
fdasrsf Documentation

Release 1.4.5

J. Derek Tucker

Aug 06, 2019

CONTENTS

1	Functional Alignment	3
2	Functional Principal Component Analysis	7
3	Elastic Principal Component Regression	9
4	Gaussian Generative Models	11
5	Functional Principal Least Squares	13
6	Elastic Regression	15
7	Elastic Principal Component Regression	21
8	SRVF Geodesic Computation	23
9	Utility Functions	27
10	Curve Functions	33
11	Indices and tables	39
	Python Module Index	41
	Index	43

A python package for functional data analysis using the square root slope framework and curves using the square root velocity framework which performs pair-wise and group-wise alignment as well as modeling using functional component analysis and regression.

FUNCTIONAL ALIGNMENT

Group-wise function alignment using SRSF framework and Dynamic Programming

moduleauthor:: Derek Tucker <jdtuck@sandia.gov>

`time_warping.align_fPCA(f, time, num_comp=3, showplot=True, smoothdata=False)`

aligns a collection of functions while extracting principal components. The functions are aligned to the principal components

Parameters

- **f** (*np.ndarray*) – numpy ndarray of shape (M,N) of N functions with M samples
- **time** (*np.ndarray*) – vector of size M describing the sample points
- **num_comp** – number of fPCA components
- **showplot** – Shows plots of results using matplotlib (default = T)
- **smooth_data** (*bool*) – Smooth the data using a box filter (default = F)
- **sparam** (*double*) – Number of times to run box filter (default = 25)

Return type tuple of numpy array

Return fn aligned functions - numpy ndarray of shape (M,N) of N functions with M samples

Return qn aligned srvfs - similar structure to fn

Return q0 original srvf - similar structure to fn

Return mqn srvf mean or median - vector of length M

Return gam warping functions - similar structure to fn

Return q_pca srsf principal directions

Return f_pca functional principal directions

Return latent latent values

Return coef coefficients

Return U eigenvectors

Return orig_var Original Variance of Functions

Return amp_var Amplitude Variance

Return phase_var Phase Variance

`time_warping.align_fPLS(f, g, time, comps=3, showplot=True, smoothdata=False, delta=0.01, max_itr=100)`

This function aligns a collection of functions while performing principal least squares

Parameters

- **f** (*np.ndarray*) – numpy ndarray of shape (M,N) of N functions with M samples
- **g** (*np.ndarray*) – numpy ndarray of shape (M,N) of N functions with M samples
- **time** (*np.ndarray*) – vector of size M describing the sample points
- **comps** – number of fPLS components
- **showplot** – Shows plots of results using matplotlib (default = T)
- **smooth_data** (*bool*) – Smooth the data using a box filter (default = F)
- **delta** – gradient step size
- **max_itr** – maximum number of iterations

Return type tuple of numpy array

Return fn aligned functions - numpy ndarray of shape (M,N) of N

functions with M samples :return gn: aligned functions - numpy ndarray of shape (M,N) of N functions with M samples :return qfn: aligned srfs - similar structure to fn :return qgn: aligned srfs - similar structure to fn :return qf0: original srfs - similar structure to fn :return qg0: original srfs - similar structure to fn :return gam: warping functions - similar structure to fn :return wqf: srsf principal weight functions :return wqg: srsf principal weight functions :return wf: srsf principal weight functions :return wg: srsf principal weight functions :return cost: cost function value

`time_warping.srsf_align(f, time, method='mean', omethod='DP', showplot=True, smoothdata=False, lam=0.0)`

This function aligns a collection of functions using the elastic square-root slope (srsf) framework.

Parameters

- **f** – numpy ndarray of shape (M,N) of N functions with M samples
- **time** – vector of size M describing the sample points
- **method** – (string) warp calculate Karcher Mean or Median

(options = “mean” or “median”) (default=”mean”) :param omethod: optimization method (DP, DP2, RBFGS) (default = DP) :param showplot: Shows plots of results using matplotlib (default = T) :param smoothdata: Smooth the data using a box filter (default = F) :param parallel: run in parallel (default = F) :param lam: controls the elasticity (default = 0) :type lam: double :type smoothdata: bool :type f: np.ndarray :type time: np.ndarray

Return type tuple of numpy array

Return fn aligned functions - numpy ndarray of shape (M,N) of N

functions with M samples :return qn: aligned srfs - similar structure to fn :return q0: original srfs - similar structure to fn :return fmean: function mean or median - vector of length M :return mqn: srfs mean or median - vector of length M :return gam: warping functions - similar structure to fn :return orig_var: Original Variance of Functions :return amp_var: Amplitude Variance :return phase_var: Phase Variance

Examples >>> import tables >>> fun=tables.open_file("../Data/simu_data.h5") >>> f = fun.root.f[:] >>> f = f.transpose() >>> time = fun.root.time[:] >>> out = srsf_align(f,time)

`time_warping.srsf_align_pair(f, g, time, method='mean', showplot=True, smoothdata=False, lam=0.0)`

This function aligns a collection of functions using the elastic square- root slope (srsf) framework.

Parameters

- **f** (*np.ndarray*) – numpy ndarray of shape (M,N) of N functions with M samples

- **g** – numpy ndarray of shape (M,N) of N functions with M samples
- **time** (*np.ndarray*) – vector of size M describing the sample points
- **method** – (string) warp calculate Karcher Mean or Median (options = “mean” or “median”) (default=“mean”)
- **showplot** – Shows plots of results using matplotlib (default = T)
- **smoothdata** (*bool*) – Smooth the data using a box filter (default = F)
- **lam** (*double*) – controls the elasticity (default = 0)

Return type tuple of numpy array

Return fn aligned functions - numpy ndarray of shape (M,N) of N functions with M samples

Return gn aligned functions - numpy ndarray of shape (M,N) of N functions with M samples

Return qfn aligned srvfs - similar structure to fn

Return qgn aligned srvfs - similar structure to fn

Return qf0 original srvf - similar structure to fn

Return qg0 original srvf - similar structure to fn

Return fmean f function mean or median - vector of length N

Return gmean g function mean or median - vector of length N

Return mqfn srvf mean or median - vector of length N

Return mqgn srvf mean or median - vector of length N

Return gam warping functions - similar structure to fn

FUNCTIONAL PRINCIPAL COMPONENT ANALYSIS

Vertical and Horizontal Functional Principal Component Analysis using SRSF

moduleauthor:: Derek Tucker <jdtuck@sandia.gov>

fPCA.**horizfPCA** (*gam, time, no=2, showplot=True*)

This function calculates horizontal functional principal component analysis on aligned data

Parameters

- **gam** – numpy ndarray of shape (M,N) of N warping functions
- **time** – vector of size M describing the sample points
- **no** (*int*) – number of components to extract (default = 2)
- **showplot** (*bool*) – Shows plots of results using matplotlib (default = T)

