# pyEDM Version 0.1.2 May 27, 2019

pyEDM is a Python package interface to the cppEDM C++ library of empirical dynamic modeling (EDM) algorithms. It is loaded within Python by import EDM and returns Pandas DataFrame objects.

# **Table of Contents**

Introduction	
Installation.	
Usage	3
Parameters	
Application Programming Interface (API)	5
Embed.	
Simplex	6
SMap	
CCM	
Multiview	
EmbedDimension.	10
PredictInterval	11
PredictNonlinear	
ComputeError	
Application Notes	
Examples.	
References	16

University of California at San Deigo Scripps Institute of Oceangraphy Sugihara Lab

Joseph Park, Cameron Smith

# Introduction

pyEDM is a Python interface to the C++ library cppEDM. Input and output objects are based on Pandas DataFrame objects. Core algorithms are listed in table 1.

Algorithm	API Interface	Reference
Simplex projection	Simplex()	Sugihara and May (1990)
Sequential Locally Weighted Global Linear Maps (S-map)	SMap()	Sugihara (1994)
Predictions from multivariate embeddings	<pre>Simplex(), SMap()</pre>	Dixon et. al. (1999)
Convergent cross mapping	CCM()	Sugihara et. al. (2012)
Multiview embedding	Multiview()	Ye and Sugihara (2016)

Convenience functions to prepare and evaluate data are listed in table 2.

Function	Purpose	Parameter Range
Embed()	Timeseries delay dimensional embedding	User defined
MakeBlock()	Timeseries delay dimensional embedding	User defined
EmbedDimension()	Evaluate prediction skill vs. embedding dimension	E = [1, 10]
<pre>PredictInterval()</pre>	Evaluate prediction skill vs. forecast interval	Tp = [1, 10]
PredictNonlinear()	Evaluate prediction skill vs. SMap nonlinear localisation	θ = 0.01, 0.1, 0.3, 0.5, 0.75, 1, 1.5, 2, 3, 4, 5, 6, 7, 8, 9
ComputeError()	Pearson ρ, RMSE, MAE	
<pre>Examples()</pre>	Example function calls and plots	

# Installation

```
OSX and Windows (Python 3):
    pyEDM is available from the Python Package Index (PyPI):
    <a href="https://pypi.org/project/EDM_SugiharaLab">https://pypi.org/project/EDM_SugiharaLab</a>
    pip install EDM_SugiharaLab
    or
    python -m pip install EDM_SugiharaLab
```

#### Linux:

PyPI does not support C++ extension libraries on Linux.

1) Build the cppEDM libEDM.a from  $\underline{github.com/SugiharaLab/cppEDM}$  by running "make" in the cppEDM/src/ directory with the "-fPIC" compiler flag:

```
make CFLAGS="-std=c++11 -DCCM_THREADED -DMULTIVIEW_VALUES_OVERLOAD -O3 -fPIC"
```

- 2) Download pyEDM from <a href="mailto:github.com/SugiharaLab/pyEDM">github.com/SugiharaLab/pyEDM</a>. Copy the cppEDM/lib/libEDM.a into pyEDM/lib.
- 3) Install the EDM Python module from pyEDM/: "python -m pip install . --user"

# Usage

```
>>> import EDM
>>> EDM.Examples()

or

>>> from EDM import *
>>> Examples()
```

Parameters

API parameter names and purpose are listed in table 3.

Parameter	Type	Default	Purpose
pathIn	string	"./"	Input data file path
dataFile	string	" "	Data file name
dataFrame	Pandas DataFrame	None	Input DataFrame
pathOut	string	"./"	Output file path
predictFile	string	" "	Prediction output file
lib	string	" "	library start : stop row indices
pred	string	" "	prediction start : stop row indices
E	int	0	Data dimension
Тр	int	0	Prediction interval
knn	int	0	Number nearest neighbors
tau	int	1	Embedding delay
theta	float	0	SMap localisation
columns	string	" "	Column names or indices for prediction
target	string	" "	Target library column name or index
embedded	bool	false	Is data an embedding?
verbose	bool	false	Echo messages
smapFile	string	" "	SMap coefficient output file
libSizes_str	string	" "	CCM library sizes
sample	int	0	CCM number of random samples
random	bool	true	CCM use random samples?
seed	unsigned	0	RNG seed, $0 = \text{random seed}$

# Application Programming Interface (API)

### **Embed**

Create a data block of Takens (1981) time-delay embedding from each of the columns in the csv file or dataFrame. The columns parameter can be a list of column names, or a list of column indices. If columns is a list of indices, then column names are created as V1, V2...

