

## **EASTIRS : Evolutionary Algorithm Slicing Timeseries Into Related Segments**

(User Notes by Richard Forsyth, Sept 2014)

This program identifies sections of sequential data with similar values, thus chopping a series into segments. It has been written in Python3 and is released under the GNU Public License for general usage. (Current version is eastirs3.py: the trailing digit in the program name is a version number that may change if the software is revised.)

### **Why I Wrote this Software**

I originally wrote a C version of this program in 1994. The recent Python edition is, I believe, a slight improvement. EASTIRS is a special-purpose clustering program. It tries to identify natural break-points in sequential data, thus partitioning a series into segments, or phases, with similar values.

In essence it performs constrained clustering, but does much the same job more commonly described by statisticians as change-point analysis. Finding natural subsections of temporally organized data is a task with many applications in economics, medicine, process control and other fields. Personally, I am motivated to apply it to stylochronometry, i.e. changes in an author's verbal habits over time which, if regular, could allow estimating the dates of undated works.

EASTIRS expects to be given 2 input sequences: a time-stamp variable (t) and a response variable (y). Thus it looks for break-points in a function  $y = f(t)$ . Actually it isn't restricted to traditional time-series: the t-variable doesn't have to be spaced at equal intervals and it doesn't even have to be a time marker. It can be any variable that makes sense as defining an ordering on the y values. (For practical convenience, if your data has only a single data stream of y values, the program will attach the positive integers as a default t-variable.)

At present the program deals only with univariate time series, but I hope to develop and release a multivariate version eventually.

### **Setting Up**

First you need Python3. If you don't have it already, the latest version can be downloaded and installed from the Python website: [www.python.org](http://www.python.org). This is usually quite straightforward. The only snag is if you have Python2 and want to keep using it. Then you'll probably have to set up a specific command to run whichever version you use less frequently.

Next step is to unpack the eastirs.zip file. After unpacking it (into a top-level folder called "eastirs", unless you want to do quite a lot of editing), you should find the following subfolders.

```
datasets
op
p3
parapath
```

The programs are in p3. Sample data sets for testing will be found in datasets. Subfolder op is the default location for output files and parapath is a convenient place for storing parameter files, which will be explained later. In Windows, it is most convenient to install eastirs at the top level of the C:\ drive, at least to start with; otherwise you'll have to edit the sample parameter files to make sure their datfile parameters point to the correct locations.

## Data Format

The program expects to read its input values from data files such as can be exported from R (R Core Team, 2013) or Excel, with a header line giving column names and using the tab character as a delimiter. Data files can also be created in a text editor such as Notepad++ (<http://notepad-plus-plus.org/>), preferably in utf-8 encoding.

The first five lines of the sample datafile lynxdat.dat are listed below to illustrate this format.

```
year  lynx  diff
1821  269    0
1822  321    52
1823  585    264
1824  871    286
.....
```

This dataset is a well-studied time series. It records trappings of lynx in Canada from 1821 to 1934. If you examine it you will see that it consists of repeated boom and bust cycles, presumably as the lynx population expands to unsustainable levels and then crashes.

The first line names the variables (columns); subsequent lines give values for each of these 3 variables, separated by tabs.

With this example, the obvious t-variable is the year, but there are 2 possible y-variables, lynx (the number of lynx caught that year) and diff (the difference in lynx trappings from year to year). In other words, one can look for phases either in the levels themselves or in the changes of level.

## Preparing a Parameter File

When you run eastirs3.py it will ask for the name of a parameter file. Below is a listing of parameter file lynx.txt which comes with the distribution in parapath.

```
comment  applying eastirs to canadian lynx trappings data :
jobname  lynx
datfile  c:\eastirs\datasets\lynxdat.dat
##targvar  lynx
##targvar  diff
##choose 1 of above.
timevar  year
varmode  vc
ntrials  65536
```

A parameter file is just a plain text file with one item per line. Each line should begin with the parameter name, then 1 or more blank spaces, then the parameter value. The following table interprets the above parameter file, line by line.

Parameter	Default value	Function
comment	[None]	This (or in fact any unrecognized parameter name, e.g. "##") can be used to insert reminders about what the file is meant to do.
jobname	eastirs	This gives the job a name. Any text string can be the value. It isn't necessary but it is useful as the jobname will be used as a prefix to the program's output files, so it can be seen that they form a group.
datfile	[None]	This should be the full file specification of a file where the input data is stored (in tab-delimited form with a header line naming the

		columns).
timevar	[None]	This gives the column name of the variable to be used as the time-stamp that defines the sequence of the y-values.
targvar	[None]	This gives the name of the column in the data file that contains the target variable, i.e. the values of the series itself.
varmode	vc	This selects which 'fitness function' (see below) is to be used. Several functions have been implemented but at present I don't recommend any except "vc", which is the default value.
ntrials	49152	EASTIRS uses an evolutionary algorithm to optimize the serial subdivision of the data, according to the fitness function selected by varmode. This parameter specifies how many evolutionary trials to make, i.e. how many gene-strings will be created during the optimization process.

