

# Package: fmrilss (via r-universe)

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**Type** Package

**Title** Least Squares Separate (LSS) Analysis for fMRI Data

**Version** 0.1.0

**Description** Implements efficient least squares separate (LSS) analysis for functional magnetic resonance imaging (fMRI) data. LSS is used to estimate trial-by-trial activation patterns in event-related fMRI designs. The package provides both R and C++ implementations for computational efficiency.

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**Encoding** UTF-8

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## Contents

benchmark_mixed_solve . . . . .	3
calculate_recovery_metrics . . . . .	4
compare_hrf_recovery . . . . .	4
create_lwu_grid . . . . .	5
estimate_voxel_hrf . . . . .	6
fit_oasis_grid . . . . .	7
fmrlss_options . . . . .	8
generate_lwu_data . . . . .	8
generate_rapid_design . . . . .	9
item_build_design . . . . .	10
item_compute_u . . . . .	11
item_cv . . . . .	13
item_fit . . . . .	14
item_from_lsa . . . . .	15
item_predict . . . . .	17
item_slice_fold . . . . .	17
lsa . . . . .	18
lss . . . . .	19
lss_beta_cpp . . . . .	24
lss_cpp_optimized . . . . .	25
lss_design . . . . .	26
lss_fit_wrappers . . . . .	29
lss_naive . . . . .	29
lss_naive_fit . . . . .	31
lss_optimized . . . . .	32
lss_optimized_fit . . . . .	33
lss_sbhm . . . . .	34
lss_sbhm_design . . . . .	36
lss_with_hrf . . . . .	38
LSSBeta . . . . .	39
mixed_precompute . . . . .	40
mixed_solve . . . . .	40
mixed_solve_optimized . . . . .	42
oasis_options . . . . .	43
plot_hrf_comparison . . . . .	44
prewhiten_options . . . . .	45
project_confounds . . . . .	46
project_confounds_cpp . . . . .	47
sbhm_build . . . . .	48
sbhm_hrf . . . . .	50
sbhm_match . . . . .	50

<i>benchmark_mixed_solve</i>	3
sbhm_prepass . . . . .	52
sbhm_project . . . . .	54
stglmnet_options . . . . .	55
VoxelHRF . . . . .	56
<b>Index</b>	<b>57</b>

---

benchmark\_mixed\_solve *Benchmark Mixed Model Implementations*

---

## Description

Compare performance between the standard `mixed_solve` implementation and the optimized `mixed_solve_optimized` version.

## Usage

```
benchmark_mixed_solve(X, Z, K = NULL, Y, n_reps = 5)
```

## Arguments

X	Fixed effects design matrix
Z	Random effects design matrix
K	Kinship matrix (optional, defaults to identity)
Y	Response matrix (n x V)
n_reps	Number of repetitions for benchmarking

## Value

Data frame with timing results

## Examples

```
## Not run:
X <- matrix(rnorm(100 * 2), 100, 2)
Z <- matrix(rnorm(100 * 3), 100, 3)
Y <- matrix(rnorm(100 * 5), 100, 5)
benchmark_mixed_solve(X, Z, Y = Y, n_reps = 2)

## End(Not run)
```

```
calculate_recovery_metrics  
Calculate HRF Recovery Metrics
```

---

**Description**

Evaluates how well each method recovered the true HRF

**Usage**

```
calculate_recovery_metrics(results, true_hrf)
```

**Arguments**

results	Output from compare_hrf_recovery
true_hrf	Ground truth HRF

**Value**

Data frame with recovery metrics

**Examples**

```
## Not run:  
onsets <- generate_rapid_design(n_events = 4, total_time = 60, seed = 1)  
sim <- generate_lwu_data(onsets, total_time = 60, n_voxels = 2, seed = 1)  
grid <- create_lwu_grid(n_tau = 2, n_sigma = 2, n_rho = 2)  
res <- compare_hrf_recovery(sim, hrf_grid = grid)  
calculate_recovery_metrics(res, sim$true_hrf)  
  
## End(Not run)
```

---

```
compare_hrf_recovery Compare HRF Recovery Methods
```

---

**Description**

Compares OASIS, SPMG1, SPMG3, and FIR for HRF recovery

**Usage**

```
compare_hrf_recovery(data, hrf_grid = NULL)
```

**Arguments**

data                Synthetic data from generate\_lwu\_data  
 hrf\_grid            Optional pre-computed HRF grid for OASIS

**Value**

List with results from all methods

**Examples**

```
## Not run:
onsets <- generate_rapid_design(n_events = 4, total_time = 60, seed = 1)
sim <- generate_lwu_data(onsets, total_time = 60, n_voxels = 2, seed = 1)
grid <- create_lwu_grid(n_tau = 2, n_sigma = 2, n_rho = 2)
res <- compare_hrf_recovery(sim, hrf_grid = grid)
names(res)

## End(Not run)
```

---

create\_lwu\_grid                *Create LWU HRF Grid for OASIS Search*

---

**Description**

Generates a grid of LWU HRF models with varying parameters

**Usage**

```
create_lwu_grid(
  tau_range = c(4, 8),
  sigma_range = c(1.5, 3.5),
  rho_range = c(0.1, 0.6),
  n_tau = 5,
  n_sigma = 3,
  n_rho = 3
)
```

**Arguments**

tau\_range            Range of tau values to test  
 sigma\_range        Range of sigma values to test  
 rho\_range          Range of rho values to test  
 n\_tau                Number of tau values in grid  
 n\_sigma             Number of sigma values in grid  
 n\_rho                Number of rho values in grid

**Value**

List of HRF models and their parameters

**Examples**

```
grid <- create_lwu_grid(n_tau = 2, n_sigma = 2, n_rho = 2)
nrow(grid$parameters)
```

---

estimate\_voxel\_hrf      *Estimate Voxel-wise HRF Basis Coefficients*

---

**Description**

Fits a GLM to estimate HRF basis coefficients for every voxel.

**Usage**

```
estimate_voxel_hrf(Y, events, basis, nuisance_regs = NULL)
```

**Arguments**

Y	Numeric matrix of BOLD data (time x voxels).
events	Data frame with onset, duration and condition columns.
basis	HRF object from the fmrihrf package.
nuisance_regs	Optional numeric matrix of nuisance regressors.

**Value**

A [VoxelHRF](#) object containing at least:

coefficients	Matrix of HRF basis coefficients.
basis	The HRF basis object used.
conditions	Character vector of modeled conditions.

**Examples**

```
## Not run:
set.seed(1)
Y <- matrix(rnorm(100), 50, 2)
events <- data.frame(onset = c(5, 25), duration = 1,
                    condition = "A")
basis <- fmrihrf::hrf_gamma()
sframe <- fmrihrf::sampling_frame(blocklens = nrow(Y), TR = 1)
times <- fmrihrf::samples(sframe, global = TRUE)
rset <- fmrihrf::regressor_set(onsets = events$onset,
                             fac = factor(1:nrow(events)),
                             hrf = basis, duration = events$duration,
```

```

span = 30)
X <- fmrihrf::evaluate(rset, grid = times, precision = 0.1, method = "conv")
coef <- matrix(rnorm(ncol(X) * ncol(Y)), ncol(X), ncol(Y))
Y <- X %*% coef + Y * 0.1
est <- estimate_voxel_hrf(Y, events, basis)
str(est)

## End(Not run)

```

fit\_oasis\_grid

*Fit OASIS with HRF Grid Search***Description**

Fits OASIS models with different HRF parameters and selects best

**Usage**

```
fit_oasis_grid(Y, onsets, sframe, hrf_grid, ridge_x = 0.01, ridge_b = 0.01)
```

**Arguments**

Y	Data matrix (time x voxels)
onsets	Event onset times
sframe	Sampling frame
hrf_grid	List of HRF models to test
ridge_x	Ridge parameter for design matrix
ridge_b	Ridge parameter for aggregator

**Value**

List with best HRF index, parameters, and beta estimates

**Examples**

```

## Not run:
onsets <- generate_rapid_design(n_events = 4, total_time = 60, seed = 1)
sim <- generate_lwu_data(onsets, total_time = 60, n_voxels = 2, seed = 1)
grid <- create_lwu_grid(n_tau = 2, n_sigma = 2, n_rho = 2)
fit <- fit_oasis_grid(sim$Y, sim$onsets, sim$sframe, grid)
fit$best_params

## End(Not run)

```

---

fmrilss\_options      *Option constructors for nested interfaces*

---

### Description

These helpers create validated option lists for lss() and friends.

### Value

No value itself. This topic groups the documented constructors stglmnet\_options(), oasis\_options(), and prewhiten\_options().

