

# autoScale.py – A program for automatic finite-size scaling analyses: A user’s guide

O. Melchert\*

*Institut für Physik, Carl-von-Ossietzky Universität Oldenburg,  
26111 Oldenburg, Germany*

## Abstract

autoScale.py is a program that performs an automatic finite-size scaling analysis for given sets of simulated data. It implements a quite general scaling assumption and optimizes an initial set of scaling parameters that enforce a data collapse of the different data sets. The presented guide describes how the program works, it presents a detailed example and finally gives some hints on how to improve the results of a scaling analysis.

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\* E-mail: melchert@theorie.physik.uni-oldenburg.de

# 1 What is autoScale.py?

autoScale.py [1] is a python [2] implementation of a program that performs an automatic finite-size scaling (FSS) analysis. More precise, autoScale.py uses *data collapse techniques* so as to quantify the property of scaling.

Upon introduction of properly scaled variables, autoScale.py extracts numerical values for critical points and critical exponents that describe a given critical phenomenon. For the purpose of illustration consider a quantity  $y(x, L)$  that depends on two variables,  $x$  and  $L$ . The precise meaning of the quantity  $y$  depends on the actual problem. E.g., in connection to percolation it may describe the relative size of the largest cluster of occupied sites. Practically it can be any observable for which one aims to extract the critical behavior. The variables  $x$  and  $L$  are also problem dependent and represent adjustable parameters, e.g., in the problem of random percolation, these are the occupation probability and the system size. Now, the scaling assumption states that if the above quantity is considered to obey scaling, it can be expressed as

$$y(x, L) = L^{-b} f[(x - x_c)L^a], \quad (1)$$

wherein  $a$  and  $b$  are dimensionless critical exponents,  $x_c$  is called critical point and  $f[\cdot]$  is a scaling function. To support intuition: if  $L$  plays the role of a length scale, then the exponent  $a$  measures the “scaling dimension” of the observable  $x$ . Likewise, the exponent  $b$  measures the scaling dimension of the quantity  $y$ .

According to Eq. 1, data curves of  $y(x, L)$  for different values of  $x$  and  $L$  fall on top of each other if  $y(x, L)L^b$  is plotted against the combined quantity  $u \equiv (x - x_c)L^a$  and if the free parameters  $a$  and  $b$  of the scaling assumption are chosen properly. Therein, the latter quantity  $u$  corresponds to a polynomial approximation of the scaling function  $f[u]$  up to lowest order in  $u$ . This is certainly valid close to the critical point  $x_c$ , where  $u \ll 1$ , and it usually suffices to get reliable estimates for critical points and exponents. Hence, to put it more procedural, one can estimate critical exponents quite precise if one employs the scaling assumption above, starts with a rough guess for the numerical values of the scaling parameters therein and adjusts them so as to yield a satisfactory data collapse.

If one tries to characterize a critical phenomenon by means of computer simulations, such a scaling analysis is indispensable in order to infer critical points/exponents from the simulation data. Since the reliability of the critical properties thus obtained depends on the quality of the corresponding data collapse, it is desirable to perform the scaling analysis with the assistance of a computer. One should not leave this crucial task to the competence of the bare eye. Moreover, an automatic scaling analysis performed by algorithmic means, ensures that the data collapse is attained in a systematic and reproducible manner. Up to now there is no “ultimate” method that yields an optimal data collapse, and within the community of computational experimentalists

there is –up to now– no consensus of how to perform a proper finite-size scaling analysis. Instead, there are several methods [4, 3, 5, 6, 7] that find application once in a while. Here, `autoScale.py` implements the method described in Ref. [4]. Until now, `autoScale.py` has successfully been used to perform the scaling analyses in Refs. [8, 9, 10, 11].

## 2 Program description

As pointed out above, `autoScale.py` can be used as a black box for performing automatic FSS analyses. In order to benefit from `autoScale.py` you will first need some unscaled data (see subsection 2.1), that you wish to postprocess via a FSS analysis. Just supply the raw data and an “educated guess” for the appropriate scaling parameters that yield a data collapse, and `autoScale.py` will take care of data scaling and scaling–parameter optimization.

