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**si4ul**

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## SI4UL.CHANGEPOINT\_SI MODULE

`si4ul.changepoint_si.optseg_si(x, sigma=1, beta=1.5)`  
computing valid p-values for optimal changepoint by Selective Inference using Dynamic Programming.

**Parameters**

- **x** (*array-like of shape (point-num)*) – time series data.
- **sigma** (*float*) – standard deviation in distribution of time series data.
- **beta** (*float*) – regularization factor.

**Returns** changepoint list and p-values of each changepoint.

**Return type** (array-like of shape (changepoint-num), array-like of shape (changepoint-num))

**Examples**

```
>>> seg, p_list = changepoint_si.optseg_si(x)
>>> print(seg)
[25, 40, 59, 80, 100, 125, 140, 159, 180]
>>> print(p_list)
[6.439051311970013e-06, 5.451462826100586e-07, 3.589542368255502e-07, 7.
↪ 74132481356728e-05, 0.11719543493338598, 6.4387982662212394e-06, 1.
↪ 1776732917248327e-06, 3.589542368255725e-07, 1.8180641069769048e-09]
```

`si4ul.changepoint_si.optseg_si_oc(x, sigma=1, beta=1.5)`  
computing valid p-values for optimal changepoint by over-comditiioning Selective Inference.

**Parameters**

- **x** (*array-like of shape (point-num)*) – time series data.
- **sigma** (*float*) – standard deviation in distribution of time series data.
- **beta** (*float*) – regularization factor.

**Returns** changepoint list and p-values of each changepoint.

**Return type** (array-like of shape (changepoint-num), array-like of shape (changepoint-num))

## Examples

```
>>> seg, p_list = changepoint_si.optseg_si(x)
>>> print(seg)
[25, 40, 59, 75, 80, 100, 125, 140, 159, 175, 180]
>>> print(p_list)
[0.013528694810211626, 0.05567852225768205, 0.329173206633249, 0.36014111520463954, ↵
↵0.4101971284236369, 0.6981932657047393, 0.16996861755494708, 0.3719537702838958, ↵
↵0.3592986205789473, 0.36014111520464676, 0.1196678816881915]
```

```
si4ul.changepoint_si.plot_changepoint_detection(x, sg_results, p_value_list, alpha, underlying=None,
                                                segment_size=0, title='OptSeg-SI')
```

the result of optimal changepoint after SI.

### Parameters

- **x** (*array-like of shape (point-num)*) – time series data.
- **sg\_results** (*array-like of shape (changepoint-num)*) – changepoint list.
- **p\_value\_list** (*array-like of shape (changepoint-num)*) – p-values of each changepoint.
- **alpha** (*float*) – significance level.
- **underlying** (*array-like of shape (true changepoint-num)*) – mean values of true segment.
- **segment\_size** (*float*) – true segment size.
- **title** (*string*) – plot title.

## SI4UL.MULTISEQ\_CP\_SI MODULE

`si4ul.multiseq_cp_si.multiseq_cp_dc_si(X, K, L, Xi=1, Sigma=1, test='hom', width=0, phi=0.5)`  
computing valid p-values for changepoint with Double-CUSUM by Selective Inference.

### Parameters

- **X** (*ndarray of shape (component, location)*) – multi-dimensional sequence.
- **K** (*int*) – the number of change locations.
- **L** (*int*) – minimum segment length.
- **Xi** (*float or ndarray, optional*) – component's variance. Defaults to 1.
- **Sigma** (*float or ndarray, optional*) – location's variance. Defaults to 1.
- **test** (*str, optional*) – Set 'hom' for homotopy search, 'oc' for over-conditioning, 'naive' for naive test. Defaults to 'homotopy'.
- **width** (*int, optional*) – same cp width. Defaults to 0
- **phi** (*float, optional*) – Double-CUSUM's parameter. Defaults to 0.5

**Returns** change-location, change-component and p-values of each changepoint.

**Return type** (array-like of shape (changepoint-num))

### Examples

```
>>> result = multiseq_cp_dc_si(X, 1, 5)
>>> print(result)
[[10, 0, 1.1237052306791954e-12], [10, 1, 2.050601922239704e-09]]
```

`si4ul.multiseq_cp_si.multiseq_cp_scan_si(X, K, L, Xi=1, Sigma=1, test='hom', width=0)`  
computing valid p-values for changepoint with scan statistic by Selective Inference.