### Examples

```
stglmnet_options(mode = "fixed", lambda = 0.1)
oasis_options(ridge_x = 0.1, ridge_b = 0.1)
prewhiten_options(method = "ar", p = 1)
```

---

generate\_lwu\_data      *Generate Synthetic fMRI Data with LWU HRF*

---

### Description

Creates synthetic fMRI time series using specified LWU HRF parameters

### Usage

```
generate_lwu_data(
  onsets,
  tau = 6,
  sigma = 2.5,
  rho = 0.35,
  TR = 1,
  total_time = 300,
  n_voxels = 10,
  amplitudes = NULL,
  noise_sd = 0.2,
  seed = NULL
)
```

**Arguments**

onsets	Vector of event onset times in seconds
tau	LWU tau parameter (time-to-peak)
sigma	LWU sigma parameter (width)
rho	LWU rho parameter (undershoot amplitude)
TR	Repetition time in seconds
total_time	Total scan time in seconds
n_voxels	Number of voxels to simulate
amplitudes	Event amplitudes (scalar or vector)
noise_sd	Standard deviation of noise
seed	Random seed

**Value**

List with Y (data matrix), true\_hrf, true\_betas, and design info

**Examples**

```
## Not run:
onsets <- generate_rapid_design(n_events = 4, total_time = 60, seed = 1)
sim <- generate_lwu_data(onsets, total_time = 60, n_voxels = 2, seed = 1)
dim(sim$Y)

## End(Not run)
```

---

generate\_rapid\_design *OASIS HRF Recovery Testing Functions*

---

**Description**

Functions to test OASIS's ability to recover HRF parameters from rapid event-related designs with overlapping HRFs. Generate Rapid Event-Related Design

**Usage**

```
generate_rapid_design(  
  n_events = 25,  
  total_time = 300,  
  min_isi = 2,  
  max_isi = 4,  
  seed = NULL  
)
```

**Arguments**

n_events	Number of events to generate
total_time	Total time in seconds
min_isi	Minimum inter-stimulus interval in seconds
max_isi	Maximum inter-stimulus interval in seconds
seed	Random seed for reproducibility

**Details**

Creates a rapid event-related design with specified ISI range

**Value**

Numeric vector of event onset times

**Examples**

```
generate_rapid_design(n_events = 5, total_time = 40, seed = 1)
```

---

item\_build\_design      *Build ITEM design metadata*

---

**Description**

Build and validate trial-wise design objects used by the ITEM helper layer. The returned object has class `item_bundle` and carries trial-level metadata needed by `item_cv()` and `item_slice_fold()`.

**Usage**

```
item_build_design(  
  X_t,  
  T_target = NULL,  
  run_id = NULL,  
  C_transform = NULL,  
  trial_id = NULL,  
  trial_hash = NULL,  
  meta = list(),  
  diagnostics = list(),  
  validate = TRUE  
)
```

**Arguments**

<code>X_t</code>	Numeric trial-wise design matrix with shape <code>n_time</code> x <code>n_trials</code> .
<code>T_target</code>	Optional supervised targets with <code>n_trials</code> rows. Accepts: numeric matrix/data.frame, numeric vector (regression), or factor/character/logical vector (classification labels).
<code>run_id</code>	Optional run/session identifier of length <code>n_trials</code> . If NULL, all trials are assigned to a single run.
<code>C_transform</code>	Optional transformation matrix used to map <code>X_t</code> to the working design matrix <code>X</code> . Must have <code>n_trials</code> rows when provided.
<code>trial_id</code>	Optional trial identifier vector of length <code>n_trials</code> . Defaults to <code>colnames(X_t)</code> when available, else <code>Trial_1..Trial_n</code> .
<code>trial_hash</code>	Optional hash used by alignment guards. If supplied, <code>item_cv(..., check_hash = TRUE)</code> validates it.
<code>meta</code>	Optional metadata list.
<code>diagnostics</code>	Optional diagnostics list to attach to the bundle.
<code>validate</code>	Logical; when TRUE run strict structure checks.

**Value**

An object of class `item_bundle` with fields: `Gamma`, `X_t`, `C_transform`, `T_target`, `U`, `U_by_run`, `run_id`, `trial_id`, `trial_hash`, `trial_info`, `meta`, and `diagnostics`.

**Examples**

```
bundle <- item_build_design(
  X_t = diag(4),
  T_target = factor(c("A", "B", "A", "B")),
  run_id = c(1, 1, 2, 2)
)
bundle$trial_info
```

---

<code>item_compute_u</code>	<i>Compute ITEM trial covariance matrix</i>
-----------------------------	---

---

**Description**

Compute the trial covariance term as the inverse of a ridge-stabilized normal-equation system, using stable solve paths with fallbacks.

**Usage**

```

item_compute_u(
  X_t,
  V = NULL,
  v_type = c("cov", "precision"),
  ridge = 0,
  method = c("chol", "svd", "pinv"),
  run_id = NULL,
  output = c("matrix", "by_run"),
  tol = sqrt(.Machine$double.eps)
)

```

**Arguments**

<code>X_t</code>	Numeric trial-wise design matrix ( $n\_time \times n\_trials$ ).
<code>V</code>	Optional temporal covariance/precision object. Accepted forms: <ul style="list-style-type: none"> <li>• NULL (identity),</li> <li>• dense/sparse matrix (<math>n\_time \times n\_time</math>),</li> <li>• run-block list of square matrices whose block sizes sum to <math>n\_time</math>.</li> </ul>
<code>v_type</code>	Whether <code>V</code> is covariance ("cov") or precision ("precision").
<code>ridge</code>	Non-negative ridge term added to the trial-wise system matrix before inversion.
<code>method</code>	Preferred solver path ("chol", "svd", or "pinv").
<code>run_id</code>	Optional trial-level run ids (length $n\_trials$ ). Required only when <code>output = "by_run"</code> .
<code>output</code>	Return full <code>U</code> ("matrix") or split run blocks ("by_run").
<code>tol</code>	Numerical tolerance for rank/solver fallbacks.

**Value**

Numeric matrix `U` by default, or a named list `U_by_run` when `output = "by_run"`. Returned object includes `item_diagnostics` attribute with rank/condition/solver details.

**Examples**

```

X_t <- diag(4)
item_compute_u(X_t)
item_compute_u(X_t, run_id = c(1, 1, 2, 2), output = "by_run")

```

---

item_cv	<i>Crossvalidated ITEM decoding</i>
---------	-------------------------------------

---

### Description

Run deterministic leave-one-run-out (LOSO) crossvalidation for classification or regression using ITEM decoder weights.

### Usage

```
item_cv(
  Gamma,
  T_target = NULL,
  U = NULL,
  run_id = NULL,
  mode = c("classification", "regression"),
  metric = NULL,
  ridge = 0,
  method = c("chol", "svd", "pinv"),
  class_levels = NULL,
  trial_id = NULL,
  trial_hash = NULL,
  check_hash = FALSE
)
```

### Arguments

Gamma	Trial-wise beta matrix ( $n_{\text{trials}} \times n_{\text{features}}$ ) or an <code>item_bundle</code> object.
T_target	Supervised targets ( $n_{\text{trials}} \times p$ ) or target vector. Ignored when Gamma is an <code>item_bundle</code> .
U	Trial covariance as full matrix ( $n_{\text{trials}} \times n_{\text{trials}}$ ) or run-block list. Ignored when Gamma is an <code>item_bundle</code> .
run_id	Run/session id vector ( $n_{\text{trials}}$ ). Ignored when Gamma is an <code>item_bundle</code> .
mode	Decoding mode: "classification" or "regression".
metric	Optional metric name. Classification: "accuracy" (default), "balanced_accuracy". Regression: "correlation" (default), "rmse".
ridge	Ridge passed to <code>item_fit()</code> .
method	Solver preference for <code>item_fit()</code> .
class_levels	Optional fixed class order for classification.
trial_id	Optional trial id vector (used if Gamma is not a bundle).
trial_hash	Optional trial hash (used if Gamma is not a bundle).
check_hash	Logical; validate stored trial hash before CV.

**Value**

Object of class `item_cv_result` with per-fold metrics, aggregate metric summary, and trial-level predictions.

**Examples**

```
Gamma <- matrix(
  c(1, 0,
    0.9, 0.1,
    0.1, 0.9,
    0, 1),
  ncol = 2,
  byrow = TRUE
)
item_cv(
  Gamma = Gamma,
  T_target = factor(c("A", "A", "B", "B")),
  U = diag(4),
  run_id = c(1, 1, 2, 2)
)
```

---

 item\_fit

*Fit ITEM decoder weights*


---

**Description**

Fit ITEM weights with a ridge-stabilized generalized least-squares solve.

**Usage**

```
item_fit(
  Gamma_train,
  T_train,
  U_train,
  ridge = 0,
  method = c("chol", "svd", "pinv"),
  tol = sqrt(.Machine$double.eps)
)
```

**Arguments**

<code>Gamma_train</code>	Numeric matrix ( <code>n_train</code> x <code>n_features</code> ).
<code>T_train</code>	Numeric target matrix ( <code>n_train</code> x <code>p</code> ).
<code>U_train</code>	Trial covariance ( <code>n_train</code> x <code>n_train</code> ) or run-block list.
<code>ridge</code>	Non-negative ridge term added to the left-hand system.
<code>method</code>	Preferred solver path ("chol", "svd", "pinv").
<code>tol</code>	Numerical tolerance for rank/solver fallbacks.

**Value**

Numeric weight matrix  $W_{\hat{}}$  ( $n_{\text{features}} \times p$ ) with `item_diagnostics` attribute.

**Examples**

```
Gamma_train <- matrix(
  c(1, 0,
    0.9, 0.1,
    0.1, 0.9),
  ncol = 2,
  byrow = TRUE
)
T_train <- rbind(c(1, 0), c(1, 0), c(0, 1))
W_hat <- item_fit(Gamma_train, T_train, diag(3))
item_predict(Gamma_train, W_hat)
```

---

 item\_from\_lsa

---

*Build an ITEM bundle from LS-A estimates*


---

**Description**

Convenience wrapper that runs `lsa()` to estimate trial-wise amplitudes, computes  $U$ , and returns an `item_bundle` ready for crossvalidation.