In the example above, the lines beginning "##targvar" are comments. To activate either choice of target (y) variable you could simply delete the "##" at the start of one of these lines, although this isn't strictly necessary, since the program will ask for a target variable if none is specified in the parameter file. (Likewise with time-stamp variable.)

### Running EASTIRS

When you run eastirs3.py it will ask for a parameter file. If this file is in the same directory as the program or in the parapath subfolder you won't have to give the full path specification, just its name (.txt extension will be presumed if no extension is given).

You should see on screen something like the listing below, which comes from a run using the spots101.txt parameter file. This runs the program on another of the supplied sample sets, mean daily sunspot numbers from 1913 to 2013 inclusive.

```
c:\myfolder>python c:\eastirs\p3\eastirs3.py

C:\eastirs\p3\eastirs3.py 3.3 Fri Sep 5 16:13:23 2014
command-line args. = 1
prepath : C:\eastirs\p3
working folder: C:\myfolder
script usage: python C:\eastirs\p3\eastirs3.py <parafilename>
please give parameter file name : c:\eastirs\parapath\spots101
Paths to search for parameter file :
['C:\\\\parapath', 'C:\\myfolder', '..', '.', 'C:\\Users\\Richard\\parapath',
'C:\\Users\\Richard']
c:\eastirs\parapath spots101
trying to open : c:\eastirs\parapath\spots101.txt
c:\eastirs\parapath\spots101.txt opened for reading.
102 2
data rows = 101
data cols = 2
['midyear', 'spotnum']
Usable variables :
0 midyear
1 spotnum
Time-stamp chosen is column 0 midyear
midyear
[1913.5, 1914.5, 1915.5, 1916.5, 1917.5, 1918.5, 1919.5, 1920.5, 1921.5, 1922.5]
....
[2004.5, 2005.5, 2006.5, 2007.5, 2008.5, 2009.5, 2010.5, 2011.5, 2012.5, 2013.5]
time-series y-variable :
1 spotnum
basic stats of spotnum :
```

```
id      0
mean    63.001
std1    47.8434
std2    48.082
var1    2288.99
var2    2311.8799
```

[some lines omitted here to save space .... ]

C:\eastirs\p3\eastirs3.py done on Fri Sep 5 16:15:08 2014  
after 78.484 seconds.

The only user input required here has been marked in **bold face**, i.e. the program launch command and the name of the parameter file, `spots101`, which is found in folder `c:\eastirs\parapath\` with `.txt` extension (both defaults).

### Interpreting the output

The listing below shows output derived from another dataset supplied with the distribution, `aircraft.dat`. This contains 103 examples of military aircraft used in World War II. (More details are given in `aircraft.txt` in the `datasets` subfolder). This is not a temporal sequencing problem; rather, in this case, the program is examining the relationship between the variable `tip2tail` (length of the aircraft in metres) and its `wingspan` (also in metres). Longer aircraft tend to have greater wingspans: the program is in effect looking for change-points in this relationship.

C:\eastirs\p3\eastirs3.py  
Fri Sep 5 15:52:05 2014

Source file name : c:\eastirs\datasets\aircraft.dat  
Sequence variable : tip2tail  
Response variable : wingspan  
wingspan mean = 16.6274757  
wingspan variance = 50.7165588

Fitness mode : vc  
Best score = 0.8552925

Best partition :

Rank	Case	Gene	Group	tip2tail	wingspan
1	43	1	1	5.6900	9.3000
2	54	0	1	6.1300	9.1800
3	53	0	1	6.3000	10.0000
4	46	0	1	7.5500	11.4800
5	1	0	1	7.7800	11.0600
6	8	0	1	7.7900	10.9700
7	12	0	1	7.9500	11.0000
8	82	0	1	8.0300	10.6700
9	51	0	1	8.1500	10.3000
10	3	0	1	8.1600	10.6200
11	10	0	1	8.2000	10.5800
12	5	0	1	8.2100	11.0100
13	7	0	1	8.2500	9.7000
14	37	0	1	8.3000	10.5000
15	67	0	1	8.3600	9.8300
16	49	0	1	8.4600	9.8000
17	57	0	1	8.5000	9.2100
18	26	0	1	8.7500	9.5000
19	2	0	1	8.7600	10.2100
20	91	0	1	8.7600	11.5800
21	31	0	1	8.8400	10.4900
22	11	0	1	8.8500	10.5800
23	15	0	1	8.8800	12.0000
24	50	0	1	8.9000	9.8000
25	25	0	1	8.9200	10.8300