### Parameters

- **X** (*ndarray of shape (component, location)*) – multi-dimensional sequence.
- **K** (*int*) – the number of change locations.
- **L** (*int*) – minimum segment length.
- **Xi** (*float or ndarray, optional*) – component's variance. Defaults to 1.
- **Sigma** (*float or ndarray, optional*) – location's variance. Defaults to 1.
- **test** (*str, optional*) – Set 'hom' for homotopy search, 'oc' for over-conditioning, 'naive' for naive test. Defaults to 'homotopy'.

- **width** (*int, optional*) – same cp width. Defaults to 0

**Returns** change-location, change-component and p-values of each changepoint.

**Return type** (array-like of shape (changepoint-num))

### Examples

```
>>> result = multiseq_cp_scan_si(X, 1, 5)
>>> print(result)
[[10, 0, 1.1237052306791954e-12], [10, 1, 2.050601922239704e-09]]
```

`si4ul.multiseq_cp_si.plot_multiseq(X, true_cp=None, true_mean=None)`

Plot of multi-dimensional sequence.

#### Parameters

- **X** (*ndarray of shape (component, location)*) – multi-dimensional sequence.
- **true\_cp** (*array-like of shape (components, true-cp-num+2)*) – the true change point position
- **true\_mean** (*array-like of shape (components, true-cp-num+1)*) – true population mean

`si4ul.multiseq_cp_si.plot_multiseq_si(X, result, alpha=0.05, true_cp=None, true_mean=None)`

the result of multiseq changepoint after SI.

#### Parameters

- **X** (*ndarray of shape (component, location)*) – multi-dimensional sequence.
- **result** (*array-like of shape (changepoint-num)*) – change-location, change-component and p-values list
- **alpha** (*float*) – significance level. Defaults to 0.05
- **true\_cp** (*array-like of shape (components, true-cp-num+2)*) – the true change point position
- **true\_mean** (*array-like of shape (components, true-cp-num+1)*) – true population mean



## SI4UL.KMEANS\_SI MODULE

`si4ul.kmeans_si.all_clusters_combination_test(obs_model, test_gene=None, sigma=1.0)`  
post clustering inference for all cluster combinations. If `test_gene` is set, test is `PCI_gene`. otherwise, test is `PCI_cluster`.

### Parameters

- **obs\_model** (`KMeans`) – refer to document of `KMeans`.
- **test\_gene** (`int`) – feature to compare.
- **sigma** (`float`) – standard deviation in distribution.

**Returns** matrix of test statistics, matrix of homotopy `PCI` p-value and matrix of naive p-value.

**Return type** (array-like of shape(3, cluster\_num, cluster\_num))

### Examples

```
>>> print(kmeans_si.all_clusters_combination_test(obs_model))
pci_cluster
(array([[nan, 5.24520442, 4.53785448], [nan, nan, 5.38552569], [nan, nan, nan]]),
array([[nan, 0.01863257, 0.00028306], [nan, nan, 0.00359755], [nan, nan, nan]]),
array([[nan, 1.06122705e-06, 3.37658148e-05], [nan, nan, 5.03368420e-07], [nan, nan,
↪ nan]]))
```

`si4ul.kmeans_si.kmeans(X, n_clusters)`  
k-means clustering algorithm.

### Parameters

- **X** (array-like of shape  $(n, d)$ ) – data matrix.
- **n\_clusters** (`int`) – number of cluster.

**Returns** refer to document of `KMeans`.

**Return type** `KMeans`

## Examples

```
>>> print(kmeans_si.kmeans(X, K))
<si4ul.si.kmeans_si.KMeans at 0x102aef700>
```

```
si4ul.kmeans_si.pci_cluster(obs_model, comparison_clusters, sigma=1.0, max_iter=1000, random_seed=0,
                             z_max=20)
```

post clustering inference for test between clusters.

### Parameters

- **obs\_model** ([KMeans](#)) – refer to document of KMeans.
- **comparison\_clusters** (*array-like of shape(2)*) – set of clusters to compare.
- **sigma** (*float*) – standard deviation in distribution.
- **max\_iter** (*int*) – upper limit count of iteration in k-means algorithm.
- **random\_seed** (*int*) – seed of random for determine initial cluster.
- **z\_max** (*float*) – upper limit of parameter z on test statistics vector.

**Returns** test statistics, homotopy PCI p-value and naive p-value.

**Return type** (float, float, float)

## Examples

```
>>> print(kmeans_si.pci_cluster(obs_model, comparison_clusters))
(5.245204424402314, 0.018632573868904267, 1.0612270479959528e-06)
```

```
si4ul.kmeans_si.pci_gene(obs_model, comparison_clusters, test_gene, sigma=1.0, max_iter=1000,
                          random_seed=0, z_max=20)
```

post clustering inference for test between clusters about a feature.