The quality of the data collapse, i.e. a measure of how well the scaling assumption fits the given data, is measured by the mean square distance of the data sets to the unknown master curve in units of the standard error [4]. Upon execution of `autoScale.py`, the quality (or more precise: the scaling parameters that determine the quality) is optimized via the downhill simplex algorithm of Nelder and Mead (see [12], Chapter 10.4).

The algorithmic procedure used to obtain the data collapse employs repeated application of linear least-squares methods [12] and goodness-of-fit tests [12, 13]. Finally, `autoScale.py` provides numerical values for the scaling parameters, error estimates for the scaling parameters and a measure for the quality of the respective data collapse.

In the following, subsection 2.1 will specify the format of the input data that is passed to `autoScale.py` and subsection 2.2 it will explain how `autoScale.py` works. Finally, subsection 2.3 briefly outlines the general idea of the downhill simplex method.

### 2.1 Required format of the input data

As a precondition for `autoScale.py` to work, you will need some input data in a specific format. If you are familiar with the python programming language, you can easily extend `autoScale.py` by a function similar to the class method `myRawData.fetchData()`, that reads data in your favored data format. The standard format accepted by `autoScale.py` is described in the following.

A data file is expected to contain three columns of numbers, there may be more but only the first three are considered. These columns are expected to list the  $x$ -values,  $y$ -values and the corresponding standard errors  $dy$  in the form:

```
# data file name: orderParam_L512.dat
```

```
# <x-Values> <y-Values> <dy-Values>
0.565000000 0.019801567 0.000058048
0.566750000 0.022313848 0.000068007
0.568500000 0.025335819 0.000079926
0.570250000 0.029096301 0.000095645
0.572000000 0.033696019 0.000114802
... ..
```

Note that `autoScale.py` treats lines starting with the symbol `#` as a comment and it disregards empty lines. Suppose you have produced data in the above format for several system sizes, say  $L = 32, 64, 128, 256$  and  $512$ , for which you aim to perform a FSS analysis.

Create a configuration file, e.g. `inputFiles.dat`, that lists the paths to the data files to be scaled along with the corresponding system sizes. For instance:

```
# configuration file name: inputFiles.dat
# <path to file> <system size L>
./ORDER_PARAMETER/orderParam_L32.dat 32
./ORDER_PARAMETER/orderParam_L64.dat 64
./ORDER_PARAMETER/orderParam_L128.dat 128
./ORDER_PARAMETER/orderParam_L256.dat 256
./ORDER_PARAMETER/orderParam_L512.dat 512
```

and you're almost done. `autoScale.py` will read this configuration file and accumulate the raw data from the specified data files to perform a scaling analysis.

## 2.2 Invoking `autoScale.py`

In advance, you should have an idea what scaling laws will fit your needs, and at least a rough guess regarding the values of the scaling parameters therein. Currently, `autoScale.py` implements the following scaling transformation:

$$\begin{aligned} x &\mapsto (x - x_c) \cdot L^a \\ y &\mapsto y \cdot L^b \\ dy &\mapsto dy \cdot L^b. \end{aligned}$$

If there are different scaling laws needed to fit your observables, and if you are familiar with the python programming language, you can easily extend `autoScale.py` by implementing a scaling assumption similar to the class `myScaleAssumption` that properly fits your requirements.

Invoking `autoScale.py` with the option `-help` as `python autoScale.py -help` yields information on how to use the program:

```
melchert@comphy03:~/PYTHON/FSS_EXAMPLE> python autoScale.py -help
NAME
    autoScale.py -- a program for automated finite size scaling analyses
SYNTAX
```

```
python autoScale.py -f inFile [-o outFile] [-xc val, -a val, -b val]
                    [-xr val val] [-showS] [-getError]

python autoScale.py [-help] [-version]

OPTIONS
-help                -- write usage and exit program
-version            -- write version number and exit
-f <inFile>         -- configuration file containing list of
                    paths to data files
-o <outFile>        -- path to output file (default: stdout)
-xc <float>         -- estimate for critical point (default: 0.0)
                    if called as '-xc!', <float> is fixed during
                    parameter optimization
-a <float>          -- estimate of exponent a (default: 0.0)
                    if called as '-a!', <float> is fixed during
                    parameter optimization
-b <float>          -- estimate of exponent b (default: 0.0)
                    if called as '-b!', <float> is fixed during
                    parameter optimization
-xr <float> <float> -- lower/upper boundary of interval on
                    rescaled x-axis for which scaling
                    analysis should be performed
-showS             -- report quality 'S' during minimization
                    procedure
-getError          -- compute errors for scaling parameters
                    using S+1 analysis

EXAMPLE
python autoScale.py -f dataFiles.dat -xc 0.592541 -a 0.754524 -b 0.107421
                    -xr -1. 1. -getError -o test.out -showS
```