Return type tuple of numpy ndarray

Return q_pca srsf principal directions

Return f_pca functional principal directions

Return latent latent values

Return coef coefficients

Return U eigenvectors

fPCA.**jointfPCA** (*fn, time, qn, q0, gam, no=2, showplot=True*)

This function calculates joint functional principal component analysis on aligned data

Parameters

- **fn** – numpy ndarray of shape (M,N) of N aligned functions with M samples
- **time** – vector of size N describing the sample points
- **qn** – numpy ndarray of shape (M,N) of N aligned SRSF with M samples
- **no** (*int*) – number of components to extract (default = 2)
- **showplot** (*bool*) – Shows plots of results using matplotlib (default = T)

Return type tuple of numpy ndarray

Return q_pca srsf principal directions

Return f_pca functional principal directions

Return latent latent values

Return coef coefficients

Return U eigenvectors

`fPCA.vertfPCA(fn, time, qn, no=2, showplot=True)`

This function calculates vertical functional principal component analysis on aligned data

Parameters

- **fn** – numpy ndarray of shape (M,N) of N aligned functions with M samples
- **time** – vector of size N describing the sample points
- **qn** – numpy ndarray of shape (M,N) of N aligned SRSF with M samples
- **no** (*int*) – number of components to extract (default = 2)
- **showplot** (*bool*) – Shows plots of results using matplotlib (default = T)

Return type tuple of numpy ndarray

Return q_pca srsf principal directions

Return f_pca functional principal directions

Return latent latent values

Return coef coefficients

Return U eigenvectors

ELASTIC PRINCIPAL COMPONENT REGRESSION

Elastic Functional Boxplots

moduleauthor:: Derek Tucker <jdtuck@sandia.gov>

`boxplots.ampbox` (*ft, f_median, qt, q_median, time, alpha=0.05, k_a=1*)

This function constructs the amplitude boxplot using the elastic square-root slope (srsf) framework.

Parameters

- **ft** – numpy ndarray of shape (M,N) of N functions with M samples
- **f_median** – vector of size M describing the median
- **qt** – numpy ndarray of shape (M,N) of N srsf functions with M samples
- **q_median** – vector of size M describing the srsf median
- **time** – vector of size M describing the time
- **alpha** – quantile value (e.g.,=.05, i.e., 95%)
- **k_a** – scalar for outlier cutoff (e.g.,=1)

Return type tuple of numpy array

Return fn aligned functions - numpy ndarray of shape (M,N) of N

functions with M samples :return Q1: First quartile :return Q3: Second quartile :return Q1a: First quartile based on alpha :return Q3a: Second quartile based on alpha :return minn: minimum extreme function :return maxx: maximum extreme function :return outlier_index: indexes of outlier functions :return f_median: median function :return q_median: median srsf :return plt: surface plot mesh

`boxplots.phbox` (*gam, time, alpha=0.05, k_a=1*)

This function constructs phase boxplot for functional data using the elastic square-root slope (srsf) framework.

Parameters

- **gam** – numpy ndarray of shape (M,N) of N warping functions with M samples
- **alpha** – quantile value (e.g.,=.05, i.e., 95%)
- **k_a** – scalar for outlier cutoff (e.g.,=1)

Return type tuple of numpy array

Return fn aligned functions - numpy ndarray of shape (M,N) of N

functions with M samples :return Q1: First quartile :return Q3: Second quartile :return Q1a: First quartile based on alpha :return Q3a: Second quartile based on alpha :return minn: minimum extreme function :return maxx: maximum extreme function :return outlier_index: indexes of outlier functions :return median_x: median warping function :return psi_median: median srsf of warping function :return plt: surface plot mesh

GAUSSIAN GENERATIVE MODELS

Gaussian Model of functional data

moduleauthor:: Derek Tucker <jdtuck@sandia.gov>

`gauss_model.gauss_model` (*fn*, *time*, *qn*, *gam*, *n=1*, *sort_samples=False*)

This function models the functional data using a Gaussian model extracted from the principal components of the *srvfs*

Parameters

- **fn** (*np.ndarray*) – numpy ndarray of shape (M,N) of N aligned functions with M samples
- **time** (*np.ndarray*) – vector of size M describing the sample points
- **qn** (*np.ndarray*) – numpy ndarray of shape (M,N) of N aligned *srvfs* with M samples
- **gam** (*np.ndarray*) – warping functions
- **n** (*integer*) – number of random samples
- **sort_samples** (*bool*) – sort samples (default = T)

Return type tuple of numpy array

Return fs random aligned samples

Return gams random warping functions

Return ft random samples

FUNCTIONAL PRINCIPAL LEAST SQUARES

Partial Least Squares using SVD

moduleauthor:: Derek Tucker <jdtuck@sandia.gov>

fPLS.**pls_svd**(*time, qf, qg, no, alpha=0.0*)

This function computes the partial least squares using SVD

Parameters

- **time** – vector describing time samples
- **qf** – numpy ndarray of shape (M,N) of N functions with M samples
- **qg** – numpy ndarray of shape (M,N) of N functions with M samples
- **no** – number of components
- **alpha** – amount of smoothing (Default = 0.0 i.e., none)

Return type numpy ndarray

Return wqf f weight function

Return wqg g weight function

Return alpha smoothing value

Return values singular values

ELASTIC REGRESSION

Warping Invariant Regression using SRSF

moduleauthor:: Derek Tucker <jdtuck@sandia.gov>

`regression.elastic_logistic(f, y, time, B=None, df=20, max_itr=20, cores=-1, smooth=False)`

This function identifies a logistic regression model with phase-variability using elastic methods

Parameters

- **f** (*np.ndarray*) – numpy ndarray of shape (M,N) of N functions with M samples
- **y** – numpy array of labels (1/-1)
- **time** (*np.ndarray*) – vector of size M describing the sample points
- **B** – optional matrix describing Basis elements
- **df** – number of degrees of freedom B-spline (default 20)
- **max_itr** – maximum number of iterations (default 20)
- **cores** – number of cores for parallel processing (default all)

Return type tuple of numpy array

Return alpha alpha parameter of model

Return beta beta(t) of model

Return fn aligned functions - numpy ndarray of shape (M,N) of M

functions with N samples :return qn: aligned srvfs - similar structure to fn :return gamma: calculated warping functions :return q: original training SRSFs :return B: basis matrix :return b: basis coefficients :return Loss: logistic loss

`regression.elastic_mlogistic(f, y, time, B=None, df=20, max_itr=20, cores=-1, delta=0.01, parallel=True, smooth=False)`

This function identifies a multinomial logistic regression model with phase-variability using elastic methods

