

# Package ‘LZeroSpikeInference’

October 18, 2017

**Type** Package

**Title** Exact Spike Train Inference via L0 Optimization

**Version** 1.0.3

**Description**

An implementation of algorithms described in Jewell and Witten (2017) <arXiv:1703.08644>.

**License** GPL-3

**Encoding** UTF-8

**LazyData** true

**RoxygenNote** 6.0.1

**Suggests** testthat

**Imports** graphics, stats

**NeedsCompilation** no

**Author** Sean Jewell [aut, cre]

**Maintainer** Sean Jewell <swjewell@uw.edu>

**Repository** CRAN

**Date/Publication** 2017-10-18 03:33:29 UTC

## R topics documented:

cv.estimateSpikes . . . . .	2
estimateSpikes . . . . .	4
LZeroSpikeInference . . . . .	5
plot.cvSpike . . . . .	6
plot.estimatedSpikes . . . . .	6
plot.simdata . . . . .	7
print.cvSpike . . . . .	8
print.estimatedSpikes . . . . .	8
print.simdata . . . . .	9
simulateAR1 . . . . .	9

<b>Index</b>	<b>11</b>
--------------	-----------

---

cv.estimateSpikes      *Cross-validate and optimize model parameters*

---

### Description

Cross-validate and optimize model parameters

### Usage

```
cv.estimateSpikes(dat, type = "ar1", gam = NULL, lambdas = NULL,
  nLambdas = 10, hardThreshold = TRUE)
```

### Arguments

dat	fluorescence trace (a vector)
type	type of model, must be one of AR(1) 'ar1', or AR(1) with intercept 'intercept'
gam	a scalar value for the AR(1)/AR(1) + intercept decay parameter
lambdas	vector of tuning parameters to use in cross-validation
nLambdas	number of tuning parameters to estimate the model (grid of values is automatically produced)
hardThreshold	boolean specifying whether the calcium concentration must be non-negative (in the AR-1 problem)

### Details

We perform cross-validation over a one-dimensional grid of  $\lambda$  values. For each value of  $\lambda$  in this grid, we solve the corresponding optimization problem, that is, one of

**AR(1)-model:** minimize  $c_1, \dots, c_T$   $0.5 \sum_{t=1}^T (y_t - c_t)^2 + \lambda \sum_{t=2}^T 1_{c_t \neq \gamma c_{t-1}}$  for the global optimum, where  $y_t$  is the observed fluorescence at the  $t$ th timepoint.

If `hardThreshold = T` then the additional constraint  $c_t \geq 0$  is added to the optimization problem above.

**AR(1) with intercept:** minimize  $c_1, \dots, c_T, b_1, \dots, b_T$   $0.5 \sum_{t=1}^T (y_t - c_t - b_t)^2 + \lambda \sum_{t=2}^T 1_{c_t \neq \gamma c_{t-1}, b_t \neq b_{t-1}}$  where the indicator variable  $1_{(A,B)}$  equals 1 if the event  $A \cup B$  holds, and equals zero otherwise.

on a training set using a candidate value for  $\gamma$ . Given the resulting set of changepoints, we solve a constrained optimization problem for  $\gamma$ . We then refit the optimization problem with the optimized value of  $\gamma$ , and then evaluate the mean squared error (MSE) on a hold-out set. Note that in the final output of the algorithm, we take the square root of the optimal value of  $\gamma$  in order to address the fact that the cross-validation scheme makes use of training and test sets consisting of alternately-spaced timesteps.

If there is a tuning parameter  $\lambda_{\text{T}}$  in the path  $[\lambda_{\text{Min}}, \lambda_{\text{Max}}]$  that produces a fit with less than 1 spike per 10,000 timesteps the path is truncated to  $[\lambda_{\text{Min}}, \lambda_{\text{T}}]$  and a warning is produced.