26	35	0	1	9.0000	7.2000
27	41	0	1	9.0400	9.9200
28	18	0	1	9.0600	12.0000
29	17	0	1	9.1600	12.0000
30	79	0	1	9.1900	10.3700
31	85	0	1	9.5100	11.3900
32	76	0	1	9.5700	11.2300
33	71	0	1	9.5800	12.1900
34	19	0	1	9.7000	10.8000
35	72	0	1	9.7300	12.6700
36	100	0	1	9.8200	11.3000
37	27	0	1	9.9200	11.2400
38	77	0	1	9.9600	11.2300
39	90	0	1	10.0700	12.6600
40	103	0	1	10.1700	12.4700
41	14	0	1	10.2000	14.3650
42	32	0	1	10.2000	10.4900
43	28	0	1	10.2200	11.5000
44	92	1	2	10.2400	13.0600

[.... 43 lines omitted to save space ....]

88	6	0	4	18.4000	24.8000
89	30	0	4	18.5000	19.0000
90	38	1	5	18.9000	29.2500
91	89	0	5	19.4400	29.1300
92	84	0	5	19.4700	31.7000
93	21	0	5	19.6300	24.8900
94	83	0	5	20.4700	33.5300
95	59	0	5	21.1500	31.0900
96	78	0	5	21.3000	25.0600
97	70	0	5	21.3600	31.7500
98	58	0	5	21.5000	25.6000
99	80	0	5	22.8000	31.6200
100	33	0	5	23.4600	30.8550
101	74	0	5	26.0300	34.3800
102	75	0	5	26.5900	30.2000
103	81	0	5	30.1800	43.0500

Segment statistics :

Segment 1 at 5.6900 n = 43 :  
 median = 10.8000 mean = 10.8192 variance = 1.4387

Segment 2 at 10.2400 n = 14 :  
 median = 14.2350 mean = 14.2721 variance = 2.0334

Segment 3 at 12.1900 n = 12 :  
 median = 16.5100 mean = 16.6350 variance = 3.0975

Segment 4 at 13.5100 n = 20 :  
 median = 20.3650 mean = 20.7935 variance = 3.4605

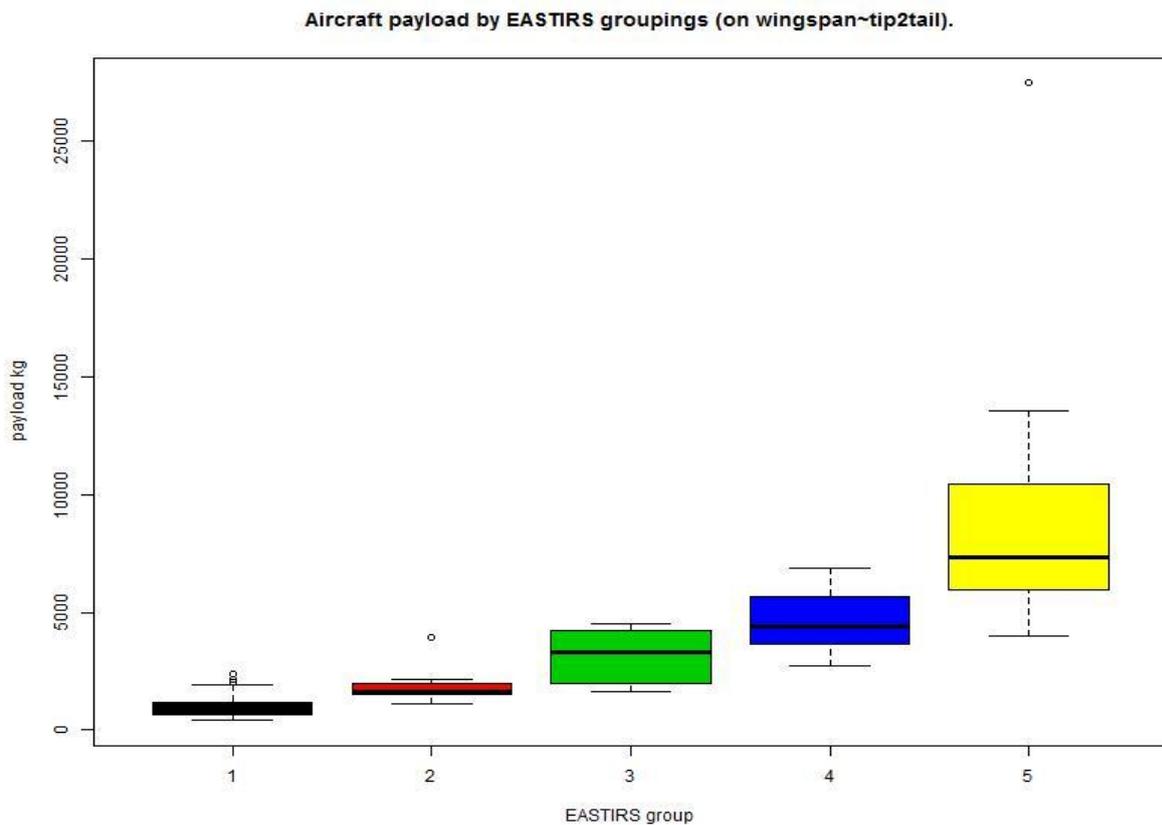
Segment 5 at 18.9000 n = 14 :  
 median = 30.9725 mean = 30.8646 variance = 21.0163