Parameters

- **f** (*np.ndarray*) – numpy ndarray of shape (M,N) of N functions with M samples
- **y** – numpy array of labels {1,2,...,m} for m classes
- **time** (*np.ndarray*) – vector of size M describing the sample points
- **B** – optional matrix describing Basis elements
- **df** – number of degrees of freedom B-spline (default 20)
- **max_itr** – maximum number of iterations (default 20)

- **cores** – number of cores for parallel processing (default all)

Return type tuple of numpy array

Return alpha alpha parameter of model

Return beta beta(t) of model

Return fn aligned functions - numpy ndarray of shape (M,N) of N

functions with M samples :return qn: aligned srvfs - similar structure to fn :return gamma: calculated warping functions :return q: original training SRSFs :return B: basis matrix :return b: basis coefficients :return Loss: logistic loss

`regression.elastic_prediction(f, time, model, y=None, smooth=False)`

This function performs prediction from an elastic regression model with phase-variability

Parameters

- **f** – numpy ndarray of shape (M,N) of N functions with M samples
- **time** – vector of size M describing the sample points
- **model** – identified model from elastic_regression
- **y** – truth, optional used to calculate SSE

Return type tuple of numpy array

Return alpha alpha parameter of model

Return beta beta(t) of model

Return fn aligned functions - numpy ndarray of shape (M,N) of N

functions with M samples :return qn: aligned srvfs - similar structure to fn :return gamma: calculated warping functions :return q: original training SRSFs :return B: basis matrix :return b: basis coefficients :return SSE: sum of squared error

`regression.elastic_regression(f, y, time, B=None, lam=0, df=20, max_itr=20, cores=-1, smooth=False)`

This function identifies a regression model with phase-variability using elastic methods

Parameters

- **f** (*np.ndarray*) – numpy ndarray of shape (M,N) of N functions with M samples
- **y** – numpy array of N responses
- **time** (*np.ndarray*) – vector of size M describing the sample points
- **B** – optional matrix describing Basis elements
- **lam** – regularization parameter (default 0)
- **df** – number of degrees of freedom B-spline (default 20)
- **max_itr** – maximum number of iterations (default 20)
- **cores** – number of cores for parallel processing (default all)

Return type tuple of numpy array

Return alpha alpha parameter of model

Return beta beta(t) of model

Return fn aligned functions - numpy ndarray of shape (M,N) of M

functions with N samples :return qn: aligned srvfs - similar structure to fn :return gamma: calculated warping functions :return q: original training SRSFs :return B: basis matrix :return b: basis coefficients :return SSE: sum of squared error

`regression.logistic_warp(beta, time, q, y)`
calculates optimal warping for function logistic regression

Parameters

- **beta** – numpy ndarray of shape (M,N) of N functions with M samples
- **time** – vector of size N describing the sample points
- **q** – numpy ndarray of shape (M,N) of N functions with M samples
- **y** – numpy ndarray of shape (1,N) responses

Return type numpy array

Return gamma warping function

`regression.logit_gradient(b, X, y)`
calculates gradient of the logistic loss

Parameters

- **b** – numpy ndarray of shape (M,N) of N functions with M samples
- **X** – numpy ndarray of shape (M,N) of N functions with M samples
- **y** – numpy ndarray of shape (1,N) responses

Return type numpy array

Return grad gradient of logisitic loss

`regression.logit_hessian(s, b, X, y)`
calculates hessian of the logistic loss

Parameters

- **s** – numpy ndarray of shape (M,N) of N functions with M samples
- **b** – numpy ndarray of shape (M,N) of N functions with M samples
- **X** – numpy ndarray of shape (M,N) of N functions with M samples
- **y** – numpy ndarray of shape (1,N) responses

Return type numpy array

Return out hessian of logistic loss

`regression.logit_loss(b, X, y)`
logistic loss function, returns $\text{Sum}\{-\log(\phi(t))\}$

Parameters

- **b** – numpy ndarray of shape (M,N) of N functions with M samples
- **X** – numpy ndarray of shape (M,N) of N functions with M samples
- **y** – numpy ndarray of shape (1,N) of N responses

Return type numpy array

Return out loss value

`regression.mlogit_gradient(b, X, Y)`
calculates gradient of the multinomial logistic loss

Parameters

- **b** – numpy ndarray of shape (M,N) of N functions with M samples
- **x** – numpy ndarray of shape (M,N) of N functions with M samples
- **y** – numpy ndarray of shape (1,N) responses

Return type numpy array

Return grad gradient

`regression.mlogit_loss(b, X, Y)`
calculates multinomial logistic loss (negative log-likelihood)

Parameters

- **b** – numpy ndarray of shape (M,N) of N functions with M samples
- **x** – numpy ndarray of shape (M,N) of N functions with M samples
- **y** – numpy ndarray of shape (1,N) responses

Return type numpy array

Return nll negative log-likelihood

`regression.mlogit_warp_grad(alpha, beta, time, q, y, max_itr=8000, tol=1e-10, delta=0.008, display=0)`
calculates optimal warping for functional multinomial logistic regression

Parameters

- **alpha** – scalar
- **beta** – numpy ndarray of shape (M,N) of N functions with M samples
- **time** – vector of size M describing the sample points
- **q** – numpy ndarray of shape (M,N) of N functions with M samples
- **y** – numpy ndarray of shape (1,N) responses
- **max_itr** – maximum number of iterations (Default=8000)
- **tol** – stopping tolerance (Default=1e-10)
- **delta** – gradient step size (Default=0.008)
- **display** – display iterations (Default=0)

Return type tuple of numpy array

Return gam_old warping function

`regression.phi(t)`
calculates logistic function, returns $1 / (1 + \exp(-t))$

Parameters **t** – scalar

Return type numpy array

Return out return value

`regression.regression_warp(beta, time, q, y, alpha)`
calculates optimal warping for function linear regression

Parameters

- **beta** – numpy ndarray of shape (M,N) of M functions with N samples
- **time** – vector of size N describing the sample points
- **q** – numpy ndarray of shape (M,N) of M functions with N samples
- **y** – numpy ndarray of shape (1,N) of M functions with N samples

responses :param alpha: numpy scalar

Return type numpy array

Return gamma_new warping function

ELASTIC PRINCIPAL COMPONENT REGRESSION

Warping PCR Invariant Regression using SRSF

moduleauthor:: Derek Tucker <jdtuck@sandia.gov>

```
pcr_regression.elastic_lpcr_regression(f, y, time, pca_method='combined', no=5,  
                                       smooth_data=False, sparam=25)
```

This function identifies a logistic regression model with phase-variability using elastic pca