Note: The returned DataFrame will have tau\*(E-1) fewer rows than the input data from the removal of partial vectors as a result of the embedding.

Note: The returned DataFrame will not have the time column.

# Simplex

Simplex projection of the input data file or DataFrame. The returned DataFrame has 3 columns "Time", "Observations", "Predictions". nan values are inserted where there is no observation or prediction. See the Parameters table for parameter definitions.

lib and pred specify [start stop] row indices of the input data for the library and predictions.

If embedded is false the data columns are embedded to dimension E with delay tau. If embedded is true the data columns are assumed to be a multivariable data block.

If knn is not specified, it is set equal to E+1.

### **SMap**

SMap projection of the input data file or DataFrame. See the Parameters table for parameter definitions.

SMap() returns a dict with two DataFrames:

The predictions DataFrame has 3 columns "Time", "Observations", "Predictions". nan values are inserted where there is no observation or prediction. If predictFile is provided the predictions will be written to it in csv format.

The coefficients DataFrame will have E+2 columns. The first column is the "Time" vector, the remaining E+1 columns are the SMap SVD fit coefficients.

lib and pred specify [start, stop] row indices of the input data for the library and predictions.

If embedded is false the data columns are embedded to dimension E with delay tau. If embedded is true the data columns are assumed to be a multivariable data block. If smapFile is provided the coefficients will be written to it in csy format.

If knn is not specified, it is set equal to the library size. If knn is specified, it must be greater than E.

```
//-----
//
//-----
dataFrame
pathOut
             = None,
             = "./",
     predictFile
     lib
     pred
     E
     Тp
     knn
              = 1,
     tau
     theta
     columns
     target
     smapFile
             = "",
     jacobians
                  // Not implemented
     embedded
             = false,
     verbose
             = true )
```

#### CCM

Convergent cross mapping via Simplex of the first vector specified in columns against target. The data cannot be multivariable, the first vector in columns is time-delay embedded to dimension E. See the Parameters table for parameter definitions.

The returned DataFrame has 3 columns. The first column is "LibSize", the second and third columns are Pearson correlation coefficients for "column: target" and "target: column" cross mapping.

libSizes specifies a string with "start stop increment" row values, i.e. "10 80 10" will evaluate library sizes from 10 to 80 in increments of 10.

If random is true, sample observations are radomly selected from the subset of each library size. If seed=0, then a random seed is generated for the random number generator. Otherwise, seed is used to initialise the random number generator.

If random is false, sample is ignored and contiguous library rows up to the current library size are used.

Note: Cross mappings are performed between column: target, and target: column. The default is to do this in separate threads. Threading can be disabled in the makefile by removing -DCCM THREADED.

Note: The entire library size is used in the Simplex prediction at each library subset size.

```
//-----
//
DataFrame CCM( pathIn = "./data/", dataFile = "", dataFrame = None, pathOut = "./",
             predictFile = "",
                        = 0,
             E
             Тp
             knn
                        = 0,
             tan
             columns
                        = "",
             target
                        = "",
             libSizes
             sample
                        = 0,
                       = true,
             random
                                // seed=0: use RNG
             seed
                       = 0,
             verbose = true );
```

#### Multiview

}

Multiview embedding and forecasting of the input data file or DataFrame. See the Parameters table for parameter definitions.

The Predictions DataFrame has 3 columns "Time", "Observations", "Predictions". nan values are inserted where there is no observation or prediction. If predictFile is provided the Predictions will be written to it in csv format.

The Combo\_rho DataFrame will have E+3 columns. The first E columns are the the column indices in the input data DataFrame that are embedded and applied to Simplex prediction. The last three columns are "rho", "MAE", "RMSE" corresponding to the prediction Pearson correlation, maximum absolute error and root mean square error.

lib and pred specify [start, stop] row indices of the input data for the library and predictions.