### 2.3 Minimization of the objective function

For the minimization of the objective function  $S$ , i.e. the optimization of the scaling parameters  $\underline{x} = (x_c, a, b)$ , `autoScale.py` uses the downhill simplex algorithm of Nelder and Mead [15]. The simplex algorithm has proved to be a reliable tool, if one deals with unconstrained multidimensional optimization.

In general, the task of the simplex algorithm (SA) is to minimize the value of a scalar function  $S(\underline{x})$  with  $\underline{x} \in \mathbb{R}^n$  that depends on  $n$  variables. To do so, the SA requires only function evaluations and no function derivatives, hence it belongs to the so called direct search methods. The SA algorithm maintains a simplex that consists of  $n + 1$  vertices  $\underline{x}^{(1)}, \dots, \underline{x}^{(n+1)}$ , enclosing a finite  $n$ -dimensional volume, along with the corresponding function values  $S^{(i)} \equiv S(\underline{x}^{(i)})$ .

As a prerequisite, one has to provide an initial simplex with  $n + 1$  trial points  $\underline{x}_{\text{ini}}^{(i)}$ . The SA will iteratively improve the objective function values  $S^{(i)}$  towards a local minimum value, until it reaches a predefined minimal extension. For the improvement of the function values, the algorithm uses four different elementary manipulations of the simplex. These are reflection, expansion, contraction and shrinkage. These manipulations govern the performance of the SA.

A typical iteration step starts by ordering the  $n + 1$  vertices according to their function values  $S^{(i)}$  in non-decreasing order. The vertex with the lowest function value ( $S^{(1)}$ ), i.e.  $\underline{x}^{(1)}$ , is referred to as *best* point. The vertex with the largest function value ( $S^{(n+1)}$ ), i.e.  $\underline{x}^{(n+1)}$ , marks the *worst* point. During one iteration, the algorithm tries to get rid of the worst function value using a sequence of geometrical transformations using the elementary manipulations mentioned above.

### 3 Example of a scaling analysis using `autoScale.py`

Within this section, the use of `autoScale.py` is demonstrated using data simulated for the model of  $2d$  random site percolation [14]. The raw data and scripts used below are contained in the supplementary archive `SCALING_ANALYSIS.tar.gz`. As observable, the order parameter of the percolation model, i.e. the relative size of the largest cluster of occupied nearest neighbor sites  $P_\infty$  is considered. Related to this observable, the scaling assumption takes the form

$$P_\infty(p, L) = L^{-\beta/\nu} f[(p-p_c)L^{1/\nu}], \quad (2)$$

where the parameter  $L$  signifies the lateral extension of the square lattice, i.e. the system size, and the parameter  $p$  indicates the occupation probability for a site on the lattice. Note that Eq. 2 uses the standard notation of percolation theory. Therein, the usual critical exponents are  $\nu$  and  $\beta$ , where  $\nu$  describes the divergence of a typical length scale as one approaches the critical point  $p_c$  and  $\beta$  is called the order parameter exponent. In terms of the scaling form presented in Eq. 1, one then has  $x = p$ ,  $y(x, L) = P_\infty(p, L)$ ,  $a = 1/\nu$  and  $b = \beta/\nu$ .

For the scaling analysis, square systems of side length  $L = 128, 256, \text{ and } 512$  are considered. First, the optimal scaling parameters are determined in subsection 3.1, then the errors of the scaling parameters are estimated in subsection 3.2, and the scaling plot that illustrates the data collapse is presented in subsection 3.3.

