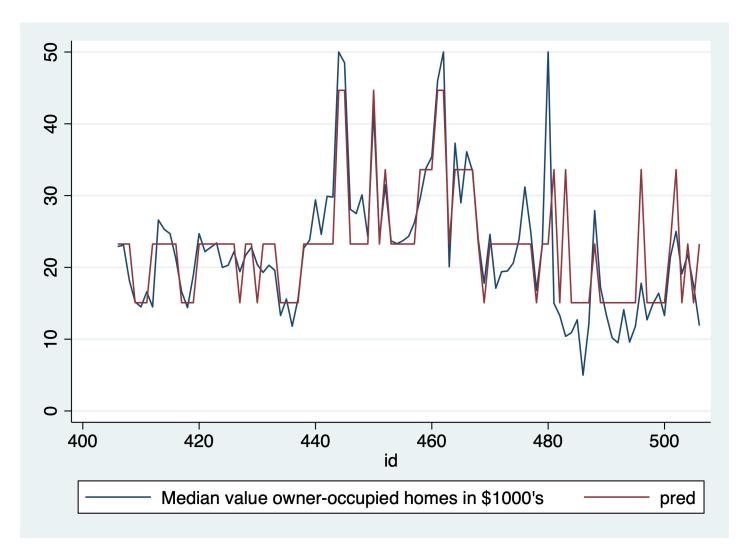
```
Learner: Tree regression
Dataset information
Target variable = "medv"
                                              Number of features = 12
N. of training units = 405
                                              N_{\bullet} of testing units = 101
N_{\bullet} of used training units = 405
                                              N_{\bullet} of used testing units = 101
Cross-validation results
                                              Number of folds = 5
Accuracy measure = explained variance
Best grid index = 1
                                              Optimal tree depth = 2
Training accuracy = .71966095
                                              Testing accuracy = .4605888
Std. err. test accuracy = .35495267
Validation results
                                              MAPE = mean absolute percentage error
MSE = mean squared error
Training MSE = 24.584194
                                              Testing MSE = 31.301179
Training MAPE % = 19.328019
                                              Testing MAPE % = 20.389068
```

Graph of cross-validation results



Out-of-sample prediction

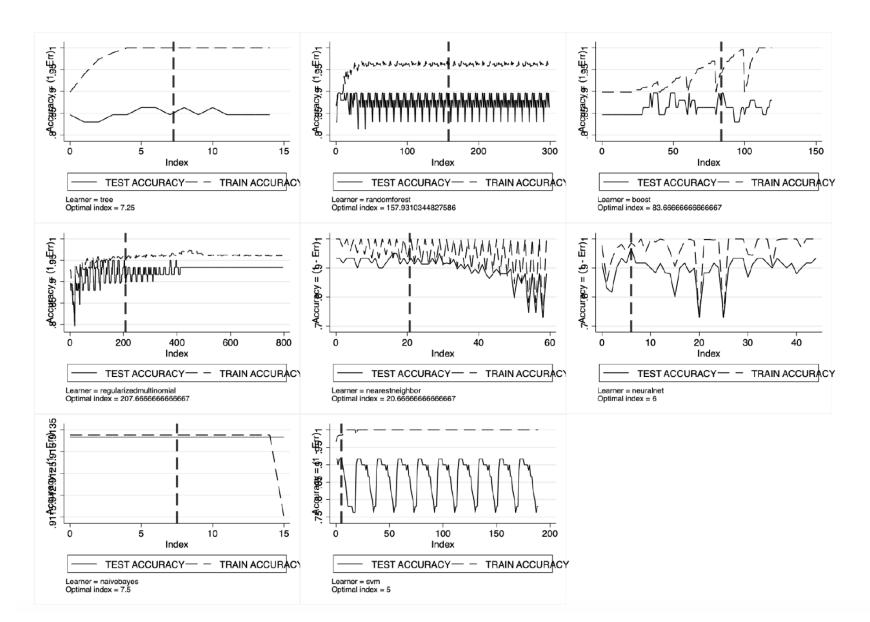
- . gen id=_n
- . line medv pred id if svar==2



Example Comparing multiple learners

Guessing whether a "new" car is a "foreign" or "domestic" one based on a series of characteristics, including price, number of repairs, weight, etc

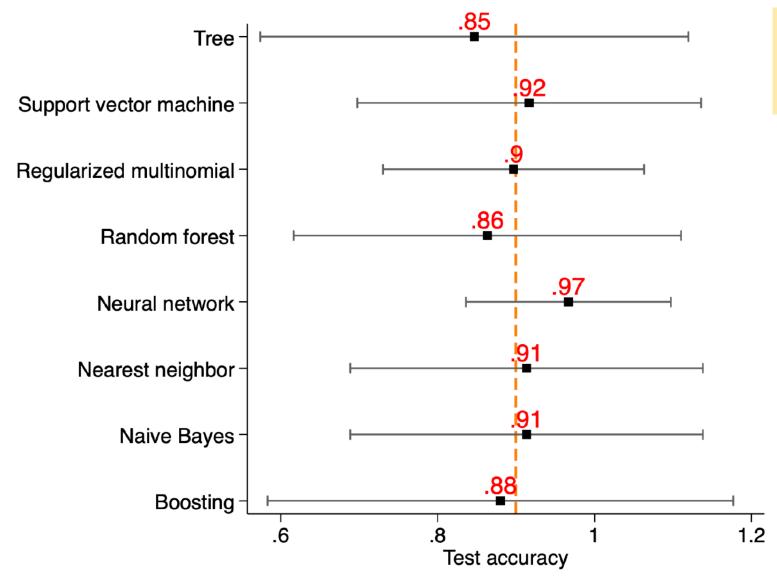
Cross-validation



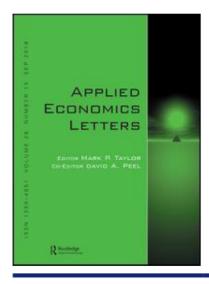
Cross-validation maximum of the classification test accuracy over a grid of learners' tuning parameters.

Accuracy measure: "error rate"

Comparing learner performance



Forest plot for comparing mean and standard deviation of different learners. Classification setting





Applied Economics Letters

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/rael20

Improving econometric prediction by machine learning

Giovanni Cerulli

References

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