**Usage**

```
item_from_lsa(
  Y,
  X_t,
  T_target,
  run_id,
  Z = NULL,
  Nuisance = NULL,
  V = NULL,
  v_type = c("cov", "precision"),
  ridge = 0,
  lsa_method = c("r", "cpp"),
  solver = c("chol", "svd", "pinv"),
  u_output = c("matrix", "by_run"),
  C_transform = NULL,
  trial_id = NULL,
  trial_hash = NULL,
  meta = list(),
  validate = TRUE
)
```

**Arguments**

Y	Numeric data matrix (n_time x n_features).
X_t	Numeric trial-wise design matrix (n_time x n_trials).
T_target	Supervised targets with n_trials rows.
run_id	Trial-level run/session identifier (n_trials).
Z	Optional nuisance matrix passed to lsa().
Nuisance	Alias for Z in lsa().
V	Optional covariance/precision for item_compute_u().
v_type	Whether V is covariance or precision.
ridge	Ridge passed to item_compute_u().
lsa_method	LS-A backend ("r" or "cpp").
solver	Solver preference for item_compute_u().
u_output	Return full U matrix or U_by_run blocks.
C_transform	Optional transform matrix used to map X_t to the working design matrix X.
trial_id	Optional trial id vector.
trial_hash	Optional trial hash.
meta	Optional metadata list.
validate	Logical; enforce strict checks before returning.

**Value**

item\_bundle with fields Gamma, X\_t, T\_target, U/U\_by\_run, run\_id, meta, and diagnostics.

**Examples**

```
set.seed(1)
X_t <- diag(4)
Y <- X_t %%% matrix(
  c(1, 0,
    0.8, 0.2,
    0.2, 0.8,
    0, 1),
  ncol = 2,
  byrow = TRUE
) + matrix(rnorm(8, sd = 0.01), 4, 2)
bundle <- item_from_lsa(
  Y = Y,
  X_t = X_t,
  T_target = factor(c("A", "B", "A", "B")),
  run_id = c(1, 1, 2, 2),
  lsa_method = "r"
)
names(bundle)
```

---

item_predict	<i>Predict targets from ITEM weights</i>
--------------	--

---

**Description**

Compute  $T_{\text{hat}} = \text{Gamma\_test} \%*\% W_{\text{hat}}$ .

**Usage**

```
item_predict(Gamma_test, W_hat)
```

**Arguments**

Gamma\_test      Numeric matrix (n\_test x n\_features).

W\_hat            Numeric matrix (n\_features x p).

**Value**

Numeric matrix of predictions (n\_test x p).

**Examples**

```
Gamma_test <- matrix(c(1, 0, 0, 1), ncol = 2, byrow = TRUE)
W_hat <- diag(2)
item_predict(Gamma_test, W_hat)
```

---

item_slice_fold	<i>Slice an ITEM bundle into train/test fold objects</i>
-----------------	--

---

**Description**

Create deterministic leave-one-run-out slices for Gamma, T\_target, and trial covariance (U or U\_by\_run).

**Usage**

```
item_slice_fold(bundle, test_run, check_hash = FALSE)
```

**Arguments**

bundle            Object of class item\_bundle.

test\_run          Run/session id to hold out for testing.

check\_hash        Logical; if TRUE, validate stored trial\_hash.

**Value**

A list with train/test slices: Gamma\_train, Gamma\_test, T\_train, T\_test, U\_train, U\_test, train\_idx, test\_idx, train\_runs, test\_run.

**Examples**

```
bundle <- item_build_design(
  X_t = diag(4),
  T_target = factor(c("A", "B", "A", "B")),
  run_id = c(1, 1, 2, 2)
)
bundle$Gamma <- matrix(c(1, 0, 0.8, 0.2, 0.2, 0.8, 0, 1), 4, 2, byrow = TRUE)
bundle$U <- diag(4)
fold <- item_slice_fold(bundle, test_run = 2)
fold$test_idx
```

lsa

*Least Squares All (LSA) Analysis***Description**

Performs a standard multiple regression analysis where all trial regressors are fitted simultaneously. This provides a reference comparison to the Least Squares Separate (LSS) approach.

**Usage**

```
lsa(Y, X, Z = NULL, Nuisance = NULL, method = c("r", "cpp"))
```

**Arguments**

Y	A numeric matrix where rows are timepoints and columns are voxels/features. This is the dependent variable data.
X	A numeric matrix where rows are timepoints and columns are trial-specific regressors. Each column represents a single trial or event.
Z	A numeric matrix of nuisance regressors (e.g., motion parameters, drift terms). Defaults to NULL.
Nuisance	An alias for Z, provided for consistency with LSS interface. If both Z and Nuisance are provided, Z takes precedence.
method	Character string specifying the computational method: <ul style="list-style-type: none"> <li>• "r" - Pure R implementation using lm.fit</li> <li>• "cpp" - C++ implementation for better performance</li> </ul>

**Details**

LSA fits the model:  $Y = X\beta + Z\gamma + \text{error}$ , where all trial regressors in X are estimated simultaneously. This is in contrast to LSS, which fits each trial separately while treating other trials as nuisance regressors.

**Value**

A numeric matrix of size  $T \times V$  containing the beta estimates for each trial regressor (rows) and each voxel (columns).

**Examples**

```
n_timepoints <- 100
n_trials <- 10
n_voxels <- 50

X <- matrix(0, n_timepoints, n_trials)
for(i in 1:n_trials) {
  start <- (i-1) * 8 + 1
  if(start + 5 <= n_timepoints) {
    X[start:(start+5), i] <- 1
  }
}

Y <- matrix(rnorm(n_timepoints * n_voxels), n_timepoints, n_voxels)
true_betas <- matrix(rnorm(n_trials * n_voxels, 0, 0.5), n_trials, n_voxels)
for(i in 1:n_trials) {
  Y <- Y + X[, i] %*% matrix(true_betas[i, ], 1, n_voxels)
}

beta_estimates <- lsa(Y, X)
```

---

lss

*Least Squares Separate (LSS) Analysis*


---

**Description**

Computes trial-wise beta estimates using the Least Squares Separate approach of Mumford et al. (2012). This method fits a separate GLM for each trial, with the trial of interest and all other trials as separate regressors.

**Usage**

```
lss(
  Y,
  X,
  Z = NULL,
  Nuisance = NULL,
  method = c("r_optimized", "cpp_optimized", "r_vectorized", "cpp", "naive", "oasis",
    "stglmnet"),
  block_size = 96,
  oasis = list(),
  stglmnet = list(),
  prewhiten = NULL
)
```

## Arguments

Y	A numeric matrix of size $n \times V$ where $n$ is the number of timepoints and $V$ is the number of voxels/variables
X	A numeric matrix of size $n \times T$ where $T$ is the number of trials. Each column represents the design for one trial
Z	A numeric matrix of size $n \times F$ representing experimental regressors to include in all trial-wise models. These are regressors we want to model and get beta estimates for, but not trial-wise (e.g., intercept, condition effects, block effects). If NULL, an intercept-only design is used. Defaults to NULL
Nuisance	A numeric matrix of size $n \times N$ representing nuisance regressors to be projected out before LSS analysis (e.g., motion parameters, physiological noise). If NULL, no nuisance projection is performed. Defaults to NULL
method	Character string specifying which implementation to use. Options are: <ul style="list-style-type: none"> <li>• "r_optimized" - Optimized R implementation (recommended, default)</li> <li>• "cpp_optimized" - Optimized C++ implementation with parallel support</li> <li>• "r_vectorized" - Standard R vectorized implementation</li> <li>• "cpp" - Standard C++ implementation</li> <li>• "naive" - Simple loop-based R implementation (for testing)</li> <li>• "oasis" - OASIS method with HRF support and ridge regularization</li> <li>• "stglmnet" - overlap-aware elastic-net backend using glmnet</li> </ul>
block_size	An integer specifying the voxel block size for parallel processing, only applicable when method = "cpp_optimized". Defaults to 96.
oasis	A list of options for the OASIS method (ridge, SE, design construction, etc.). See Details and <a href="#">oasis_options</a> for the full list. <b>Note:</b> oasis\$whiten is deprecated and ignored. Use the prewhiten parameter instead for all temporal whitening.
stglmnet	A list of options for the method = "stglmnet" backend. See Details and <a href="#">stglmnet_options</a> for the common fields.
prewhiten	A list of prewhitening options using the <b>fmriAR</b> package, or NULL (no whitening, the default). See Details and <a href="#">prewhiten_options</a> for the full list.

## Details

The LSS approach fits a separate GLM for each trial, where each model includes:

- The trial of interest (from column  $i$  of  $X$ )
- All other trials combined (sum of all other columns of  $X$ )
- Experimental regressors ( $Z$  matrix) - these are modeled to get beta estimates but not trial-wise

If Nuisance regressors are provided, they are first projected out from both  $Y$  and  $X$  using standard linear regression residualization.