#### 3.1 Determine the optimal scaling parameters

If one settles for an approximation of the scaling function up to lowest order in the respective argument, as mentioned above in section 1, one can expect that the scaling assumption holds best close to the critical point and that there are corrections to the scaling behavior outside the critical scaling window. In this regard, it might be useful to restrict the scaling analysis to a finite interval on the rescaled abscissa. By trend, if one performs the scaling analysis for an interval  $\Delta x$  of decreasing width that contains the critical point, then the quality of the data collapse improves. However, one should always find a fair compromise between a small value of  $S$  and a reasonably large interval  $\Delta x$  on the rescaled abscissa.

To get a grip on how sensitive the scaling parameters are with respect to the interval  $\Delta x$ , one can perform a repeated scaling analysis by using, e.g., a shell script similar to the following

```
# FILE: scalingScript.sh
# TASK: invoke scaling analysis program for different intervals xr
# USAGE: bash scalingScript.sh
for MAX in 1.5 1.25 1.0 0.75 ;
do
  for MIN in -2.25 -2.0 -1.75 -1.5 -1.25 -1. -0.75 ;
  do
    python autoScale.py -f inputFiles.dat -o scaled_L512_256_128.out \
      -xc 0.5927 -a 0.75 -b 0.104 -showS -xr ${MIN} ${MAX}
  done
done
```

The output file `scaled_L512_256_128.out` then contains the results of the scaling analyses in the form:

```
dx = [-2.250000:1.500000] xc = 0.592571 a = 0.753171 b = 0.106964 s = 1.993244
dx = [-2.250000:1.250000] xc = 0.592619 a = 0.752468 b = 0.106216 s = 1.505830
dx = [-1.750000:1.000000] xc = 0.592687 a = 0.749537 b = 0.105055 s = 1.153121
dx = [-1.500000:1.000000] xc = 0.592708 a = 0.747566 b = 0.104459 s = 1.076691
dx = [-1.000000:1.000000] xc = 0.592686 a = 0.748386 b = 0.104841 s = 0.735622
dx = [-1.000000:0.750000] xc = 0.592689 a = 0.749151 b = 0.104670 s = 0.767656
dx = [-0.750000:0.750000] xc = 0.592709 a = 0.746708 b = 0.104098 s = 0.769959
```

Note that only a few lines of the output file are shown.

According to the scaling analysis, the best data collapse ( $S \approx 0.74$ ) was obtained for the interval  $\Delta x \in [-1.0 : 1.0]$ . The respective scaling parameters read  $x_c = 0.592686$ ,  $a = 0.748386$ , and  $b = 0.104841$ . However, there are no errorbars, yet. They will be determined next.

## 3.2 Estimate errors of the scaling parameters

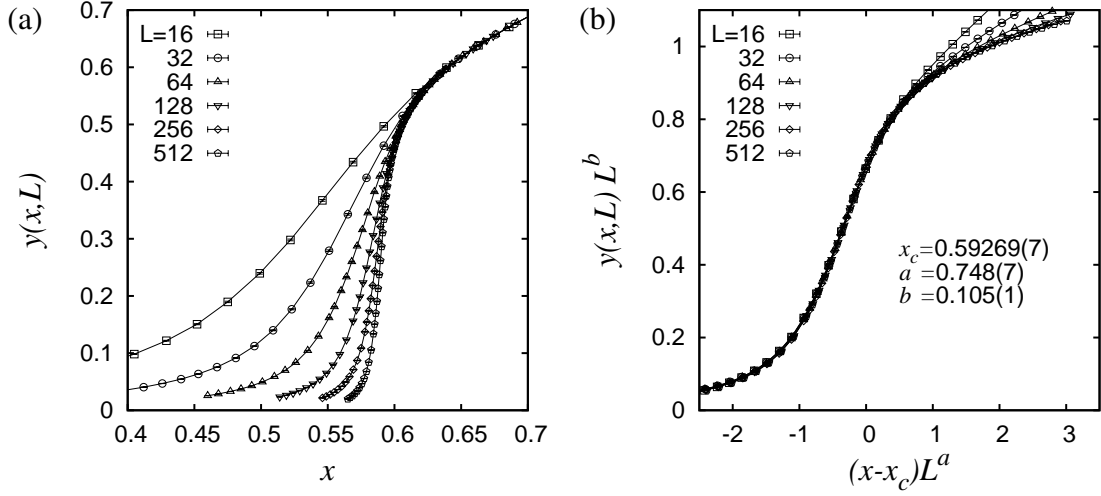
`autoScale.py` estimates the errorbars for the scaling parameters above by means of a so called  $S + 1$  analysis, as described in [4]. Therefore, `autoScale.py` simply needs to be called with the additional command line parameter `-getError` as

```
python autoScale.py -f inputFiles.dat -o error.out \
  -xc 0.5927 -a 0.75 -b 0.104 -xr -1.0 1.0 -getError
```