Parameters

- **f** (*np.ndarray*) – numpy ndarray of shape (M,N) of N functions with M samples
- **y** – numpy array of N responses
- **time** (*np.ndarray*) – vector of size M describing the sample points
- **pca_method** – string specifying pca method (options = “combined”, “vert”, or “horiz”, default = “combined”)
- **no** – scalar specify number of principal components (default=5)
- **smooth_data** – smooth data using box filter (default = F)
- **sparam** – number of times to apply box filter (default = 25)

Return type tuple of numpy array

Return alpha alpha parameter of model

Return b regressor vector

Return y response vector

Return warp_data alignment object from srsf_align

Return pca fpca object from corresponding pca method

Return Loss logistic loss

Return pca.method string of pca method

```
pcr_regression.elastic_mlpcr_regression(f, y, time, pca_method='combined', no=5,  
                                       smooth_data=False, sparam=25)
```

This function identifies a logistic regression model with phase-variability using elastic pca

Parameters

- **f** (*np.ndarray*) – numpy ndarray of shape (M,N) of N functions with M samples
- **y** – numpy array of N responses
- **time** (*np.ndarray*) – vector of size M describing the sample points

- **pca_method** – string specifying pca method (options = “combined”, “vert”, or “horiz”, default = “combined”)
- **no** – scalar specify number of principal components (default=5)
- **smooth_data** – smooth data using box filter (default = F)
- **sparam** – number of times to apply box filter (default = 25)

Return type tuple of numpy array

Return alpha alpha parameter of model

Return b regressor vector

Return y response vector

Return warp_data alignment object from srsf_align

Return pca fpca object from corresponding pca method

Return Loss logistic loss

Return pca.method string of pca method

```

pcr_regression.elastic_pcr_regression(f, y, time, pca_method='combined', no=5,
                                     smooth_data=False, sparam=25, parallel=False,
                                     C=None)

```

This function identifies a regression model with phase-variability using elastic pca

Parameters

- **f** (*np.ndarray*) – numpy ndarray of shape (M,N) of N functions with M samples
- **y** – numpy array of N responses
- **time** (*np.ndarray*) – vector of size M describing the sample points
- **pca_method** – string specifying pca method (options = “combined”, “vert”, or “horiz”, default = “combined”)
- **no** – scalar specify number of principal components (default=5)
- **smooth_data** – smooth data using box filter (default = F)
- **sparam** – number of times to apply box filter (default = 25)
- **parallel** – run in parallel (default = F)
- **C** – scale balance parameter for combined method (default = None)

Return type tuple of numpy array

Return alpha alpha parameter of model

Return b regressor vector

Return y response vector

Return warp_data alignment object from srsf_align

Return pca fpca object from corresponding pca method

Return SSE sum of squared errors

Return pca.method string of pca method

SRVF GEODESIC COMPUTATION

geodesic calculation for SRVF (curves) open and closed)

moduleauthor:: Derek Tucker <jdtuck@sandia.gov>

`geodesic.back_parallel_transport` (*u1*, *alpha*, *basis*, *T=100*, *k=5*)
backwards parallel translates q1 and q2 along manifold

Parameters

- **u1** – numpy ndarray of shape (2,M) of M samples
- **alpha** – numpy ndarray of shape (2,M) of M samples
- **basis** – list numpy ndarray of shape (2,M) of M samples
- **T** – Number of samples of curve (Default = 100)
- **k** – number of samples along path (Default = 5)

Return type numpy ndarray

Return utilde translated vector

`geodesic.calc_alphadot` (*alpha*, *basis*, *T=100*, *k=5*)
calculates derivative along the path alpha

Parameters

- **alpha** – numpy ndarray of shape (2,M) of M samples
- **basis** – list of numpy ndarray of shape (2,M) of M samples
- **T** – Number of samples of curve (Default = 100)
- **k** – number of samples along path (Default = 5)

Return type numpy ndarray

Return alphadot derivative of alpha

`geodesic.calculate_energy` (*alphadot*, *T=100*, *k=5*)
calculates energy along path

Parameters

- **alphadot** – numpy ndarray of shape (2,M) of M samples
- **T** – Number of samples of curve (Default = 100)
- **k** – number of samples along path (Default = 5)

Return type numpy scalar

Return E energy

`geodesic.calculate_gradE(u, utilde, T=100, k=5)`
calculates gradient of energy along path

Parameters

- **u** – numpy ndarray of shape (2,M) of M samples
- **utilde** – numpy ndarray of shape (2,M) of M samples
- **T** – Number of samples of curve (Default = 100)
- **k** – number of samples along path (Default = 5)

Return type numpy scalar

Return gradE gradient of energy

Return normgradE norm of gradient of energy

`geodesic.cov_integral(alpha, alphadot, basis, T=100, k=5)`
Calculates covariance along path alpha

Parameters

- **alpha** – numpy ndarray of shape (2,M) of M samples (first curve)
- **alphadot** – numpy ndarray of shape (2,M) of M samples
- **basis** – list numpy ndarray of shape (2,M) of M samples
- **T** – Number of samples of curve (Default = 100)
- **k** – number of samples along path (Default = 5)

Return type numpy ndarray

Return u covariance

`geodesic.find_basis_normal_path(alpha, k=5)`
computes orthonormalized basis vectors to the normal space at each of the k points (q-functions) of the path alpha

Parameters

- **alpha** – numpy ndarray of shape (2,M) of M samples (path)
- **k** – number of samples along path (Default = 5)

Return type numpy ndarray

Return basis basis vectors along the path

`geodesic.geod_dist_path_strt(beta, k=5)`
calculate geodesic distance for path straightening

Parameters

- **beta** – numpy ndarray of shape (2,M) of M samples
- **k** – number of samples along path (Default = 5)

Return type numpy scalar

Return dist geodesic distance

`geodesic.geod_sphere(beta1, beta2, k=5)`
This function calculates the geodesic between open curves beta1 and beta2 with k steps along path

Parameters

- **beta1** – numpy ndarray of shape (2,M) of M samples
- **beta2** – numpy ndarray of shape (2,M) of M samples
- **k** – number of samples along path (Default = 5)

Return type numpy ndarray

Return dist geodesic distance

Return path geodesic path

Return O rotation matrix

`geodesic.init_path_geod(beta1, beta2, T=100, k=5)`

Initializes a path in $\text{cal}\{C\}$. beta1, beta2 are already standardized curves. Creates a path from beta1 to beta2 in shape space, then projects to the closed shape manifold.

Parameters

- **beta1** – numpy ndarray of shape (2,M) of M samples (first curve)
- **beta2** – numpy ndarray of shape (2,M) of M samples (end curve)
- **T** – Number of samples of curve (Default = 100)
- **k** – number of samples along path (Default = 5)

Return type numpy ndarray

Return alpha a path between two q-functions

Return beta a path between two curves

Return O rotation matrix

`geodesic.init_path_rand(beta1, beta_mid, beta2, T=100, k=5)`

Initializes a path in $\text{cal}\{C\}$. beta1, beta_mid, beta2 are already standardized curves. Creates a path from beta1 to beta_mid to beta2 in shape space, then projects to the closed shape manifold.