Summed subgroup variance = 31.0463918

The listing begins by recording information about the run's settings, including the 2 variables chosen for analysis as time-stamp and response. (There are 16 variables in this dataset.) The main body of the listing (abbreviated by omitting 43 rows in the middle) gives details of the best segmentation found. This is ordered by the t-variable values and gives the corresponding value of the y-variable for each t-value. It also shows the genestring that defines the resulting segmentation and the group (numbered from 1) to which each data pair belongs. The listing concludes by giving some summary statistics of each grouping. (See Upton & Cook (2006) if uncertain about statistical terminology.)

In this example, the program has decided that there are five subgroups, from very small aircraft (43 of them, mostly fighters) to very large (14 of them, 13 being heavy bombers).

An analyst would doubtless want to explore further how these groups differ, e.g. by seeing if the x-y gradient in the first group differs from that in the last group. To enable such further analyses, the program produces 2 output files: a list file (indicated by a name ending in "\_list.txt" unless specified otherwise), and a dump file (indicated by a name ending in "\_dump.dat" unless specified otherwise). The list file is what has been shown above. The dump file is just the input data with an extra column appended that contains the numeric segment label for each case, in tab-delimited format with a header line. This can be read into Excel or R for further processing. The graph below is an example of the sort of post-processing that can be done (in R for this example) with a dump file.



This graph is a boxplot generated from the aircraft.dat data, with the groupings derived from EASTIRS appended (i.e. the "\_dump.dat" file read back into R). It shows the distributions of payload (laden less unladen weight in kilograms) in each subgroup. Payload was not part of the grouping process, which was based on fuselage length and wingspan; it is derived from the difference of 2 other variables. Yet only 2 of these five derived groupings overlap in their middle 50% range on payload (groups 3 and 4). Thus the groupings based on one pair of variables are predictive in terms of a different pair of variables. Of course we know that longer aeroplanes with greater wing spans can normally carry heavier payloads, but that is why this is a test dataset. In general, this kind of structural relationship will be unknown, so the fact that the partitioning process reveals it can be seen as a sign that the process has value in data exploration.

### How the program works

The problem of constrained clustering is peculiarly well suited to solution by an evolutionary

approach, since a clustering can be described by a binary string in which 1 signifies the start of a new segment at a particular point and 0 indicates the continuation of a segment. Bitstrings of this type are exactly what evolutionary/genetic algorithms work with most effectively. They can be chopped up and recombined or mutated very simply to produce fresh candidate solutions, thus searching the space of all possible segmentations.

The evolutionary optimizer used here can be found in the py3seal.py library, on folder p3. It is a streamlined version of a technique described in section 4.1 of Forsyth (1996).

<http://www.richardsandesforyth.net/pubs/ppsn1996.pdf>

To apply evolutionary optimization to this kind of problem, a 'fitness function' must be defined. This gives a quantitative evaluation of the quality of any given segmentation. I have experimented with several fitness functions but so far the only one I consider satisfactory is selected by giving "vc" as the value of the varmode parameter. (This is the default if no varmode parameter is supplied.)