This results in the output file `error.out`:

```
# S+1 error analysis yields:
# Scaling analysis restricted to
xr = [-1.000000 : 1.000000]
# <scalePar> <-Err> <+Err>
xc = 0.592686 0.000075 0.000075
a = 0.748386 0.005913 0.007462
b = 0.104841 0.000975 0.000975
```

Since the calculation of the errors requires some additional effort, it should not be performed during repeated calls of `autoScale.py`, as in subsection 3.2 above. However, once the optimal parameters are identified, the option `-getError` can be used to get



**Figure 1:** Illustration of the data collapse technique for the order parameter of the site percolation problem in  $2d$ . (a) unscaled data for different system sizes  $L$  close to the critical point. Each data point represents an average over  $\approx 12\,800$  individual occupied/empty configurations simulated at the respective values of  $x$  and  $L$ . (b) data collapse after the scaling parameter optimization using `autoScale.py` according to the scaling assumption Eq. 1.

a grip on the errorbars of the scaling parameters. By convention, the larger of the two values  $\langle + / - \text{Err} \rangle$  is taken as the final error bar for the respective scaling parameter.

### 3.3 Illustration of the data collapse

Here, the result of the FSS analysis is illustrated for the order parameter of the percolation model, as introduced in the preface to the present section. In this regard, Fig. 1(a) shows the unscaled data and Fig. 1(b) illustrates the data collapse obtained for the optimized scaling parameters  $x_c$ ,  $a$  and  $b$ . In Figs. 1(a),(b), each data point represents an average over  $\approx 12\,800$  individual occupied/empty configurations, simulated at the respective values of  $x$  and  $L$ . With increasing system size, the critical region narrows as  $\sim L^{-a}$ , see Fig. 1(a). If the data curves for different system sizes are superposed and rescaled in a proper manner, they fall on top of each other, as evident from Fig. 1(b). If one settles for an approximation of the scaling function up to lowest order in the respective argument, as mentioned above in section 1, one can expect that the scaling assumption holds best close to the critical point and that there are corrections to the scaling behavior outside the critical scaling window. This can also be seen in Fig. 1(b), where, for values  $(x - x_c)L^a > 1$  on the rescaled abscissa, the curves belonging to different system sizes  $L$  start to deviate from each other. Finally, note that the values of the optimal scaling parameters determined in subsections 3.2 and 3.3 are in agreement



with the exact exponents for  $2d$  percolation (given in the squared braces):

$$\begin{aligned}x_c &= 0.59269(7) [0.59274621(13)] \\ a &= 0.748(7) [3/4 = 0.75] \\ b &= 0.105(1) [15/144 \approx 0.1042]\end{aligned}$$

For the highly precise estimate of the numerical value for  $x_c$  in the squared braces see Ref. [16].

## 4 Limitations and tips

Within the presented section, subsection 4.1 explains some requirements that have to be fulfilled in order to use `autoScale.py`, subsection 4.2 discusses the limitations of `autoScale.py` and 4.3 explains how to obtain an initial guess for the scaling parameters using the `gnuplot` data plotting tool [17]. Finally, subsection 4.4 gives some practical tips on how to improve the outcome of a scaling analysis.

### 4.1 System requirements

In order to use `autoScale.py`, the following requirements have to be fulfilled:

- Download the source files of this preprint by choosing the download-option `other`. Save the respective source-file archive on your system and extract it in order to find the supplementary archive `SCALING_ANALYSIS.tar.gz`. Extract the supplementary archive via `tar -xzvf SCALING_ANALYSIS.tar.gz` and see the readme-file contained therein.
- `autoScale.py` has been under development since 2007. It was implemented under `Python 2.3.4` (and later versions) and it imports only basic `Python`-modules that come with any `python` installation. Accordingly, check that you have installed `Python 2.3` or a later version on your system. You can check your current `Python` version by typing `python -V`. If necessary, see [2] or ask your system administrator.
- Read this users guide and the readme-file contained in the supplementary archive `SCALING_ANALYSIS.tar.gz`.