When using method="oasis", the following options are available in the oasis list (see also [oasis\\_options](#) for a validated constructor):

- `design_spec`: A list for building trial-wise designs from event onsets using `fmrhrf`. Must contain: `sframe` (sampling frame), `cond` (list with onsets, `hrf`, and optionally `span`), and optionally `others` (list of other conditions to be modeled as nuisances). When provided, `X` can be `NULL` and will be constructed automatically.
- `K`: Explicit basis dimension for multi-basis HRF models (e.g., 3 for SPMG3). If not provided, it's auto-detected from `X` dimensions or defaults to 1 for single-basis HRFs.
- `ridge_mode`: Either "fractional" (default) or "absolute". In absolute mode, `ridge_x` and `ridge_b` are used directly as regularization parameters. In fractional mode, they represent fractions of the mean design energy for adaptive regularization.
- `ridge_x`: Ridge parameter for trial-specific regressors (default 0.05). Controls regularization strength for individual trial estimates.
- `ridge_b`: Ridge parameter for the aggregator regressor (default 0.05). Controls regularization strength for the sum of all other trials.
- `return_se`: Logical, whether to return standard errors (default `FALSE`). When `TRUE`, returns a list with `beta` (trial estimates) and `se` (standard errors) components.
- `return_diag`: Logical, whether to return design diagnostics (default `FALSE`). When `TRUE`, includes diagnostic information about the design matrix structure.
- `block_cols`: Integer, voxel block size for memory-efficient processing (default 4096). Larger values use more memory but may be faster for systems with sufficient RAM.
- `ntrials`: Explicit number of trials (used when `K > 1` to determine output dimensions). If not provided, calculated as  $\text{ncol}(X) / K$ .
- `hrf_grid`: Vector of HRF indices for grid-based HRF selection (advanced use). Allows testing multiple HRF shapes simultaneously.

#### **Prewhitening (temporal autocorrelation correction):**

Use the top-level `prewhiten` parameter for all temporal whitening. This replaces the old `oasis$whiten = "ar1"` syntax, which is now deprecated and ignored. Do *not* put AR options inside the `oasis` list; they belong in `prewhiten`.

When using `method = "stglmnet"`, the backend accepts an additional nested `stglmnet=` list for lambda selection, overlap-adaptive penalties, and optional pooled trial parameterizations. The common pattern is `stglmnet = stglmnet_options(mode = "cv")` to select lambda by cross-validation, or `stglmnet = stglmnet_options(mode = "fixed", lambda = 0.01)` for a fixed elastic-net fit. The backend reuses `fmrilss` prewhitening and nuisance-projection utilities rather than maintaining a separate whitening path.

The `prewhiten` list accepts the following fields (see also [prewhiten\\_options](#) for a validated constructor):

- `method`: Character, "ar" (default when the list is non-`NULL`), "arma", or "none". "ar" fits a pure autoregressive model; "arma" adds a moving-average component (requires  $q > 0$ ).
- `p`: AR order. An integer, or "auto" (default) to select via AIC/BIC up to `p_max`. Use `p = 1` for a simple AR(1) model (the most common choice for fMRI); higher orders are rarely needed but may help with short TRs or multi-band sequences.
- `q`: Integer MA order for ARMA models (default 0). Only relevant when `method = "arma"`.
- `p_max`: Integer, maximum AR order when `p = "auto"` (default 6).

- pooling: How AR coefficients are estimated across voxels. One of:
  - "global" (default) A single set of AR coefficients is estimated from the median autocorrelation across all voxels. Fast and usually adequate.
  - "voxel" Fit a separate AR model per voxel. Most accurate but slow; consider "parcel" instead.
  - "run" Fit one AR model per run (requires runs). Useful when noise structure differs between runs.
  - "parcel" Fit one AR model per parcel (requires parcels). Good compromise between "global" and "voxel".
- runs: Integer vector of length nrow(Y) giving run/block labels. Required for pooling = "run" and recommended whenever data span multiple runs so that whitening respects run boundaries.
- parcels: Integer vector of length ncol(Y) giving parcel labels. Required for pooling = "parcel".
- exact\_first: Character, "ar1" (default) or "none". When "ar1", the first observation of each segment is scaled by  $\sqrt{1 - \phi_1^2}$  for the exact likelihood; "none" drops the first observation instead.
- compute\_residuals: Logical (default TRUE). When TRUE, OLS residuals from the full design are computed before fitting the noise model. Set to FALSE only if Y is already residualized.

#### Typical prewhiten recipes:

```
# Simple AR(1) – good default for most fMRI data
prewhiten = list(method = "ar", p = 1)

# Auto-select AR order (AIC), global pooling
prewhiten = list(method = "ar", p = "auto")

# Per-run AR(1) for multi-run data
prewhiten = list(method = "ar", p = 1, pooling = "run",
                 runs = blockids)

# Parcel-based AR with atlas labels
prewhiten = list(method = "ar", p = 1, pooling = "parcel",
                 parcels = atlas_labels)

# Or use the validated constructor:
prewhiten = prewhiten_options(method = "ar", p = 1, pooling = "run",
                              runs = blockids)
```

Prewhitening is applied before the LSS analysis to account for temporal autocorrelation in the fMRI time series. Both Y and all design matrices (X, Z, Nuisance) are filtered through the same whitening operator so that OLS on the whitened system is equivalent to GLS on the original data.

The OASIS method provides a mathematically equivalent but computationally optimized version of standard LSS. It reformulates the per-trial GLM fitting as a single matrix operation, eliminating

redundant computations. This is particularly beneficial for designs with many trials or when processing large datasets. When  $K > 1$  (multi-basis HRFs), the output will have  $K \times n_{\text{trials}}$  rows, with basis functions for each trial arranged sequentially.

### Value

A numeric matrix of size  $T \times V$  containing the trial-wise beta estimates. Note: Currently only returns estimates for the trial regressors ( $X$ ). Beta estimates for the experimental regressors ( $Z$ ) are computed but not returned.

### References

Mumford, J. A., Turner, B. O., Ashby, F. G., & Poldrack, R. A. (2012). Deconvolving BOLD activation in event-related designs for multivoxel pattern classification analyses. *NeuroImage*, 59(3), 2636-2643.

### Examples

```
n_timepoints <- 100
n_trials <- 10
n_voxels <- 50

X <- matrix(0, n_timepoints, n_trials)
for(i in 1:n_trials) {
  start <- (i-1) * 8 + 1
  if(start + 5 <= n_timepoints) {
    X[start:(start+5), i] <- 1
  }
}

Y <- matrix(rnorm(n_timepoints * n_voxels), n_timepoints, n_voxels)
true_betas <- matrix(rnorm(n_trials * n_voxels, 0, 0.5), n_trials, n_voxels)
for(i in 1:n_trials) {
  Y <- Y + X[, i] %*% matrix(true_betas[i, ], 1, n_voxels)
}

beta_estimates <- lss(Y, X)

Z <- cbind(1, scale(1:n_timepoints))
beta_estimates_with_regressors <- lss(Y, X, Z = Z)

Nuisance <- matrix(rnorm(n_timepoints * 6), n_timepoints, 6)
beta_estimates_clean <- lss(Y, X, Z = Z, Nuisance = Nuisance)

## Not run:
beta_oasis <- lss(Y, X, method = "oasis",
                 oasis = list(ridge_x = 0.1, ridge_b = 0.1,
                              ridge_mode = "fractional"))

result_with_se <- lss(Y, X, method = "oasis",
                    oasis = list(return_se = TRUE))
beta_estimates <- result_with_se$beta
```

```

standard_errors <- result_with_se$se

sframe <- sampling_frame(blocklens = 200, TR = 1.0)

beta_auto <- lss(Y, X = NULL, method = "oasis",
  oasis = list(
    design_spec = list(
      sframe = sframe,
      cond = list(
        onsets = c(10, 30, 50, 70, 90, 110, 130, 150),
        hrf = HRF_SPMG1,
        span = 25
      ),
      others = list(
        list(onsets = c(20, 40, 60, 80, 100, 120, 140))
      )
    )
  )
)

beta_multibasis <- lss(Y, X = NULL, method = "oasis",
  oasis = list(
    design_spec = list(
      sframe = sframe,
      cond = list(
        onsets = c(10, 30, 50, 70, 90),
        hrf = HRF_SPMG3,
        span = 30
      )
    ),
    K = 3
  )
)

## End(Not run)

```

---

lss\_beta\_cpp

*Vectorized LSS Beta Computation Using C++*


---

### Description

Fast C++ implementation of least squares separate (LSS) beta estimation using vectorized matrix operations. Computes all trial betas in a single pass without loops.

### Usage

```
lss_beta_cpp(C_projected, Y_projected)
```

### Arguments

C_projected	Projected trial regressors (n x T) from project_confounds_cpp
Y_projected	Projected data (n x V) from project_confounds_cpp

**Details**

This vectorized implementation computes all LSS betas simultaneously using matrix algebra. It's significantly faster than per-trial loops and automatically benefits from BLAS multithreading. The algorithm handles numerical edge cases by setting problematic denominators to NaN.

For best performance on large datasets, ensure your R installation uses optimized BLAS (like OpenBLAS or Intel MKL).

**Value**

Beta matrix (T x V) with LSS estimates for each trial and voxel

**Examples**

```
## Not run:
result <- project_confounds_cpp(X_confounds, Y_data, C_trials)
betas <- lss_beta_cpp(result$Q_dmat_ran, result$residual_data)

## End(Not run)
```

---

lss\_cpp\_optimized      *A wrapper for the optimized C++ LSS implementation*

---

**Description**

A wrapper for the optimized C++ LSS implementation

**Usage**

```
lss_cpp_optimized(Y, bdes)
```

**Arguments**

Y                    the voxel by time data matrix  
bdes                 the block design list created by block\_design

**Value**

a matrix of beta estimates

**Examples**

```

set.seed(1)
Y <- matrix(rnorm(16), 8, 2)
X_trials <- matrix(0, 8, 2)
X_trials[2:3, 1] <- 1
X_trials[5:6, 2] <- 1
bdes <- list(
  dmat_base = matrix(1, 8, 1),
  dmat_fixed = NULL,
  dmat_ran = X_trials
)
lss_cpp_optimized(Y, bdes)

```

---

lss\_design

*LSS Analysis with fmridesign Objects*


---

**Description**

Perform Least Squares Separate (LSS) analysis using `event_model` and `baseline_model` objects from the `fmridesign` package. This provides a streamlined interface for complex designs with multi-condition, parametric modulators, and structured nuisance handling.