This fitness function (which the program tries to maximize) yields a numerical value which can be summarized as

$$1.0 - ((\text{dev1} + \text{dev2}) / \max(1, n - g)) / \text{var2}$$

where var2 is the overall variance of the y-variable; dev1 is the summed squared deviation of each y-value in each group (segment) from its local mean; dev2 is the sum of the squared deviations of the arithmetic means of each group from the overall mean of the y-variable; n is the number of data points in the series, and g is the number of segments in the candidate solution.

The underlying idea is that dev1 quantifies the lack of homogeneity in the groups, while dev2 quantifies the lack of parsimony in the segmentation. Both these are treated as costs, then added together and divided by a number corresponding to the degrees of freedom of the partitioning. This result is then scaled by the overall variance and subtracted from 1.0 since the evolutionary function is a maximizer.

## Acknowledgements

Thank you for reading this far. :-)

## References

Forsyth, R.S. (1996). IOGA: an instance-oriented genetic algorithm. In: Voight, H.-M., Ebeling, W., Rechenberg, I. & Schwefel, H.-P. (eds.) *Parallel Problem Solving from Nature -- PPSN IV*. Berlin: Springer.

<http://www.richardsandesforyth.net/pubs/ppsn1996.pdf>

R Core Team (2013). R: A language and environment for statistical computing. *R Foundation for statistical Computing*, Vienna, Austria.

<http://www.R-project.org/>.

Upton, G. & Cook, I. (2006). *Oxford Dictionary of Statistics*, second ed. Oxford: Oxford University Press.

## Appendix 1 : Parameter Files

Parameters used by **eastirs3.py** are described below. Normally only the first five in this table need to be specified by a user, though for long sequences you might want to increase ntrials.

Parameter	Default value	Function
comment	[None]	This (or in fact any unrecognized parameter name, e.g. "##") can be used to insert reminders about what the file is meant to do.
jobname	eastirs	This gives the job a name. Any text string can be the value. It isn't necessary but it is useful as the jobname will be used as a prefix to the program's output files, so it can be seen that they form a group.
datfile	[None]	This should be the full file specification of a file that indicates where the input data is stored (in tab-delimited form with a header line naming the columns).
timevar	[None]	This gives the column name of the variable to be used as the time-stamp that defines the sequence of the y-values.
targvar	[None]	This gives the name of the column in the data file that contains the target variable, i.e. the values of the series itself.
outpath	.\op\	Directory to receive output files. By default this is the op subfolder of the parent directory of the program.
varmode	vc	This selects which 'fitness function' (see below) is to be used. Several functions have been implemented but at present I don't recommend any except "vc", which is the default value.
ntrials	49152	EASTIRS uses an evolutionary algorithm to optimize the subdivision of the data, according to the fitness function selected by varmode. This parameter specifies how many evolutionary trials to make, i.e. how many gene-strings will be created during the optimization process. [*]
skipvars	[None]	A list of names of variables to be ignored, separated by commas. Won't really be needed until/unless the program becomes multivariate.
listfile	[None]	File for human-readable output. If none is specified, the file will have the jobname followed by "_list.txt".
dumpfile	[None]	File to receive extended input data with column appended (called seg_ment) giving the subgroup number of each case, in tab-delimited form suitable to read into R with the read.delim() function for post-processing. If none is given, the file will have the jobname followed by "_dump.dat".
outfile	eastirs.txt	File that will receive parameter setting information, for reference.

[\*] With modest-sized series, up to about 200 data points, EASTIRS is surprisingly effective. However, the search space expands exponentially as 2 to the power of the number of data points, so theory as well as practical experience suggests that with sequences of thousands of data points it is unlikely to converge on a near-optimal solution in a reasonable time.

N.B. At present, if you have more than 1 blank lines in a parameter file, the input routine chokes. I do plan to fix this at some stage; in the mean time, it is quite easy to delete empty lines using a text editor.

## Appendix 2 : Sample Datafiles

These are provided in the datasets subfolder.

### **aircraft.dat**

This dataset contains information (16 columns) concerning 103 makes of military aircraft used in World War II. For further details, see aircraft.txt in the same subfolder.

### **lynxdat.dat**

This is the classic Canadian lynx time series, as obtained from the lynx dataset provided with the R package.

<http://www.R-project.org/>.

### **michuron.dat**

This data records the annual mean level of Lake Huron (which is the same as Lake Michigan) over the years 1918 to 2013, obtained from the U.S. National Oceanic and Atmospheric Administration website.

<http://www.glerl.noaa.gov/data/now/wlevels/levels.html>

### **spots101.dat**

This data series records the mean daily sunspot numbers observed during the period 1913 to 2013 inclusive. Original source: WDC-SILSO, Royal Observatory of Belgium, Brussels.

<http://www.sidc.be/silso/datafiles>