### 4.2 Limitations of `autoScale.py`

Unfortunately, `autoScale.py` is not guaranteed to find an optimal set of scaling parameters at all. This is due to the drawback that multidimensional minimization algorithms, as the downhill simplex algorithm, are likely spoiled by the immediate payoff

arising from local minima in the fitness landscape. Once caught by such a local minimum, it is hard to escape from it and the scaling parameters are likely to converge to non-optimal values. A remedy for this would be to restart the scaling analysis for a different “guess” of the initial scaling parameters and to check the quality of the resulting scaling parameters visually by using data plotting tools as, e.g., `gnuplot` [17]. However, if the initial scaling parameters are reasonably close to the optimal parameters, the minimization procedure will work well.

### 4.3 Scaling parameters: how to obtain an initial guess

As pointed out above, the quality of the initial scaling parameters is crucial for a successful finite-size scaling analysis. In this regard, one can already obtain estimates for the scaling parameters that are sufficiently close to the optimum in order to ensure a good performance of the FSS routine by means of simple data plotting tools. Unfortunately, the `gnuplot` program itself cannot process command line arguments. This makes it very inconvenient to tune the scaling parameters by hand. However, the following shell script is a workaround that can be used to create a scaling plot and to visually inspect the data collapse for a given set of scaling parameters that are passed as command line arguments:

```
# FILE: scalingPlot.sh
# TASK: create scaling plot to inspect data collapse
# USAGE: bash scalingPlot.sh <xc> <a> <b>
P='./ORDER_PARAMETER' # path to input files
gnuplot -persist << EOF

set key samplen 1. left # customize key
set xl "(x-xc) L^a"; set yl "y L^b" # set x,y labels
xc=$1; a=$2; b=$3 # set scaling parameters
set label 1 "xc=$1\na=$2\nb=$3" at graph 0.7,0.2 # list scaling parameters
sx(x,L)=(x-xc)*L**a; sy(y,L)=y*L**b # def scaling assumption

p "$P/orderParam_L16.dat" u (sx(\$1,16)): (sy(\$2,16)) w lp t "L=16"\
, "$P/orderParam_L32.dat" u (sx(\$1,32)): (sy(\$2,32)) w lp t " 32"\
, "$P/orderParam_L64.dat" u (sx(\$1,64)): (sy(\$2,64)) w lp t " 64"\
, "$P/orderParam_L128.dat" u (sx(\$1,128)): (sy(\$2,128)) w lp t " 128"\
, "$P/orderParam_L256.dat" u (sx(\$1,256)): (sy(\$2,256)) w lp t " 256"\
, "$P/orderParam_L512.dat" u (sx(\$1,512)): (sy(\$2,512)) w lp t " 512"
EOF
```

This script can be used to obtain a rough guess for the scaling parameters that enter the scaling assumption. Consequently, `autoScale.py` can be used to optimize these initial parameters.

### 4.4 Scaling analysis: how to improve the result

There are several options to improve the results of a scaling analysis:

- Leave out small system sizes. This will reduce systematic errors that are due to finite-size effects.
- Use at least three data sets. This will ensure that the master function, computed by `autoScale.py` in order to determine the quality of the data collapse, behaves quite smooth.
- Increase the number of interpolation points in the critical region. This will significantly improve the master function.
- Increase the number of samples that make up the individual data points. This will improve the statistics of the raw data and also lead to a somewhat smaller error of the optimal scaling parameters.

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## References

- [1] The source code of `autoScale.py` is contained in the supplementary archive `SCALING_ANALYSIS.tar.gz`.
- [2] Python is a high-level general-purpose programming language that can be applied to many different classes of problems, see <http://www.python.org/>
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- [17] Gnuplot is a command-line driven interactive data and function plotting utility, see <http://www.gnuplot.info>