### Parameters

- **obs\_model** ([KMeans](#)) – refer to document of KMeans.
- **comparison\_clusters** (*array-like of shape(2)*) – set of clusters to compare.
- **sigma** (*float*) – standard deviation in distribution.
- **test\_gene** (*int*) – feature to compare.
- **max\_iter** (*int*) – upper limit count of iteration in k-means algorithm.
- **random\_seed** (*int*) – seed of random for determine initial cluster.
- **z\_max** (*float*) – upper limit of parameter z on test statistics vector.

**Returns** test statistics, homotopy PCI p-value and naive p-value.

**Return type** (float, float, float)

## Examples

```
>>> print(kmeans_si.pci_gene(obs_model, comparison_clusters, gene_id))
(0.26352301450242993, 0.4212956294190716, 0.20005529456703786)
```

`si4ul.kmeans_si.plot_histogram(obs_model, comparison_clusters, test_gene, is_plot_norm=False)`  
 plot histogram of distribution per cluster using test.

### Parameters

- **obs\_model** ([KMeans](#)) – refer to document of KMeans.
- **comparison\_clusters** (*array-like of shape(2)*) – set of clusters to compare.
- **test\_gene** (*int*) – feature to plot.
- **is\_plot\_norm** (*bool*) – whether plot normal distribution in background.

`si4ul.kmeans_si.plot_p_matrix(matrix, digit=3, alpha=0.05)`  
 plot matrix of p-value that is calculated by each cluster combinations.

### Parameters

- **matrix** (*array-like of shape(cluster\_num, cluster\_num)*) – matrix of p-value.
- **digit** (*int*) – digit number to display.
- **alpha** (*float*) – significant level.

`si4ul.kmeans_si.plot_scatter(obs_model, comparison_clusters, show_dims)`  
 plot scatter data in inputted 2-dims per cluster using test.

### Parameters

- **obs\_model** ([KMeans](#)) – refer to document of KMeans.
- **comparison\_clusters** (*array-like of shape(2)*) – set of clusters to compare.
- **show\_dims** (*array-like of shape(2)*) – set of dims to show.

`si4ul.kmeans_si.plot_statistics_matrix(matrix, digit=3)`  
 plot matrix of statistics that is calculated by each cluster combinations.

### Parameters

- **matrix** (*array-like of shape(cluster\_num, cluster\_num)*) – matrix of test statistics.
- **digit** (*int*) – digit number to display.

`si4ul.kmeans_si.plot_violin(obs_model, test_gene)`  
 plot violin per cluster using test and other.

### Parameters

- **obs\_model** ([KMeans](#)) – refer to document of KMeans.
- **test\_gene** (*int*) – feature to plot.

## 3.1 si4ul.si.kmeans\_si module

**class** si4ul.si.kmeans\_si.KMeans(*X, n\_clusters, max\_iter=1000, random\_seed=0*)

Bases: object

this class returns the results of k-means clustering. we can get from kmeans\_si.kmeans(). other kmeans\_si APIs need this object to input.

**cluster\_centers\_**

cluster center matrix.

**Type** array-like of shape(*n\_clusters, d*)

**count**

count of iteration in k-means algorithm.

**Type** int

**labels\_**

label vector that each data join.

**Type** array-like of shape(*n*)

**label\_num\_list**

list of the number of data contained in the cluster.

**Type** array-like of shape(*n\_clusters*)

**max\_iter**

upper limit count of iteration in k-means algorithm.

**Type** int

**n\_clusters**

number of cluster.

**Type** int

**random\_seed**

seed of random for determine initial cluster.

**Type** int

**X**

data matrix.