Parameters

- **beta1** – numpy ndarray of shape (2,M) of M samples (first curve)
- **betamid** – numpy ndarray of shape (2,M) of M samples (mid curve)
- **beta2** – numpy ndarray of shape (2,M) of M samples (end curve)
- **T** – Number of samples of curve (Default = 100)
- **k** – number of samples along path (Default = 5)

Return type numpy ndarray

Return alpha a path between two q-functions

Return beta a path between two curves

Return O rotation matrix

`geodesic.path_straightening(beta1, beta2, betamid, init='rand', T=100, k=5)`

Perform path straightening to find geodesic between two shapes in either the space of closed curves or the space of affine standardized curves. This algorithm follows the steps outlined in section 4.6 of the manuscript.

Parameters

- **beta1** – numpy ndarray of shape (2,M) of M samples (first curve)

- **beta2** – numpy ndarray of shape (2,M) of M samples (end curve)
- **betamid** – numpy ndarray of shape (2,M) of M samples (mid curve Default = NULL, only needed for init “rand”)
- **init** – initialize path geodesic or random (Default = “rand”)
- **T** – Number of samples of curve (Default = 100)
- **k** – number of samples along path (Default = 5)

Return type numpy ndarray

Return dist geodesic distance

Return path geodesic path

Return pathsqnc geodesic path sequence

Return E energy

`geodesic.update_path(alpha, beta, gradE, delta, T=100, k=5)`

Update the path along the direction -gradE

Parameters

- **alpha** – numpy ndarray of shape (2,M) of M samples
- **beta** – numpy ndarray of shape (2,M) of M samples
- **gradE** – numpy ndarray of shape (2,M) of M samples
- **delta** – gradient parameter
- **T** – Number of samples of curve (Default = 100)
- **k** – number of samples along path (Default = 5)

Return type numpy scalar

Return alpha updated path of srvfs

Return beta updated path of curves

UTILITY FUNCTIONS

Utility functions for SRSF Manipulations

moduleauthor:: Derek Tucker <jdtuck@sandia.gov>

`utility_functions.SqrtMean(gam)`

calculates the srsf of warping functions with corresponding shooting vectors

Parameters **gam** – numpy ndarray of shape (M,N) of M warping functions with N samples

Return type 2 numpy ndarray and vector

Return mu Karcher mean psi function

Return gam_mu vector of dim N which is the Karcher mean warping function

Return psi numpy ndarray of shape (M,N) of M SRSF of the warping functions

Return vec numpy ndarray of shape (M,N) of M shooting vectors

`utility_functions.SqrtMeanInverse(gam)`

finds the inverse of the mean of the set of the diffeomorphisms gamma

Parameters **gam** – numpy ndarray of shape (M,N) of M warping functions with N samples

Return type vector

Return gamI inverse of gam

`utility_functions.SqrtMedian(gam)`

calculates the median srsf of warping functions with corresponding shooting vectors

Parameters **gam** – numpy ndarray of shape (M,N) of M warping functions with N samples

Return type 2 numpy ndarray and vector

Return gam_median Karcher median warping function

Return psi_meidan vector of dim N which is the Karcher median srsf function

Return psi numpy ndarray of shape (M,N) of M SRSF of the warping functions

Return vec numpy ndarray of shape (M,N) of M shooting vectors

`utility_functions.cumtrapzmid(x, y, c, mid)`

cumulative trapezoidal numerical integration taken from midpoint

Parameters

- **x** – vector of size N describing the time samples
- **y** – vector of size N describing the function
- **c** – midpoint

- **mid** – midpiont location

Return type vector

Return fa cumulative integration

`utility_functions.diffop(n, binsize=1)`

Creates a second order differential operator

Parameters

- **n** – dimension
- **binsize** – dx (default = 1)

Return type numpy ndarray

Return m matrix describing differential operator

`utility_functions.elastic_distance(f1, f2, time, lam=0.0)`

” calculates the distances between function, where f1 is aligned to f2. In other words calculates the elastic distances

Parameters

- **f1** – vector of size N
- **f2** – vector of size N
- **time** – vector of size N describing the sample points
- **lam** – controls the elasticity (default = 0.0)

Return type scalar

Return Dy amplitude distance

Return Dx phase distance

`utility_functions.f_K_fold(Nobs, K=5)`

generates sample indices for K-fold cross validation

:param Nobs number of observations :param K number of folds

Return type numpy ndarray

Return train train indexes (Nobs*(K-1)/K X K)

Return test test indexes (Nobs*(1/K) X K)

`utility_functions.f_to_srsf(f, time, smooth=False)`

converts f to a square-root slope function (SRSF)

Parameters

- **f** – vector of size N samples
- **time** – vector of size N describing the sample points

Return type vector

Return q srsf of f

`utility_functions.geigen(Amat, Bmat, Cmat)`

generalized eigenvalue problem of the form

$\max \text{tr } L'AM / \sqrt{\text{tr } L'BL \text{tr } M'CM}$ w.r.t. L and M

:param Amat numpy ndarray of shape (M,N) :param Bmat numpy ndarray of shape (M,N) :param Bmat numpy ndarray of shape (M,N)

Return type numpy ndarray

Return values eigenvalues

Return Lmat left eigenvectors

Return Mmat right eigenvectors

`utility_functions.gradient_spline(time, f, smooth=False)`

This function takes the gradient of f using b-spline smoothing

Parameters

- **time** – vector of size N describing the sample points
- **f** – numpy ndarray of shape (M,N) of M functions with N samples
- **smooth** – smooth data (default = F)

Return type tuple of numpy ndarray

Return f0 smoothed functions functions

Return g first derivative of each function

Return g2 second derivative of each function

`utility_functions.innerprod_q(time, q1, q2)`

calculates the innerproduct between two srsfs

:param time vector describing time samples :param q1 vector of srsf 1 :param q2 vector of srsf 2

Return type scalar

Return val inner product value

`utility_functions.invertGamma(gam)`

finds the inverse of the diffeomorphism gamma

Parameters **gam** – vector describing the warping function

Return type vector

Return gamI inverse of gam

`utility_functions.optimum_reparam(q1, time, q2, method='DP', lam=0.0, f1o=0.0, f2o=0.0)`

calculates the warping to align srsf q2 to q1

Parameters

- **q1** – vector of size N or array of NxM samples of first SRSF
- **time** – vector of size N describing the sample points
- **q2** – vector of size N or array of NxM samples samples of second SRSF
- **method** – method to apply optimization (default="DP") options are "DP", "DP2" and "RBFSGS"
- **lam** – controls the amount of elasticity (default = 0.0)

