

# sTrainSeq

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sTrainSeq

*Function to implement training via sequential algorithm*

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## Description

sTrainSeq is supposed to perform sequential training algorithm. It requires three inputs: a "sMap" or "sInit" object, input data, and a "sTrain" object specifying training environment. The training is implemented iteratively, each training cycle consisting of: i) randomly choose one input vector; ii) determine the winner hexagon/rectangle (BMH) according to minimum distance of codebook matrix to the input vector; ii) update the codebook matrix of the BMH and its neighbors via updating formula (see "Note" below for details). It also returns an object of class "sMap".

## Usage

```
sTrainSeq(sMap, data, sTrain, verbose = T)
```

## Arguments

sMap	an object of class "sMap" or "sInit"
data	a data frame or matrix of input data
sTrain	an object of class "sTrain"
verbose	logical to indicate whether the messages will be displayed in the screen. By default, it sets to TRUE for display

## Value

an object of class "sMap", a list with following components:

- nHex: the total number of hexagons/rectanges in the grid
- xdim: x-dimension of the grid
- ydim: y-dimension of the grid
- lattice: the grid lattice
- shape: the grid shape
- coord: a matrix of nHex x 2, with each row corresponding to the coordinates of a hexagon/rectangle in the 2D map grid
- init: an initialisation method

- neighKernel: the training neighborhood kernel
- codebook: a codebook matrix of nHex x ncol(data), with each row corresponding to a prototype vector in input high-dimensional space
- call: the call that produced this result

### Note

Updating formula is:  $m_i(t+1) = m_i(t) + \alpha(t) * h_{wi}(t) * [x(t) - m_i(t)]$ , where

- $t$  denotes the training time/step
- $i$  and  $w$  stand for the hexagon/rectangle  $i$  and the winner BMH  $w$ , respectively
- $x(t)$  is an input vector randomly chosen (from the input data) at time  $t$
- $m_i(t)$  and  $m_i(t+1)$  are respectively the prototype vectors of the hexagon  $i$  at time  $t$  and  $t+1$
- $\alpha(t)$  is the learning rate at time  $t$ . There are three types of learning rate functions:
  - For "linear" function,  $\alpha(t) = \alpha_0 * (1 - t/T)$
  - For "power" function,  $\alpha(t) = \alpha_0 * (0.005/\alpha_0)^{t/T}$
  - For "invert" function,  $\alpha(t) = \alpha_0/(1 + 100 * t/T)$
  - Where  $\alpha_0$  is the initial learning rate (typically,  $\alpha_0 = 0.5$  at "rough" stage,  $\alpha_0 = 0.05$  at "finetune" stage),  $T$  is the length of training time/step (often being set to input data length, i.e., the total number of rows)
- $h_{wi}(t)$  is the neighborhood kernel, a non-increasing function of i) the distance  $d_{wi}$  between the hexagon/rectangle  $i$  and the winner BMH  $w$ , and ii) the radius  $\delta_t$  at time  $t$ . There are five kernels available:
  - For "gaussian" kernel,  $h_{wi}(t) = e^{-d_{wi}^2/(2*\delta_t^2)}$
  - For "cutgaussian" kernel,  $h_{wi}(t) = e^{-d_{wi}^2/(2*\delta_t^2)} * (d_{wi} \leq \delta_t)$
  - For "bubble" kernel,  $h_{wi}(t) = (d_{wi} \leq \delta_t)$
  - For "ep" kernel,  $h_{wi}(t) = (1 - d_{wi}^2/\delta_t^2) * (d_{wi} \leq \delta_t)$
  - For "gamma" kernel,  $h_{wi}(t) = 1/\Gamma(d_{wi}^2/(4 * \delta_t^2) + 2)$

### See Also

[sTrainology](#), [visKernels](#)

### Examples

```
# 1) generate an iid normal random matrix of 100x10
data <- matrix( rnorm(100*10,mean=0,sd=1), nrow=100, ncol=10)

# 2) from this input matrix, determine nHex=5*sqrt(nrow(data))=50,
# but it returns nHex=61, via "sHexGrid(nHex=50)", to make sure a supra-hexagonal grid
sTopol <- sTopology(data=data, lattice="hexa", shape="suprahex")

# 3) initialise the codebook matrix using "uniform" method
sI <- sInitial(data=data, sTopol=sTopol, init="uniform")

# 4) define trainology at "rough" stage
sT_rough <- sTrainology(sMap=sI, data=data, algorithm="sequential",
stage="rough")

# 5) training at "rough" stage
sM_rough <- sTrainSeq(sMap=sI, data=data, sTrain=sT_rough)
```

```
# 6) define trainology at "finetune" stage
sT_finetune <- sTrainology(sMap=sI, data=data, algorithm="sequential",
stage="finetune")

# 7) training at "finetune" stage
sM_finetune <- sTrainSeq(sMap=sM_rough, data=data, sTrain=sT_rough)
```