**Usage**

```

lss_design(
  Y,
  event_model,
  baseline_model = NULL,
  method = "oasis",
  oasis = list(),
  prewhiten = NULL,
  blockids = NULL,
  validate = TRUE,
  ...
)

```

**Arguments**

- |                             |  |
|-----------------------------|--|
| <code>Y</code>              | Numeric matrix of fMRI data (timepoints $\times$ voxels).  |
| <code>event_model</code>    | An <code>event_model</code> object from <code>fmridesign::event_model()</code> . This defines the trial-wise or condition-wise task design. For LSS, typically created with <code>trialwise()</code> to generate one regressor per trial.  |
| <code>baseline_model</code> | Optional <code>baseline_model</code> object from <code>fmridesign::baseline_model()</code> . Defines drift correction, block intercepts, and nuisance regressors. If <code>NULL</code> , basic baseline intercepts are auto-injected: per-run intercepts derived from <code>blockids</code> (or the sampling frame) are used to ensure proper baseline modeling. |

method	LSS method to use. Currently only "oasis" is supported for event_model integration.
oasis	List of OASIS-specific options: ridge regularization (ridge_x, ridge_b, ridge_mode), standard errors (return_se), etc. See <a href="#">oasis_options</a> and the Details section of <a href="#">lss</a> for the full list. Note: design_spec is not used when providing event_model, and oasis\$whiten is deprecated — use prewhiten instead.
prewhiten	Optional prewhitening specification as a list (or NULL for no whitening). Controls temporal autocorrelation correction via the <b>fmriAR</b> package. Key fields: method ("ar", "arma", "none"), p (AR order or "auto"), pooling ("global", "voxel", "run", "parcel"), and runs/parcels. See <a href="#">prewhiten_options</a> and <a href="#">lss</a> for full details and examples.
blockids	Optional block/run identifiers for event_model. If NULL, extracted from event_model\$blockids.
validate	Logical. If TRUE (default), performs validation checks on design compatibility, collinearity, and temporal alignment.
...	Additional arguments passed to the underlying LSS method.

## Details

### Design Specification:

The event\_model should typically use trialwise() for LSS:

```
emod <- event_model(onset ~ trialwise(basis = "spmgl"),
  data = events,
  block = ~run,
  sampling_frame = sframe)
```

For factorial designs (e.g., estimating condition-level betas separately):

```
emod <- event_model(onset ~ hrf(condition),
  data = events,
  block = ~run,
  sampling_frame = sframe)
```

### Baseline Model:

If provided, baseline\_model components are mapped as follows:

- drift and block terms → Z parameter (fixed effects)
- nuisance term → Nuisance parameter (confounds)

### Multi-Run Handling:

Both event\_model and baseline\_model must use the same sampling\_frame. Run structure is automatically respected. Event onsets should be run-relative (resetting to 0 each run) as per fmridesign convention - conversion to global time is handled automatically.

### Prewhitening:

Use the prewhiten parameter (not the oasis list) for temporal autocorrelation correction. For multi-run data, pass prewhiten = list(method = "ar", p = 1, pooling = "run", runs = blockids) so that whitening respects run boundaries. See [lss](#) and [prewhiten\\_options](#) for full details.

**Validation:**

When `validate = TRUE`, the function checks:

- Temporal alignment: `nrow(Y)` matches total scans in `sampling_frame`
- Collinearity: Design matrix condition number  $< 30$  (suppressed when ridge is already configured via `oasis$ridge_x` or `oasis$ridge_b`)
- Compatibility: `event_model` and `baseline_model` use same `sampling_frame`

**Value**

Matrix of trial-wise beta estimates ( $\text{trials} \times \text{voxels}$ ), or  $(\text{trials} \times \text{basis\_functions}) \times \text{voxels}$  for multi-basis HRFs.

**See Also**

[lss](#) for the traditional matrix-based interface, `fmridesign::event_model` for event model creation, `fmridesign::baseline_model` for baseline model creation

**Examples**

```
## Not run:
library(fmridesign)
library(fmrihrf)

sframe <- sampling_frame(blocklens = c(150, 150), TR = 2)

trials <- data.frame(
  onset = c(10, 30, 50, 70, 90, 110,
            10, 30, 50, 70, 90, 110),
  run = rep(1:2, each = 6)
)

emod <- event_model(
  onset ~ trialwise(basis = "spm1"),
  data = trials,
  block = ~run,
  sampling_frame = sframe
)

motion <- list(
  matrix(rnorm(150 * 6), 150, 6),
  matrix(rnorm(150 * 6), 150, 6)
)

bmodel <- baseline_model(
  basis = "bs",
  degree = 5,
  sframe = sframe,
  nuisance_list = motion
)

Y <- matrix(rnorm(300 * 1000), 300, 1000)
```

```
beta <- lss_design(Y, emod, bmodel, method = "oasis")  
  
dim(beta)  
  
## End(Not run)
```

---

lss_fit_wrappers	<i>Convenience wrappers for modern lss() usage</i>
------------------	--

---

### Description

These functions provide a modern-signature entry point for methods that historically required a block-design (bdes) object.

### Value

No value itself. This topic groups `lss_naive_fit()` and `lss_optimized_fit()`.

### Examples

```
set.seed(1)  
Y <- matrix(rnorm(16), 8, 2)  
X <- matrix(0, 8, 2)  
X[2:3, 1] <- 1  
X[5:6, 2] <- 1  
lss_naive_fit(Y, X)
```

---

lss_naive	<i>Naive Least Squares Separate (LSS) Analysis</i>
-----------	--

---

### Description

Performs LSS analysis using the naive approach where each trial model is fit separately. This is the conceptually simplest implementation but less efficient than the optimized [lss](#) function.

### Usage

```
lss_naive(Y = NULL, bdes, dset = NULL)
```

**Arguments**

Y	A numeric matrix where rows are timepoints and columns are voxels/features. If NULL, the function will attempt to extract data from dset.
bdes	A list containing design matrices with components: <ul style="list-style-type: none"> <li>• dmat_base: Base design matrix (e.g., intercept, drift terms)</li> <li>• dmat_fixed: Fixed effects design matrix (optional)</li> <li>• dmat_ran: Random/trial design matrix for LSS analysis</li> <li>• fixed_ind: Indices for fixed effects (optional)</li> </ul>
dset	Optional dataset object. If provided and Y is NULL, data will be extracted using <code>get_data_matrix</code> .

**Details**

This function implements the LSS approach by fitting a separate GLM for each trial. Following the method described by Mumford et al. (2012), the model for each trial includes:

- The regressor for the trial of interest.
- A single regressor representing all other trials (the sum of their individual regressors).
- All base regressors (e.g., intercept, drift terms).
- All fixed effects regressors (if any).

While less efficient than the optimized `lss` function, this implementation is conceptually clear and serves as a reference for validation.

**Value**

A numeric matrix with dimensions (n\_events x n\_voxels) containing the LSS beta estimates for each trial and voxel.

**See Also**

[lss](#) for the optimized implementation

**Examples**

```
set.seed(1)
n_timepoints <- 20
n_trials <- 4
n_voxels <- 3

X <- matrix(0, n_timepoints, n_trials)
for (i in seq_len(n_trials)) {
  onset <- 1 + (i - 1) * 4
  X[onset:(onset + 2), i] <- 1
}

Z <- cbind(Intercept = 1, Linear = seq_len(n_timepoints))
Y <- matrix(rnorm(n_timepoints * n_voxels), n_timepoints, n_voxels)
```

```

for (i in seq_len(n_trials)) {
  Y <- Y + X[, i] %% matrix(rnorm(n_voxels, sd = 0.2), 1, n_voxels)
}

bdes <- list(
  dmat_base = Z,
  dmat_ran = X,
  dmat_fixed = NULL,
  fixed_ind = NULL
)

beta_estimates_naive <- lss_naive(Y = Y, bdes = bdes)

beta_estimates_fast <- lss(Y = Y, X = X, Z = Z)
max(abs(beta_estimates_naive - beta_estimates_fast))

```

---

lss\_naive\_fit

*Naive LSS with modern signature*


---

### Description

Equivalent to calling `lss(..., method = "naive")`.

### Usage

```
lss_naive_fit(Y, X, Z = NULL, Nuisance = NULL, prewhiten = NULL)
```

### Arguments

Y	Numeric matrix (timepoints x voxels).
X	Trial design matrix (timepoints x trials).
Z	Optional experimental regressors.
Nuisance	Optional nuisance regressors to project out.
prewhiten	Optional prewhitening options list (see <code>prewhiten_options()</code> ).

### Value

A numeric matrix (trials x voxels) of beta estimates.

### Examples

```

set.seed(1)
Y <- matrix(rnorm(16), 8, 2)
X <- matrix(0, 8, 2)
X[2:3, 1] <- 1
X[5:6, 2] <- 1
lss_naive_fit(Y, X)

```

---

lss_optimized	<i>Optimized LSS Analysis (Pure R)</i>
---------------	--

---

### Description

An optimized version of the LSS analysis that avoids creating large intermediate matrices, providing a significant speedup and lower memory usage for the pure R implementation.