If multiview is not specified it is set to sqrt(C) where C is the number of E-dimensional combinations out of all available data vectors.

If knn is not specified, it is set equal to E+1.

# EmbedDimension

Evaluate Simplex prediction skill for embedding dimensions from 1 to 10. The returned DataFrame has columns "E" and "rho". See the Parameters table for parameter definitions.

Note: nThreads defines the number of worker threads for the 10 embeddings. The maximum number of threads is 10.

### **PredictInterval**

Evaluate Simplex prediction skill for forecast intervals from 1 to 10. The returned DataFrame has columns "Tp" and "rho". See the Parameters table for parameter definitions.

Note: nThreads defines the number of worker threads for the 10 prediction interval forecasts. The maximum number of threads is 10.

# PredictNonlinear

Evaluate SMap prediction skill for localisation parameter  $\theta$  from 0.01 to 9. The returned DataFrame has columns "theta" and "rho". See the Parameters table for parameter definitions.

Note: nThreads defines the number of worker threads for the 15  $\theta$  value forecasts.

# ComputeError

Compute Pearson correlation coefficient, maximum absolute error (MAE) and root mean square error (RMSE) between two vectors.

ComputeError() returns a dict:

# **Application Notes**

All data input files are assumed to be in csv format. The files are assumed to have a single line header with column names. If column names are not detected in the header line, then column names are created as V1, V2... It is required that the first column be a vector of times or time indices.

SMap() should be called with DataFrame that have columns explicity corresponding to dimensions E. This means that if a multivariate data set is used, it should Not be called with an embedding from Embed() since Embed() will add lagged coordinates for each variable. These extra columns will then not correspond to the intended dimensions in the matrix inversion and prediction reconstruction. In this case, use the embedded parameter set to true so that the columns selected correspond to the proper dimension.

# **Examples**

```
df = EmbedDimension( "./data/", "TentMap rEDM.csv", None, "./", "",
                     "1 100", "201 500", 1, 1,
                     "TentMap", "", False, False, 4 )
df = PredictInterval( "./data/", "TentMap rEDM.csv", None, "./", "",
                      "1 100", "201 500", 2, 1,
                      "TentMap", "", False, False, 4 )
df = PredictNonlinear( "./data/", "TentMapNoise rEDM.csv", None, "./", "",
                       "1 100", "201 500", 2, 1, 1,
                       "TentMap", "", False, False, 4 )
df = Simplex( "./data/", "block 3sp.csv", None, "./", "",
              "1 99", "100 198", 3, 1, 0, 1,
              "x_t y_t z_t", "x_t", True, True, True )
df = Simplex( "./data/", "block 3sp.csv", None, "./", "",
              "1 99", "100 195", 3, 1, 0, 1,
              "x t", "x t", False, True, True)
M = Multiview( "./data/", "block_3sp.csv", None, "./", "",
               "1 100", "101 198", 3, 1, 0, 1,
               "x t y t z t", "x t", 0, False, 4, True )
S = SMap( "./data/", "circle.csv", None, "./", "",
          "1 100", "101 198", 2, 1, 0, 1, 4,
          "x y", "x", "", "", True, True, True)
df = CCM( "./data/", "sardine_anchovy_sst.csv", None, "./", "",
          3, 0, 0, 1, "anchovy", "np sst",
          "10 80 10", 100, True, 0, True, True )
```

# References

Dixon, P. A., M. Milicich, and G. Sugihara, 1999. Episodic fluctuations in larval supply. Science 283:1528–1530.

Sugihara G. and May R. 1990. Nonlinear forecasting as a way of distinguishing chaos from measurement error in time series. Nature, 344:734–741.

Sugihara G. 1994. Nonlinear forecasting for the classification of natural time series. Philosophical Transactions: Physical Sciences and Engineering, 348 (1688): 477–495.

Sugihara G., May R., Ye H., Hsieh C., Deyle E., Fogarty M., Munch S., 2012. Detecting Causality in Complex Ecosystems. Science 338:496-500.

Takens, F. Detecting strange attractors in turbulence. Lect. Notes Math. 898, 366–381 (1981).

Ye H., and G. Sugihara, 2016. Information leverage in interconnected ecosystems: Overcoming the curse of dimensionality. Science 353:922–925.