Return type vector

Return gam describing the warping function used to align q2 with q1

`utility_functions.optimum_reparam_pair(q, time, q1, q2, lam=0.0)`
calculates the warping to align srsf pair q1 and q2 to q

Parameters

- **q** – vector of size N or array of NxM samples of first SRSF
- **time** – vector of size N describing the sample points
- **q1** – vector of size N or array of NxM samples of second SRSF
- **q2** – vector of size N or array of NxM samples of second SRSF
- **lam** – controls the amount of elasticity (default = 0.0)

Return type vector

Return gam describing the warping function used to align q2 with q1

`utility_functions.outlier_detection(q, time, mq, k=1.5)`
calculates outlier's using geodesic distances of the SRSFs from the median

Parameters

- **q** – numpy ndarray of N x M of M SRS functions with N samples
- **time** – vector of size N describing the sample points
- **mq** – median calculated using `time_warping.srsf_align()`
- **k** – cutoff threshold (default = 1.5)

Returns q_outlier: outlier functions

`utility_functions.randomGamma(gam, num)`
generates random warping functions

Parameters

- **gam** – numpy ndarray of N x M of M of warping functions
- **num** – number of random functions

Returns rgam: random warping functions

`utility_functions.resamplefunction(x, n)`
resample function using n points

Parameters

- **x** – functions
- **n** – number of points

Return type numpy array

Return xn resampled function

`utility_functions.rgam(N, sigma, num)`
Generates random warping functions

Parameters

- **N** – length of warping function
- **sigma** – variance of warping functions
- **num** – number of warping functions

Returns gam: numpy ndarray of warping functions

`utility_functions.smooth_data(f, sparam)`

This function smooths a collection of functions using a box filter

Parameters

- **f** – numpy ndarray of shape (M,N) of M functions with N samples
- **sparam** – Number of times to run box filter (default = 25)

Return type numpy ndarray

Return f smoothed functions

`utility_functions.srsf_to_f(q, time, f0=0.0)`

converts q (srsf) to a function

Parameters

- **q** – vector of size N samples of srsf
- **time** – vector of size N describing time sample points
- **f0** – initial value

Return type vector

Return f function

`utility_functions.update_progress(progress)`

This function creates a progress bar

Parameters **progress** – fraction of progress

`utility_functions.warp_f_gamma(time, f, gam)`

warps a function f by gam

:param time vector describing time samples :param q vector describing srsf :param gam vector describing warping function

Return type numpy ndarray

Return f_temp warped srsf

`utility_functions.warp_q_gamma(time, q, gam)`

warps a srsf q by gam

:param time vector describing time samples :param q vector describing srsf :param gam vector describing warping function

Return type numpy ndarray

Return q_temp warped srsf

`utility_functions.zero_crossing(Y, q, bt, time, y_max, y_min, gmax, gmin)`

finds zero-crossing of optimal gamma, $\text{gam} = s \cdot \text{gmax} + (1-s) \cdot \text{gmin}$ from elastic regression model

Parameters

- **Y** – response
- **q** – predictive function
- **bt** – basis function
- **time** – time samples
- **y_max** – maximum response for warping function gmax
- **y_min** – minimum response for warping function gmin

- **gmax** – max warping function
- **gmin** – min warping fuction

Return type numpy array

Return gamma optimal warping function

CURVE FUNCTIONS

functions for SRVF curve manipulations

moduleauthor:: Derek Tucker <jdtuck@sandia.gov>

`curve_functions.calc_j(basis)`

Calculates Jacobian matrix from normal basis

Parameters **basis** – list of numpy ndarray of shape (2,M) of M samples basis

Return type numpy ndarray

Return j Jacobian

`curve_functions.calculate_variance(beta)`

This function calculates variance of curve beta

Parameters **beta** – numpy ndarray of shape (2,M) of M samples

Return type numpy ndarray

Return variance variance

`curve_functions.calculatecentroid(beta)`

This function calculates centroid of a parameterized curve

Parameters **beta** – numpy ndarray of shape (2,M) of M samples

Return type numpy ndarray

Return centroid center coordinates

`curve_functions.curve_to_q(beta)`

This function converts curve beta to srvf q

Parameters **beta** – numpy ndarray of shape (2,M) of M samples

Return type numpy ndarray

Return q srvf of curve

`curve_functions.curve_zero_crossing(Y, beta, bt, y_max, y_min, gmax, gmin)`

finds zero-crossing of optimal gamma, $\text{gam} = s * g_{\text{max}} + (1-s) * g_{\text{min}}$ from elastic curve regression model

Parameters

- **Y** – response
- **beta** – predictive function
- **bt** – basis function
- **y_max** – maximum response for warping function gmax

- **y_min** – minimum response for warping function gmin
- **gmax** – max warping function
- **gmin** – min warping function

Return type numpy array

Return gamma optimal warping function

Return O_hat rotation matrix

`curve_functions.find_basis_normal(q)`

Finds the basis normal to the srvf

Parameters **q1** – numpy ndarray of shape (2,M) of M samples

Return type list of numpy ndarray

Return basis list containing basis vectors

`curve_functions.find_best_rotation(q1, q2)`

This function calculates the best rotation between two srvfs using procustes rigid alignment

Parameters

- **q1** – numpy ndarray of shape (2,M) of M samples
- **q2** – numpy ndarray of shape (2,M) of M samples

Return type numpy ndarray

Return q2new optimal rotated q2 to q1

Return R rotation matrix

`curve_functions.find_rotation_and_seed_coord(beta1, beta2)`

This function returns a candidate list of optimally oriented and registered (seed) shapes w.r.t. beta1

Parameters

- **beta1** – numpy ndarray of shape (2,M) of M samples
- **beta2** – numpy ndarray of shape (2,M) of M samples

Return type numpy ndarray

Return beta2new optimal rotated beta2 to beta1

Return O rotation matrix

Return tau seed

`curve_functions.find_rotation_and_seed_q(q1, q2)`

This function returns a candidate list of optimally oriented and registered (seed) shapes w.r.t. beta1

Parameters

- **q1** – numpy ndarray of shape (2,M) of M samples
- **q2** – numpy ndarray of shape (2,M) of M samples

Return type numpy ndarray

Return beta2new optimal rotated beta2 to beta1

Return O rotation matrix

Return tau seed

`curve_functions.gram_schmidt` (*basis*)

Performs Gram Schmidt Orthogonalization of a basis_o

param basis list of numpy ndarray of shape (2,M) of M samples

rtype list of numpy ndarray

return basis_o orthogonalized basis

`curve_functions.group_action_by_gamma` (*q, gamma*)

This function reparameterized srvf q by gamma

Parameters

- **f** – numpy ndarray of shape (2,M) of M samples
- **gamma** – numpy ndarray of shape (2,M) of M samples