See Algorithm 3 of Jewell and Witten (2017) <arXiv:1703.08644>

**Value**

A list of values corresponding to the 2-fold cross-validation:

cvError the MSE for each tuning parameter

cvSE the SE for the MSE for each tuning parameter

lambdas tuning parameters

optimalGam matrix of (optimized) parameters, rows correspond to tuning parameters, columns correspond to optimized parameter

lambdaMin tuning parameter that gives the smallest MSE

lambda1SE 1 SE tuning parameter

indexMin the index corresponding to lambdaMin

index1SE the index corresponding to lambda1SE

**See Also**

**Estimate spikes:** [estimateSpikes](#), [print.estimatedSpikes](#), [plot.estimatedSpikes](#).

**Cross validation:** [cv.estimateSpikes](#), [print.cvSpike](#), [plot.cvSpike](#).

**Simulation:** [simulateAR1](#), [plot.simdata](#).

**Examples**

```
# Not run
# sim <- simulateAR1(n = 500, gam = 0.998, poisMean = 0.009, sd = 0.05, seed = 1)
# plot(sim)

# AR(1) model
# outAR1 <- cv.estimateSpikes(sim$f1, type = "ar1")
# plot(outAR1)
# print(outAR1)
# fit <- estimateSpikes(sim$f1, gam = outAR1$optimalGam[outAR1$index1SE, 1],
# lambda = outAR1$lambda1SE, type = "ar1")
# plot(fit)
# print(fit)

# AR(1) + intercept model
# outAR1Intercept <- cv.estimateSpikes(sim$f1, type = "intercept",
# lambda = seq(0.1, 5, length.out = 10))
# plot(outAR1Intercept)
# print(outAR1Intercept)
# fit <- estimateSpikes(sim$f1, gam = outAR1Intercept$optimalGam[outAR1Intercept$index1SE, 1],
# lambda = outAR1Intercept$lambda1SE, type = "intercept")
# plot(fit)
# print(fit)
```

---

estimateSpikes	<i>Estimate spike train, underlying calcium concentration, and change-points based on fluorescence trace.</i>
----------------	---------------------------------------------------------------------------------------------------------------

---

### Description

Estimate spike train, underlying calcium concentration, and changepoints based on fluorescence trace.

### Usage

```
estimateSpikes(dat, gam, lambda, type = "ar1", calcFittedValues = TRUE,
  hardThreshold = FALSE)
```

### Arguments

dat	fluorescence data
gam	a scalar value for the AR(1)/AR(1) + intercept decay parameter.
lambda	tuning parameter lambda
type	type of model, must be one of AR(1) 'ar1', AR(1) + intercept 'intercept'.
calcFittedValues	TRUE to calculate fitted values.
hardThreshold	boolean specifying whether the calcium concentration must be non-negative (in the AR-1 problem)

### Details

This algorithm solves the optimization problems

**AR(1)-model:** minimize  $c_1, \dots, c_T$   $0.5 \sum_{t=1}^T (y_t - c_t)^2 + \lambda \sum_{t=2}^T 1_{c_t \neq \gamma c_{t-1}}$  for the global optimum, where  $y_t$  is the observed fluorescence at the  $t$ th timepoint. If `hardThreshold = T` then the additional constraint  $c_t \geq 0$  is added to the optimization problem above.

**AR(1) with intercept:** minimize  $c_1, \dots, c_T, b_1, \dots, b_T$   $0.5 \sum_{t=1}^T (y_t - c_t - b_t)^2 + \lambda \sum_{t=2}^T 1_{c_t \neq \gamma c_{t-1}, b_t \neq b_{t-1}}$  where the indicator variable  $1_{(A,B)}$  equals 1 if the event  $A \cup B$  holds, and equals zero otherwise.

See Jewell and Witten (2017) <arXiv:1703.08644>, section 2 and 5.

Note that "changePts" and "spikes" differ by one index due to a quirk of the conventions used in the changepoint literature and the definition of a spike.