### Usage

```
lss_optimized(Y = NULL, bdes, dset = NULL, use_cpp = TRUE)
```

### Arguments

Y	A numeric matrix where rows are timepoints and columns are voxels/features.
bdes	A list containing the design matrices.
dset	Optional dataset object.
use_cpp	Logical. If TRUE (default), uses the C++ implementation. If FALSE, uses the new optimized R implementation.

### Value

A numeric matrix of LSS beta estimates.

### Examples

```
set.seed(1)
Y <- matrix(rnorm(16), 8, 2)
X_trials <- matrix(0, 8, 2)
X_trials[2:3, 1] <- 1
X_trials[5:6, 2] <- 1
bdes <- list(
  dmat_base = matrix(1, 8, 1),
  dmat_ran = X_trials,
  dmat_fixed = NULL,
  fixed_ind = NULL
)
lss_optimized(Y, bdes, use_cpp = FALSE)
```

---

lss\_optimized\_fit      *Optimized LSS with modern signature*

---

## Description

This is a convenience wrapper around `lss()` that selects one of the optimized implementations.

## Usage

```
lss_optimized_fit(  
  Y,  
  X,  
  Z = NULL,  
  Nuisance = NULL,  
  engine = c("cpp", "r"),  
  block_size = 96,  
  prewhiten = NULL  
)
```

## Arguments

Y	Numeric matrix (timepoints x voxels).
X	Trial design matrix (timepoints x trials).
Z	Optional experimental regressors.
Nuisance	Optional nuisance regressors to project out.
engine	"cpp" (default) for method="cpp_optimized" or "r" for method="r_optimized".
block_size	Block size used by the C++ optimized path.
prewhiten	Optional prewhitening options list (see <code>prewhiten_options()</code> ).

## Value

A numeric matrix (trials x voxels) of beta estimates.

## Examples

```
set.seed(1)  
Y <- matrix(rnorm(16), 8, 2)  
X <- matrix(0, 8, 2)  
X[2:3, 1] <- 1  
X[5:6, 2] <- 1  
lss_optimized_fit(Y, X, engine = "r")
```

lss\_sbhm

*End-to-End LSS with Shared-Basis HRF Matching (SBHM)***Description**

Orchestrates the SBHM pipeline: (1) prepass aggregate fit in the learned shared basis, (2) cosine matching to a library of HRFs represented in the same basis, (3) Least Squares Separate (OASIS) with the SBHM basis to obtain trial-wise r-dimensional coefficients, and (4) projection of those coefficients onto the matched coordinates to produce scalar amplitudes.

**Usage**

```
lss_sbhm(
  Y,
  sbhm,
  design_spec,
  Nuisance = NULL,
  prewhiten = NULL,
  prepass = list(),
  match = list(shrink = list(tau = 0, ref = NULL, snr = NULL), topK = 3, soft_blend =
    TRUE, blend_margin = 0.08, whiten = FALSE, sv_floor_rel = 0.05, whiten_power = 0.5,
    min_margin = NULL, min_beta_norm = NULL, fallback_ref = NULL, orient_ref = TRUE,
    alpha_source = "prepass", rank1_min = 0),
  oasis = list(),
  amplitude = list(method = "lss1", ridge = list(mode = "fractional", lambda = 0.02),
    ridge_frac = list(x = 0.02, b = 0.02), cond_gate = NULL, adaptive = list(enable =
    FALSE, base = 0.02, k0 = 1000, max = 0.08), return_se = FALSE),
  return = c("amplitude", "coefficients", "both")
)
```

**Arguments**

Y	Numeric matrix T×V of fMRI time series.
sbhm	SBHM object from sbhm_build().
design_spec	List for design construction (same as oasis\$design_spec): list(sframe=..., cond=list(onsets=..., duration=0, span=...), others=list(...)). The HRF in cond\$hrf is ignored and replaced with the SBHM basis HRF.
Nuisance	Optional T×P nuisance regressors.
prewhiten	Optional prewhitening options (see ?lss).
prepass	Optional list forwarded to sbhm_prepass() (e.g., ridge, data_fac).
match	Optional list forwarded to sbhm_match() (e.g., shrink, topK, whiten, orient_ref). Additional fields handled here: <ul style="list-style-type: none"> <li>• alpha_source: one of "prepass" (default), "trial_projection", or "oasis_rank1". "trial_projection" estimates voxel shape from per-trial projection coefficients in the shared basis.</li> </ul>

	<ul style="list-style-type: none"> <li>• rank1_min: optional minimum rank-1 variance fraction in <math>[0, 1]</math> when <code>alpha_source="oasis_rank1"</code>. Voxels below threshold fall back to prepass.</li> <li>• soft_blend logical (default TRUE): when <code>topK &gt; 1</code>, blend the top-K library coordinates per voxel using softmax weights returned by <code>sbhm_match()</code>. If <code>blend_margin</code> is provided, blending is only applied to voxels with <code>margin &lt; blend_margin</code>; others use the hard top-1 assignment.</li> <li>• blend_margin optional numeric threshold on the matching margin for conditional blending.</li> <li>• whiten_power numeric in <math>[0, 1]</math> for partial singular-value whitening (1=full, 0.5=partial).</li> <li>• min_margin optional minimum matching margin. Voxels below threshold fall back to <code>fallback_ref</code>.</li> <li>• min_beta_norm optional minimum norm of the shape summary used for matching. Voxels below threshold fall back to <code>fallback_ref</code>.</li> <li>• fallback_ref optional r-vector fallback coordinate (default <code>sbhm\$ref\$alpha_ref</code>).</li> </ul>
oasis	Optional list forwarded to <code>lss(..., method="oasis")</code> . K is set to <code>ncol(sbhm\$B)</code> if not provided, and <code>design_spec</code> is injected automatically.
amplitude	List controlling the scalar amplitude stage. Fields: <ul style="list-style-type: none"> <li>• method: one of "lss1" (default), "global_ls", "oasis_voxel".</li> <li>• ridge: for <code>global_ls</code>, either numeric (absolute) or <code>list(mode, lambda)</code>.</li> <li>• ridge_frac: for <code>lss1/oasis_voxel</code>, <code>list(x, b)</code> fractional ridge.</li> <li>• cond_gate: optional auto-fallback rule, e.g., <code>list(metric="rho", thr=0.999, fallback="lss1")</code>.</li> </ul>
return	One of "amplitude", "coefficients", or "both" (default "amplitude").

### Details

Most users should treat the `prepass`, `match`, `oasis`, and `amplitude` inputs as optional *override lists*: you can provide only the fields you want to change, and rely on defaults for everything else.

If you already use `fmrdesign`, prefer `lss_sbhm_design()` to avoid manually assembling an OASIS `design_spec`.

### Value

A list with components:

- `amplitude` `ntrials`×`V` matrix (when requested)
- `coeffs_r` `rxntrials`×`V` array of trial-wise coefficients (when requested)
- `matched_idx` length-`V` integer indices into the library
- `margin` length-`V` confidence margins (top1 - top2 cosine)
- `alpha_coords` `rxV` matched coordinates per voxel
- `diag` list with `r`, `ntrials`, and `times`

### See Also

[lss\\_sbhm\\_design\(\)](#), [sbhm\\_prepass\(\)](#), [sbhm\\_match\(\)](#)

**Examples**

```
## Not run:
library(fmrihrf)
set.seed(3)
Tlen <- 180; V <- 4
sframe <- sampling_frame(blocklens = Tlen, TR = 1)
H <- cbind(exp(-seq(0, 30, length.out = Tlen)/5),
           exp(-seq(0, 30, length.out = Tlen)/7))
sbhm <- sbhm_build(library_H = H, r = 4, sframe = sframe, normalize = TRUE)
onsets <- seq(8, 140, by = 12)
design_spec <- list(sframe = sframe, cond = list(onsets = onsets, duration = 0, span = 30))
hrf_B <- sbhm_hrf(sbhm$B, sbhm$tgrid, sbhm$span)
rr <- fmrihrf::regressor(onsets = onsets, hrf = hrf_B, duration = 0, span = 30, summate = FALSE)
Xr <- fmrihrf::evaluate(rr, grid = sbhm$tgrid, precision = 0.1, method = "conv")
alpha_true <- rnorm(ncol(sbhm$B))
Y <- matrix(rnorm(Tlen*V, sd = .6), Tlen, V)
Y[,1] <- Y[,1] + Xr %*% alpha_true
out <- lss_sbhm(Y, sbhm, design_spec)
out2 <- lss_sbhm(Y, sbhm, design_spec,
                 match = list(topK = 3, soft_blend = TRUE),
                 return = "amplitude")

names(out)

## End(Not run)
```

---

lss\_sbhm\_design

*SBHM Pipeline with fmridesign Models*


---

**Description**

Run the SBHM end-to-end pipeline using `fmridesign`'s `event_model` and optional `baseline_model`, mirroring the convenience of `lss_design()` but producing SBHM coefficients and (optionally) scalar amplitudes.