**Type** array-like of shape(*n, d*)

### Examples

```
>>> kMeans.X
array([[ 1.32473015,  0.12584954], [ 0.17229311,  2.01200624], [ 1.47662313, -1.
↪ 28557418], [ 0.1302503 , -0.43927367], [-1.41546232,  0.13654847], [-1.05260842,
↪ 1.20597647], [-0.14717876, -0.15950429], [-0.61262757,  0.05772617], [ 0.92854842,
↪ -0.49440228], [-0.80456805, -1.15935248]])
>>> kMeans.n_clusters
3
>>> kMeans.cluster_centers_
array([[ 1.47662313, -1.28557418], [ 0.55908753, -0.24183267], [-0.74259465,  0.
↪ 45058097]])
```

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```
>>> kMeans.labels_  
array([1, 2, 0, 1, 2, 2, 1, 2, 1, 2])  
>>> kMeans.label_num_list  
[1, 4, 5]  
>>> kMeans.count  
2
```



## SI4UL.SEGMENTATION\_SI MODULE

`si4ul.segmentation_si.plot_histogram(local_white)`  
plot histogram of pixel values in input image.

**Parameters** `local_white` (`LocalWhite`) – segmetation object.

`si4ul.segmentation_si.plot_histogram_region(local_white, display_statistics=False)`  
plot histogram of pixel values per region.

**Parameters** `local_white` (`LocalWhite`) – segmetation object.

`si4ul.segmentation_si.psegi_thresholding(local_white, sigma=10)`  
post segmentation inference for local white segmentation.

**Parameters**

- `local_white` (`LocalWhite`) – segmetation object.
- `sigma` (`float`) – standard deviation in distribution of input image.

**Returns** test statistics, PSegI p-value, naive p-value.

**Return type** (`float`, `float`, `float`)

### Examples

```
>>> print(segmentation_si.psegi_thresholding(local_white))
(31.08397312484288, 0.08085241645874175, 0.0)
```

`si4ul.segmentation_si.thresholding(image_path, result_dir_path, window_size=50, bias=1.1, is_blur=True, ksize=(11, 11), sigma_x=0, sigma_y=0, is_output_regions=False)`

local white segmentation algorithm. If bias is bigger than 1, algorithm can detect black object. If bias is smaller than 1, algorithm can detect white object.

**Parameters**

- `image_path` (`string`) – image path to segmentation.
- `result_dir_path` (`string`) – directory to store the segmentation results.
- `window_size` (`int`) – length of the side of the square in the nearest pixel range.
- `bias` (`float`) – bias used in threshold determination. If it's bigger than 1, algorithm can detect black object. If it's smaller than 1, algorithm can detect white object.
- `isBlur` (`bool`) – whether to use Gaussian smoothing for image preprocessing.
- `ksize` (`Tuple(int, int)`) – the side of the convolution window for Gaussian smoothing.

- **sigma\_x** (*float*) – standard deviation of x-coordinate for Gaussian smoothing.
- **sigma\_y** (*float*) – standard deviation of y-coordinate for Gaussian smoothing.
- **is\_output\_regions** (*bool*) – wheter to make images of each regions.

**Returns** reffer to document of LocalWhite.

**Return type** *LocalWhite*

### Examples

```
>>> print(segmentation_si.thresholding('./image.jpg', './result/image_18'))
<si4ul.si.segmentation_si.LocalWhite at 0x10e33efa0>
```

## 4.1 si4ul.si.segmentation\_si module

**class** si4ul.si.segmentation\_si.**LocalWhite**(*image\_path, result\_dir\_path, window\_size, bias, is\_blur, ksize, sigma\_x, sigma\_y*)

Bases: object

this class returns the results of local white segmentation. we can get from `segmentation_si.thresholding()`. other `segmentation_si` APIs need this object to input.

#### **bias**

bias used in threshold determination. If it's bigger than 1, algorithm can detect black object. If it's smaller than 1, algorithm can detect white object.

**Type** float

#### **image**

input image of segmentation.

**Type** array-like of shape (image\_height, image\_width)

#### **image\_gaussian**

image after Gaussian smoothing.

**Type** array-like of shape (image\_height, image\_width)

#### **image\_height**

height of image.

**Type** int

#### **image\_original**

image matrix read in from the input image.

**Type** array-like of shape (image\_height, image\_width)

#### **image\_path**

image path to segmentation.

**Type** string

#### **image\_width**

width of image.

**Type** int



**result\_dir\_path**

directory to store the segmentation results.

**Type** string

**window\_size**

length of the side of the square in the nearest pixel range.

**Type** int

**Examples**

```
>>> localWhite.image
array([[147, 147, 147, ..., 155, 157, 157],
       [147, 147, 148, ..., 154, 156, 156],
       [148, 148, 148, ..., 153, 154, 154],
       ...,
       [159, 158, 157, ..., 152, 151, 150],
       [159, 159, 157, ..., 152, 150, 150],
       [159, 159, 157, ..., 152, 150, 149]], dtype=uint8)
>>> localWhite.image_height, localWhite.image_width
(88, 73)
```



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