Return type numpy ndarray

Return qn reparameterized srvf

`curve_functions.group_action_by_gamma_coord` (*f, gamma*)

This function reparameterized curve f by gamma

Parameters

- **f** – numpy ndarray of shape (2,M) of M samples
- **gamma** – numpy ndarray of shape (2,M) of M samples

Return type numpy ndarray

Return fn reparameterized curve

`curve_functions.innerprod_q2` (*q1, q2*)

This function calculates the inner product in srvf space

Parameters

- **q1** – numpy ndarray of shape (2,M) of M samples
- **q2** – numpy ndarray of shape (2,M) of M samples

Return type numpy ndarray

Return val inner product

`curve_functions.inverse_exp` (*q1, q2, beta2*)

Calculate the inverse exponential to obtain a shooting vector from q1 to q2 in shape space of open curves

Parameters

- **q1** – numpy ndarray of shape (2,M) of M samples
- **q2** – numpy ndarray of shape (2,M) of M samples
- **beta2** – numpy ndarray of shape (2,M) of M samples

Return type numpy ndarray

Return v shooting vectors

`curve_functions.inverse_exp_coord` (*beta1, beta2*)

Calculate the inverse exponential to obtain a shooting vector from beta1 to beta2 in shape space of open curves

Parameters

- **beta1** – numpy ndarray of shape (2,M) of M samples

- **beta2** – numpy ndarray of shape (2,M) of M samples

Return type numpy ndarray

Return v shooting vectors

Return dist distance

`curve_functions.optimum_reparam_curve(q1, q2, lam=0.0)`
calculates the warping to align srsf q2 to q1

Parameters

- **q1** – matrix of size nxN or array of NxM samples of first SRVF
- **time** – vector of size N describing the sample points
- **q2** – matrix of size nxN or array of NxM samples of second SRVF
- **lam** – controls the amount of elasticity (default = 0.0)

Return type vector

Return gam describing the warping function used to align q2 with q1

`curve_functions.parallel_translate(w, q1, q2, basis, mode=0)`
parallel translates q1 and q2 along manifold

Parameters

- **w** – numpy ndarray of shape (2,M) of M samples
- **q1** – numpy ndarray of shape (2,M) of M samples
- **q2** – numpy ndarray of shape (2,M) of M samples
- **basis** – list of numpy ndarray of shape (2,M) of M samples
- **mode** – open 0 or closed curves 1 (default 0)

Return type numpy ndarray

Return wbar translated vector

`curve_functions.pre_proc_curve(beta, T=100)`
This function preprocessed a curve beta to set of closed curves

Parameters

- **beta** – numpy ndarray of shape (2,M) of M samples
- **T** – number of samples (default = 100)

Return type numpy ndarray

Return betanew projected beta

Return qnew projected srvf

Return A alignment matrix (not used currently)

`curve_functions.project_curve(q)`
This function projects srvf q to set of close curves

Parameters **q** – numpy ndarray of shape (2,M) of M samples

Return type numpy ndarray

Return qproj project srvf

`curve_functions.project_tangent(w, q, basis)`

projects srvf to tangent space w using basis

Parameters

- **w** – numpy ndarray of shape (2,M) of M samples
- **q** – numpy ndarray of shape (2,M) of M samples
- **basis** – list of numpy ndarray of shape (2,M) of M samples

Return type numpy ndarray

Return wproj projected q

`curve_functions.psi(x, a, q)`

This function formats variance output

Parameters

- **x** – numpy ndarray of shape (2,M) of M samples curve
- **a** – numpy ndarray of shape (2,1) mean
- **q** – numpy ndarray of shape (2,M) of M samples srvf

Return type numpy ndarray

Return psi1 variance

Return psi2 cross variance

Return psi3 curve end

Return psi4 curve end

`curve_functions.q_to_curve(q)`

This function converts srvf to beta

Parameters **q** – numpy ndarray of shape (2,M) of M samples

Return type numpy ndarray

Return beta parameterized curve

`curve_functions.resamplecurve(x, N=100)`

This function resamples a curve to have N samples

Parameters

- **x** – numpy ndarray of shape (2,M) of M samples
- **N** – Number of samples for new curve (default = 100)

Return type numpy ndarray

Return xn resampled curve

`curve_functions.scale_curve(beta)`

scales curve to length 1

Parameters **beta** – numpy ndarray of shape (2,M) of M samples

Return type numpy ndarray

Return beta_scaled scaled curve

Return scale scale factor used

`curve_functions.shift_f(f, tau)`
shifts a curve f by τ

Parameters

- **f** – numpy ndarray of shape (2,M) of M samples
- **tau** – scalar

Return type numpy ndarray

Return fn shifted curve

References:

- Tucker, J. D. 2014, Functional Component Analysis and Regression using Elastic Methods. Ph.D. Thesis, Florida State University.
- Robinson, D. T. 2012, Function Data Analysis and Partial Shape Matching in the Square Root Velocity Framework. Ph.D. Thesis, Florida State University.
- Huang, W. 2014, Optimization Algorithms on Riemannian Manifolds with Applications. Ph.D. Thesis, Florida State University.
- Srivastava, A., Wu, W., Kurtek, S., Klassen, E. and Marron, J. S. (2011). Registration of Functional Data Using Fisher-Rao Metric. arXiv:1103.3817v2 [math.ST].
- Tucker, J. D., Wu, W. and Srivastava, A. (2013). Generative models for functional data using phase and amplitude separation. Computational Statistics and Data Analysis 61, 50-66.
- J. D. Tucker, W. Wu, and A. Srivastava, “Phase-Amplitude Separation of Proteomics Data Using Extended Fisher-Rao Metric,” Electronic Journal of Statistics, Vol 8, no. 2. pp 1724-1733, 2014.
- J. D. Tucker, W. Wu, and A. Srivastava, “Analysis of signals under compositional noise With applications to SONAR data,” IEEE Journal of Oceanic Engineering, Vol 29, no. 2. pp 318-330, Apr 2014.
- Srivastava, A., Klassen, E., Joshi, S., Jermyn, I., (2011). Shape analysis of elastic curves in euclidean spaces. Pattern Analysis and Machine Intelligence, IEEE Transactions on 33 (7), 1415-1428.
- S. Kurtek, A. Srivastava, and W. Wu. Signal estimation under random time-warpings and nonlinear signal alignment. In Proceedings of Neural Information Processing Systems (NIPS), 2011.
- Wen Huang, Kyle A. Gallivan, Anuj Srivastava, Pierre-Antoine Absil. “Riemannian Optimization for Elastic Shape Analysis”, Short version, The 21st International Symposium on Mathematical Theory of Networks and Systems (MTNS 2014).
- Cheng, W., Dryden, I. L., and Huang, X. (2016). Bayesian registration of functions and curves. Bayesian Analysis, 11(2), 447-475.
- W. Xie, S. Kurtek, K. Bharath, and Y. Sun, A geometric approach to visualization of variability in functional data, Journal of American Statistical Association 112 (2017), pp. 979-993.
- Lu, Y., R. Herbei, and S. Kurtek, 2017: Bayesian registration of functions with a Gaussian process prior. Journal of Computational and Graphical Statistics, 26, no. 4, 894–904.
- Lee, S. and S. Jung, 2017: Combined analysis of amplitude and phase variations in functional data. arXiv:1603.01775 [stat.ME], 1-21.
- J. D. Tucker, J. R. Lewis, and A. Srivastava, “Elastic Functional Principal Component Regression,” Statistical Analysis and Data Mining, 10.1002/sam.11399, 2018.