**Usage**

```
lss_sbhm_design(
  Y,
  sbhm,
  event_model,
  baseline_model = NULL,
  prewhiten = NULL,
  prepass = list(),
  match = list(shrink = list(tau = 0, ref = NULL, snr = NULL), topK = 3, soft_blend =
    TRUE, blend_margin = 0.08, whiten = FALSE, sv_floor_rel = 0.05, whiten_power = 0.5,
    min_margin = NULL, min_beta_norm = NULL, fallback_ref = NULL, orient_ref = TRUE,
    alpha_source = "prepass", rank1_min = 0),
```

```

oasis = list(),
amplitude = list(method = "lss1", ridge = list(mode = "fractional", lambda = 0.02),
  ridge_frac = list(x = 0.02, b = 0.02), cond_gate = NULL, adaptive = list(enable =
  FALSE, base = 0.02, k0 = 1000, max = 0.08), return_se = FALSE),
return = c("amplitude", "coefficients", "both"),
validate = TRUE,
...
)

```

## Arguments

Y	Numeric matrix T×V of fMRI time series (timepoints × voxels).
sbhm	SBHM object as returned by <code>sbhm_build()</code> .
event_model	An <code>event_model</code> from <code>fmridesign::event_model()</code> defining the trial structure (typically created with <code>trialwise()</code> ).
baseline_model	Optional <code>baseline_model</code> from <code>fmridesign::baseline_model()</code> . Its drift, block, and nuisance terms are projected out as confounds.
prewhiten	Optional prewhitening options (see <code>?lss</code> ).
prepass	Optional list forwarded to <code>sbhm_prepass()</code> .
match	Optional list forwarded to <code>sbhm_match()</code> .
oasis	Optional list forwarded to <code>lss(..., method = "oasis")</code> . K defaults to <code>ncol(sbhm\$B)</code> .
amplitude	Amplitude options (see <code>?lss_sbhm</code> ).
return	One of "amplitude", "coefficients", or "both".
validate	Logical; when TRUE, performs basic checks (sampling frame compatibility, temporal alignment) analogous to <code>lss_design()</code> .
...	Reserved for future use.

## Details

This function wraps `lss_sbhm()` by converting the `event_model` into an OASIS `design_spec` that uses the SBHM basis HRF, and by mapping `baseline_model` terms to nuisance regressors for projection.

## Value

Same return contract as `lss_sbhm()`.

## Examples

```

## Not run:
library(fmridesign)
sframe <- fmrihrf::sampling_frame(blocklens = c(150, 150), TR = 2)
trials <- data.frame(onset = c(10,30,50, 10,30,50), run = rep(1:2, each=3))
emod <- event_model(onset ~ trialwise(basis = "spm1"), data = trials,
  block = ~run, sampling_frame = sframe)
Y <- matrix(rnorm(300*100), 300, 100)
out <- lss_sbhm_design(Y, sbhm, emod)

```

```
## End(Not run)
```

---

lss_with_hrf	<i>Perform LSS using Voxel-wise HRFs</i>
--------------	--

---

### Description

Computes trial-wise beta estimates using voxel-specific HRFs.

### Usage

```
lss_with_hrf(
  Y,
  events,
  hrf_estimates,
  nuisance_regs = NULL,
  engine = "R",
  chunk_size = 5000,
  verbose = TRUE,
  backing_dir = NULL
)
```

### Arguments

Y	Numeric matrix of BOLD data (time x voxels).
events	Data frame with onset, duration and condition columns.
hrf_estimates	A <a href="#">VoxelHRF</a> object returned by <code>estimate_voxel_hrf</code> .
nuisance_regs	Optional numeric matrix of nuisance regressors.
engine	Computational engine: "R" for pure R implementation (default), "C++" for optimized C++ (experimental).
chunk_size	Number of voxels to process per batch (C++ engine only).
verbose	Logical; display progress bar.
backing_dir	Directory for bigmemory backing files. If NULL, a temporary directory is used (C++ engine only).

### Value

An object of class [LSSBeta](#) for C++ engine, or a numeric matrix (n\_trials x n\_vox) for R engine.

**Examples**

```
## Not run:
set.seed(1)
Y <- matrix(rnorm(100), 50, 2)
events <- data.frame(onset = c(5, 25), duration = 1,
                    condition = "A")
basis <- fmrihrf::hrf_gamma()
sframe <- fmrihrf::sampling_frame(blocklens = nrow(Y), TR = 1)
times <- fmrihrf::samples(sframe, global = TRUE)
rset <- fmrihrf::regressor_set(onsets = events$onset,
                             fac = factor(1:nrow(events)),
                             hrf = basis, duration = events$duration,
                             span = 30)
X <- fmrihrf::evaluate(rset, grid = times, precision = 0.1, method = "conv")
coef <- matrix(rnorm(ncol(X) * ncol(Y)), ncol(X), ncol(Y))
Y <- X %*% coef + Y * 0.1
est <- estimate_voxel_hrf(Y, events, basis)
betas <- lss_with_hrf(Y, events, est, verbose = FALSE, engine = "R")
dim(betas)

## End(Not run)
```

LSSBeta

*LSSBeta object***Description**

Simple list-based S3 class returned by `lss_with_hrf` containing trial-wise beta estimates.

**Value**

No value itself. This topic documents the object returned by `lss_with_hrf(..., engine = "C++")`.

**Examples**

```
## Not run:
Y <- matrix(rnorm(100), 50, 2)
events <- data.frame(onset = c(5, 25), duration = 1, condition = "A")
basis <- fmrihrf::HRF_SPMG1
est <- estimate_voxel_hrf(Y, events, basis)
fit <- lss_with_hrf(Y, events, est, engine = "C++", verbose = FALSE)
class(fit)

## End(Not run)
```

---

<code>mixed_precompute</code>	<i>Precompute Workspace for Optimized Mixed Model</i>
-------------------------------	---

---

**Description**

Performs expensive matrix computations that don't depend on the response vector, allowing for efficient reuse across multiple voxels.

**Usage**

```
mixed_precompute(X, Z, K = NULL)
```

**Arguments**

<code>X</code>	Fixed effects design matrix ( $n \times p$ )
<code>Z</code>	Random effects design matrix ( $n \times q$ )
<code>K</code>	Kinship/covariance matrix for random effects ( $q \times q$ )

**Value**

Workspace object for use with `mixed_solve_optimized`

**Examples**

```
X <- matrix(1, 6, 1)
Z <- diag(6)
ws <- mixed_precompute(X, Z)
names(ws)
```

---

<code>mixed_solve</code>	<i>Mixed Model Solver</i>
--------------------------	---------------------------

---

**Description**

Solves mixed models with random effects using REML or ML estimation. This function provides a unified interface to mixed model estimation, similar to the `lss/lsa` functions in this package.

**Usage**

```
mixed_solve(
  Y,
  X = NULL,
  Z = NULL,
  K = NULL,
  Nuisance = NULL,
  method = c("REML", "ML"),
```

```

    bounds = c(1e-09, 1e+09),
    SE = FALSE,
    return_Hinv = FALSE
)

mixed_solve_cpp(
  Y,
  X = NULL,
  Z = NULL,
  K = NULL,
  Nuisance = NULL,
  method = c("REML", "ML"),
  bounds = c(1e-09, 1e+09),
  SE = FALSE,
  return_Hinv = FALSE
)

```

### Arguments

Y	Response vector or matrix. If a matrix, each column is treated as a separate response variable.
X	Design matrix for fixed effects. If NULL, defaults to intercept only.
Z	Design matrix for random effects. If NULL, defaults to identity matrix.
K	Kinship matrix for random effects. If NULL, defaults to identity matrix.
Nuisance	An alias for X, provided for consistency with lss/lsa interface. If both X and Nuisance are provided, X takes precedence.
method	Character string specifying the estimation method: <ul style="list-style-type: none"> <li>• "REML" - Restricted Maximum Likelihood (default)</li> <li>• "ML" - Maximum Likelihood</li> </ul>
bounds	Numeric vector of length 2 specifying bounds for variance component optimization. Defaults to c(1e-9, 1e9).
SE	Logical, whether to compute and return standard errors. Defaults to FALSE.
return_Hinv	Logical, whether to return the inverse of the H matrix. Defaults to FALSE.

### Details

This function fits the mixed model:  $Y = X\beta + Zu + \text{error}$ , where  $u \sim N(0, VuK)$  and  $\text{error} \sim N(0, VeI)$ . The variance components  $Vu$  and  $Ve$  are estimated using REML or ML.

### Value

A list containing:

Vu	Estimated variance component for random effects.
Ve	Estimated variance component for residuals.
beta	Estimated fixed effects coefficients.

u	Estimated random effects coefficients.
LL	Log-likelihood of the model.
beta.SE	Standard errors of fixed effects coefficients (if SE = TRUE).
u.SE	Standard errors of random effects coefficients (if SE = TRUE).
Hinv	Inverse of H matrix (if return_Hinv = TRUE).

### Examples

```
## Not run:
set.seed(123)
n <- 100
Y <- rnorm(n)
Z <- matrix(rnorm(n * 5), n, 5)
K <- diag(5)
X <- matrix(1, n, 1)

result <- mixed_solve(Y, X, Z, K)

## End(Not run)
```

---

mixed\_solve\_optimized *Optimized Mixed Model Solver*

---

### Description

An optimized implementation of mixed model estimation that precomputes expensive matrix operations and can be reused across multiple voxels for significant performance improvements.