### Value

Returns a list with elements:

changePts the set of changepoints

spikes the set of spikes

fittedValues estimated calcium concentration

**See Also**

**Estimate spikes:** [estimateSpikes](#), [print.estimatedSpikes](#), [plot.estimatedSpikes](#).

**Cross validation:** [cv.estimateSpikes](#), [print.cvSpike](#), [plot.cvSpike](#).

**Simulation:** [simulateAR1](#), [plot.simdata](#).

**Examples**

```
sim <- simulateAR1(n = 500, gam = 0.998, poisMean = 0.009, sd = 0.05, seed = 1)
plot(sim)

# AR(1) model

fit <- estimateSpikes(sim$f1, gam = 0.998, lambda = 1, type = "ar1")
plot(fit)
print(fit)

# AR(1) + intercept model
fit <- estimateSpikes(sim$f1, gam = 0.998, lambda = 1, type = "intercept")
plot(fit)
print(fit)
```

---

LZeroSpikeInference     *LZeroSpikeInference: LZeroSpikeInference: A package for estimating spike times from calcium imaging data using an L0 penalty*

---

**Description**

This package implements an algorithm for deconvolving calcium imaging data for a single neuron in order to estimate the times at which the neuron spikes.

**Details**

This package implements an algorithm for deconvolving calcium imaging data for a single neuron in order to estimate the times at which the neuron spikes. This algorithm solves the optimization problems

**AR(1)-model:** minimize  $c_1, \dots, c_T$   $0.5 \sum_{t=1}^T (y_t - c_t)^2 + \lambda \sum_{t=2}^T 1_{c_t \neq \gamma c_{t-1}}$  for the global optimum, where  $y_t$  is the observed fluorescence at the  $t$ th timepoint.

If `hardThreshold = T` then the additional constraint  $c_t \geq 0$  is added to the optimization problem above.

**AR(1) with intercept:** minimize  $c_1, \dots, c_T, b_1, \dots, b_T$   $0.5 \sum_{t=1}^T (y_t - c_t - b_t)^2 + \lambda \sum_{t=2}^T 1_{c_t \neq \gamma c_{t-1}} + \sum_{t=1}^T 1_{b_t \neq \gamma b_{t-1}}$  where the indicator variable  $1_{(A,B)}$  equals 1 if the event A cup B holds, and equals zero otherwise.

See Jewell and Witten (2017) <arXiv:1703.08644>

**See Also**

**Estimate spikes:** [estimateSpikes](#), [print.estimatedSpikes](#), [plot.estimatedSpikes](#).

**Cross validation:** [cv.estimateSpikes](#), [print.cvSpike](#), [plot.cvSpike](#).

**Simulation:** [simulateAR1](#), [plot.simdata](#).

**Examples**

```
# To reproduce Figure 1 of Jewell and Witten (2017) <arXiv:1703.08644>

sampleData <- simulateAR1(n = 500, gam = 0.998, poisMean = 0.009, sd = 0.15, seed = 8)
fit <- estimateSpikes(sampleData$f1, gam = 0.998, lambda = 8, type = "ar1")
plot(fit)
```

---

plot.cvSpike	<i>Plot mean squared error vs. tuning parameter from the cross-validation output</i>
--------------	--------------------------------------------------------------------------------------

---

**Description**

Plot mean squared error vs. tuning parameter from the cross-validation output

**Usage**

```
## S3 method for class 'cvSpike'
plot(x, ...)
```

**Arguments**

x	output from cross validation procedure
...	arguments to be passed to methods

---

plot.estimatedSpikes	<i>Plot the solution to an L0 segmentation problem</i>
----------------------	--------------------------------------------------------

---

**Description**

Plot the solution to an L0 segmentation problem

**Usage**

```
## S3 method for class 'estimatedSpikes'
plot(x, xlims = NULL, ...)
```

**Arguments**

x                    output from running estimateSpikes  
 xlims                optional parameter to specify the x-axis limits  
 ...                   arguments to be passed to methods

**See Also**

**Estimate spikes:** [estimateSpikes](#), [print.estimatedSpikes](#), [plot.estimatedSpikes](#).

**Cross validation:** [cv.estimateSpikes](#), [print.cvSpike](#), [plot.cvSpike](#).

**Simulation:** [simulateAR1](#), [plot.simdata](#).

plot.simdata

*Plot simulated data***Description**

Plot simulated data

**Usage**

```
## S3 method for class 'simdata'
plot(x, xlims = NULL, ...)
```

**Arguments**

x                    output data from simulateAR1  
 xlims                optional parameter to specify the x-axis limits  
 ...                   arguments to be passed to methods