INDICES AND TABLES

- `genindex`
- `modindex`
- `search`

PYTHON MODULE INDEX

b

boxplots, [9](#)

c

curve_functions, [33](#)

f

fPCA, [7](#)

fPLS, [13](#)

g

gauss_model, [11](#)

geodesic, [23](#)

p

pcr_regression, [21](#)

r

regression, [15](#)

t

time_warping, [3](#)

u

utility_functions, [27](#)

A

`align_fPCA()` (in module *time_warping*), 3
`align_fPLS()` (in module *time_warping*), 3
`ampbox()` (in module *boxplots*), 9

B

`back_parallel_transport()` (in module *geodesic*), 23
`boxplots` (module), 9

C

`calc_alphadot()` (in module *geodesic*), 23
`calc_j()` (in module *curve_functions*), 33
`calculate_energy()` (in module *geodesic*), 23
`calculate_gradE()` (in module *geodesic*), 24
`calculate_variance()` (in module *curve_functions*), 33
`calculatecentroid()` (in module *curve_functions*), 33
`cov_integral()` (in module *geodesic*), 24
`cumtrapzmid()` (in module *utility_functions*), 27
`curve_functions` (module), 33
`curve_to_q()` (in module *curve_functions*), 33
`curve_zero_crossing()` (in module *curve_functions*), 33

D

`diffop()` (in module *utility_functions*), 28

E

`elastic_distance()` (in module *utility_functions*), 28
`elastic_logistic()` (in module *regression*), 15
`elastic_lpcr_regression()` (in module *pcr_regression*), 21
`elastic_mlogistic()` (in module *regression*), 15
`elastic_mlpcr_regression()` (in module *pcr_regression*), 21
`elastic_pcr_regression()` (in module *pcr_regression*), 22
`elastic_prediction()` (in module *regression*), 16
`elastic_regression()` (in module *regression*), 16

F

`f_K_fold()` (in module *utility_functions*), 28
`f_to_srsf()` (in module *utility_functions*), 28
`find_basis_normal()` (in module *curve_functions*), 34
`find_basis_normal_path()` (in module *geodesic*), 24
`find_best_rotation()` (in module *curve_functions*), 34
`find_rotation_and_seed_coord()` (in module *curve_functions*), 34
`find_rotation_and_seed_q()` (in module *curve_functions*), 34
`fPCA` (module), 7
`fPLS` (module), 13

G

`gauss_model` (module), 11
`gauss_model()` (in module *gauss_model*), 11
`geigen()` (in module *utility_functions*), 28
`geod_dist_path_strt()` (in module *geodesic*), 24
`geod_sphere()` (in module *geodesic*), 24
`geodesic` (module), 23
`gradient_spline()` (in module *utility_functions*), 29
`gram_schmidt()` (in module *curve_functions*), 34
`group_action_by_gamma()` (in module *curve_functions*), 35
`group_action_by_gamma_coord()` (in module *curve_functions*), 35

H

`horizfPCA()` (in module *fPCA*), 7

I

`init_path_geod()` (in module *geodesic*), 25
`init_path_rand()` (in module *geodesic*), 25
`innerprod_q()` (in module *utility_functions*), 29
`innerprod_q2()` (in module *curve_functions*), 35
`inverse_exp()` (in module *curve_functions*), 35
`inverse_exp_coord()` (in module *curve_functions*), 35

`invertGamma()` (in module *utility_functions*), 29

J

`jointfPCA()` (in module *fPCA*), 7

L

`logistic_warp()` (in module *regression*), 17

`logit_gradient()` (in module *regression*), 17

`logit_hessian()` (in module *regression*), 17

`logit_loss()` (in module *regression*), 17

M

`mlogit_gradient()` (in module *regression*), 17

`mlogit_loss()` (in module *regression*), 18

`mlogit_warp_grad()` (in module *regression*), 18

O

`optimum_reparam()` (in module *utility_functions*), 29

`optimum_reparam_curve()` (in module *curve_functions*), 36

`optimum_reparam_pair()` (in module *utility_functions*), 29

`outlier_detection()` (in module *utility_functions*), 30

P

`parallel_translate()` (in module *curve_functions*), 36

`path_straightening()` (in module *geodesic*), 25

`pcr_regression()` (module), 21

`phbox()` (in module *boxplots*), 9

`phi()` (in module *regression*), 18

`pls_svd()` (in module *fPLS*), 13

`pre_proc_curve()` (in module *curve_functions*), 36

`project_curve()` (in module *curve_functions*), 36

`project_tangent()` (in module *curve_functions*), 36

`psi()` (in module *curve_functions*), 37

Q

`q_to_curve()` (in module *curve_functions*), 37

R

`randomGamma()` (in module *utility_functions*), 30

`regression()` (module), 15

`regression_warp()` (in module *regression*), 18

`resamplecurve()` (in module *curve_functions*), 37

`resamplefunction()` (in module *utility_functions*), 30

`rgam()` (in module *utility_functions*), 30

S

`scale_curve()` (in module *curve_functions*), 37

`shift_f()` (in module *curve_functions*), 37

`smooth_data()` (in module *utility_functions*), 30

`SqrtMean()` (in module *utility_functions*), 27

`SqrtMeanInverse()` (in module *utility_functions*), 27

`SqrtMedian()` (in module *utility_functions*), 27

`srsf_align()` (in module *time_warping*), 4

`srsf_align_pair()` (in module *time_warping*), 4

`srsf_to_f()` (in module *utility_functions*), 31

T

`time_warping()` (module), 3

U

`update_path()` (in module *geodesic*), 26

`update_progress()` (in module *utility_functions*), 31

`utility_functions()` (module), 27

V

`vertfPCA()` (in module *fPCA*), 8

W

`warp_f_gamma()` (in module *utility_functions*), 31

`warp_q_gamma()` (in module *utility_functions*), 31

Z

`zero_crossing()` (in module *utility_functions*), 31