**Value**

Plot with simulated fluorescence (dark grey circles), calcium concentration (dark green line) and spikes (dark green tick marks on x-axis)

**See Also**

**Estimate spikes:** [estimateSpikes](#), [print.estimatedSpikes](#), [plot.estimatedSpikes](#).

**Cross validation:** [cv.estimateSpikes](#), [print.cvSpike](#), [plot.cvSpike](#).

**Simulation:** [simulateAR1](#), [plot.simdata](#).

**Examples**

```
sim <- simulateAR1(n = 500, gam = 0.998, poisMean = 0.009, sd = 0.05, seed = 1)
plot(sim)
```

---

`print.cvSpike`      *Print CV results*

---

**Description**

Print CV results

**Usage**

```
## S3 method for class 'cvSpike'  
print(x, ...)
```

**Arguments**

<code>x</code>	output from CV
<code>...</code>	arguments to be passed to methods

---

`print.estimatedSpikes`      *Print estimated spikes*

---

**Description**

Print estimated spikes

**Usage**

```
## S3 method for class 'estimatedSpikes'  
print(x, ...)
```

**Arguments**

<code>x</code>	estimated spikes
<code>...</code>	arguments to be passed to methods



---

print.simdata	<i>Print simulated data</i>
---------------	-----------------------------

---

**Description**

Print simulated data

**Usage**

```
## S3 method for class 'simdata'
print(x, ...)
```

**Arguments**

x	simulated data
...	arguments to be passed to methods

---

simulateAR1	<i>Simulate fluorescence trace based on simple AR(1) generative model</i>
-------------	---------------------------------------------------------------------------

---

**Description**

Simulate fluorescence trace based on simple AR(1) generative model

**Usage**

```
simulateAR1(n, gam, poisMean, sd, seed)
```

**Arguments**

n	number of timesteps
gam	AR(1) decay rate
poisMean	mean for Poisson distributed spikes
sd	standard deviation
seed	random seed

**Details**

Simulate fluorescence trace based on simple AR(1) generative model

$$y_t = c_t + \text{eps}, \text{eps} \sim N(0, \text{sd})$$

$$c_t = \text{gam} * c_{t-1} + s_t$$

$$s_t \sim \text{Pois}(\text{poisMean})$$

**Value**

spikes, fluorescence, and calcium concentration

**See Also**

**Estimate spikes:** [estimateSpikes](#), [print.estimatedSpikes](#), [plot.estimatedSpikes](#).

**Cross validation:** [cv.estimateSpikes](#), [print.cvSpike](#), [plot.cvSpike](#).

**Simulation:** [simulateAR1](#), [plot.simdata](#).

**Examples**

```
sim <- simulateAR1(n = 500, gam = 0.998, poisMean = 0.009, sd = 0.05, seed = 1)
plot(sim)
```

# Index

`cv.estimateSpikes`, [2](#), [3](#), [5–7](#), [10](#)  
`estimateSpikes`, [3](#), [4](#), [5–7](#), [10](#)  
`LZeroSpikeInference`, [5](#)  
`LZeroSpikeInference-package`  
    (`LZeroSpikeInference`), [5](#)  
`plot.cvSpike`, [3](#), [5](#), [6](#), [6](#), [7](#), [10](#)  
`plot.estimatedSpikes`, [3](#), [5](#), [6](#), [6](#), [7](#), [10](#)  
`plot.simdata`, [3](#), [5–7](#), [7](#), [10](#)  
`print.cvSpike`, [3](#), [5–7](#), [8](#), [10](#)  
`print.estimatedSpikes`, [3](#), [5–7](#), [8](#), [10](#)  
`print.simdata`, [9](#)  
`simulateAR1`, [3](#), [5–7](#), [9](#), [10](#)