### Usage

```
mixed_solve_optimized(
  X,
  Z,
  Y,
  K = NULL,
  workspace = NULL,
  compute_se = FALSE,
  n_threads = 0
)
```

### Arguments

X	Fixed effects design matrix ( $n \times p$ )
Z	Random effects design matrix ( $n \times q$ )
Y	Response data - can be a vector (single voxel) or matrix ( $n \times V$ for multiple voxels)

K	Kinship/covariance matrix for random effects ( $q \times q$ ). Defaults to identity.
workspace	Precomputed workspace (optional, will compute if NULL)
compute_se	Whether to compute standard errors (default: FALSE)
n_threads	Number of OpenMP threads for multi-voxel (0 = auto)

**Value**

List with estimated parameters and variance components

**Examples**

```
set.seed(1)
X <- matrix(1, 6, 1)
Z <- diag(6)
Y <- matrix(rnorm(12), 6, 2)
ws <- mixed_precompute(X, Z)
fit <- mixed_solve_optimized(X, Z, Y, workspace = ws)
names(fit)
```

---

oasis_options	<i>Construct OASIS options</i>
---------------	--------------------------------

---

**Description**

Convenience constructor for the oasis= list accepted by `lss(method="oasis")`. Unknown fields are allowed via `...` for forward compatibility.

**Usage**

```
oasis_options(
  design_spec = NULL,
  K = NULL,
  ridge_mode = c("fractional", "absolute"),
  ridge_x = 0.05,
  ridge_b = 0.05,
  block_cols = 4096L,
  return_se = FALSE,
  return_diag = FALSE,
  add_intercept = TRUE,
  hrf_mode = NULL,
  ...
)
```

**Arguments**

design_spec	Optional design spec list used to build X via fmrihrf.
K	Optional basis dimension override.
ridge_mode	"fractional" (default) or "absolute".
ridge_x, ridge_b	Non-negative ridge penalties (defaults 0.05 each).
block_cols	Voxel block size for blocked products.
return_se	Logical; return standard errors.
return_diag	Logical; return diagnostics.
add_intercept	Logical; add intercept when Z is NULL.
hrf_mode	Optional mode (e.g. "voxhrf"); advanced use.
...	Additional options.

**Value**

A list with class "fmrilss\_oasis\_options".

**Examples**

```
oasis_options(ridge_mode = "fractional", ridge_x = 0.1, ridge_b = 0.1)
```

---

plot\_hrf\_comparison     *Plot HRF Recovery Comparison*

---

**Description**

Creates visualization comparing true vs recovered HRFs

**Usage**

```
plot_hrf_comparison(results, save_path = NULL)
```

**Arguments**

results	Output from compare_hrf_recovery
save_path	Optional path to save plot

**Value**

A ggplot2 plot object. When save\_path is supplied, the same plot is also written to disk.

**Examples**

```
## Not run:
onsets <- generate_rapid_design(n_events = 4, total_time = 60, seed = 1)
sim <- generate_lwu_data(onsets, total_time = 60, n_voxels = 2, seed = 1)
grid <- create_lwu_grid(n_tau = 2, n_sigma = 2, n_rho = 2)
res <- compare_hrf_recovery(sim, hrf_grid = grid)
plot_hrf_comparison(res)

## End(Not run)
```

---

```
prewhiten_options      Construct prewhitening options
```

---

**Description**

Convenience constructor for the `prewhiten=` list accepted by `lss()`.

**Usage**

```
prewhiten_options(
  method = c("none", "ar", "arma"),
  p = "auto",
  q = 0L,
  p_max = 6L,
  pooling = c("global", "voxel", "run", "parcel"),
  runs = NULL,
  parcels = NULL,
  exact_first = c("ar1", "none"),
  compute_residuals = TRUE
)
```

**Arguments**

<code>method</code>	"none", "ar", or "arma".
<code>p</code>	AR order or "auto".
<code>q</code>	MA order for ARMA.
<code>p_max</code>	Maximum AR order when <code>p="auto"</code> .
<code>pooling</code>	"global", "voxel", "run", or "parcel".
<code>runs</code>	Optional run identifiers.
<code>parcels</code>	Optional parcel ids.
<code>exact_first</code>	"ar1" or "none".
<code>compute_residuals</code>	Logical.

**Value**

A list with class "fmrilss\_prewhten\_options".

**Examples**

```
prewhiten_options(method = "ar", p = 1, pooling = "run")
```

---

project\_confounds      *Project Out Confound Variables*

---

**Description**

Computes the orthogonal projection matrix  $Q = I - X(X'X)^{-1}X'$  that projects out the space spanned by confound regressors  $X$ . This is useful for advanced users who want to cache and reuse projection matrices.

**Usage**

```
project_confounds(X)
```

**Arguments**

$X$                       Confound design matrix ( $n \times p$ ) where  $n$  is number of timepoints and  $p$  is number of confound regressors

**Details**

This function uses QR decomposition for numerical stability instead of computing the Moore-Penrose pseudoinverse directly. The resulting matrix  $Q$  can be applied to data to remove the influence of confound regressors.

**Value**

Projection matrix  $Q$  ( $n \times n$ ) that projects out the column space of  $X$

**Examples**

```
## Not run:
n <- 100
X_confounds <- cbind(1, 1:n)

Q <- project_confounds(X_confounds)

Y_clean <- Q %*% Y_raw

## End(Not run)
```

---

project\_confounds\_cpp *Project Out Confounds Using C++*

---

## Description

Fast C++ implementation for projecting out confound variables from data and trial design matrices. This uses Cholesky decomposition for numerical stability and avoids creating large projection matrices.

## Usage

```
project_confounds_cpp(X_confounds, Y_data, C_trials)
```

## Arguments

X_confounds	Confound design matrix (n x k)
Y_data	Data matrix (n x V) where V is number of voxels
C_trials	Trial design matrix (n x T) where T is number of trials

## Details

This function computes residuals  $Y - X(X'X)^{-1}X'Y$  and  $C - X(X'X)^{-1}X'C$  without explicitly forming the projection matrix  $Q = I - X(X'X)^{-1}X'$ . This approach uses ~100x less memory for large n and is numerically more stable.

## Value

List with projected data (residual\_data) and projected trials (Q\_dmat\_ran)

## Examples

```
## Not run:
n <- 200; k <- 5; V <- 1000; T <- 50
X_confounds <- cbind(1, 1:n, rnorm(n*3))
Y_data <- matrix(rnorm(n*V), n, V)
C_trials <- matrix(rnorm(n*T), n, T)

result <- project_confounds_cpp(X_confounds, Y_data, C_trials)

## End(Not run)
```

sbhm\_build

*Build a Shared-Basis HRF Library (SBHM)***Description**

Learn a low-rank shared time basis from a parameterized HRF library using `fmrihrf::hrf_library()`. The library is evaluated on the TR grid, optionally baseline-removed and L2-normalized, and decomposed via SVD into  $B = U_r$  (shared basis), singular values  $S$ , and library coordinates  $A = \text{diag}(S) \%*\% t(V_r)$ .

**Usage**

```
sbhm_build(
  library_spec = NULL,
  library_H = NULL,
  r = 6,
  sframe = NULL,
  tgrid = NULL,
  span = 32,
  normalize = TRUE,
  baseline = c(0, 0.5),
  shifts = NULL,
  ref = c("mean", "spm1")
)
```

**Arguments**

<code>library_spec</code>	Either NULL (when <code>library_H</code> is provided) or a list with: <ul style="list-style-type: none"> <li><code>fun</code>: a function compatible with <code>fmrihrf::hrf_library(fun, pgrid, ...)</code> that returns an <code>fmrihrf</code> HRF object when called with parameters.</li> <li><code>pgrid</code>: a <code>data.frame</code> of parameter combinations (see examples).</li> <li><code>span</code>: numeric, HRF span in seconds (default span).</li> <li><code>precision</code>: numeric, evaluation precision (default 0.1 sec).</li> <li><code>method</code>: evaluation method for <code>fmrihrf::evaluate()</code> (default "conv").</li> <li><code>extras</code>: optional list of additional arguments passed to <code>hrf_library</code>.</li> </ul>
<code>library_H</code>	Optional precomputed $T \times K$ matrix of candidate HRFs, already aligned to the TR grid <code>tgrid</code> (or <code>sframe</code> ). Mutually exclusive with <code>library_spec</code> .
<code>r</code>	Target rank for the shared basis (default 6). Clipped to $\min(T, K)$ .
<code>sframe</code>	Optional <code>fmrihrf::sampling_frame</code> , used to derive the global time grid when <code>tgrid</code> is not provided.
<code>tgrid</code>	Optional numeric vector of global times (in seconds). If provided, takes precedence over <code>sframe</code> .
<code>span</code>	HRF span in seconds (default 32). Used for reference HRF when needed.
<code>normalize</code>	Logical, L2-normalize library columns (default TRUE).

baseline	Numeric length-2 vector specifying a time window (in seconds) used for baseline removal (column-wise mean subtraction within this window). Set to NULL to skip.
shifts	Optional numeric vector of time shifts (in seconds). When provided, shifted copies of the library are added by linear interpolation on tgrid.
ref	Reference for coefficient-space shrinkage and orientation. One of "mean" (default) or "spm1". If "spm1", the SPM1 HRF is projected onto the learned basis to form alpha_ref.

### Value

A list with components:

- B (Txr): shared orthonormal time basis
- S (length r): singular values
- A (rxK): coordinates of library HRFs in the shared basis
- tgrid: the global time grid used (seconds)
- span: span used for reference HRF
- ref: list with alpha\_ref (length r) and name
- meta: list with r, K, normalize, baseline

### Examples

```
## Not run:
library(fmrihrf)
param_grid <- expand.grid(shape = c(6, 8, 10), rate = c(0.9, 1.0, 1.1))
gamma_fun <- function(shape, rate) fmrihrf::as_hrf(
  fmrihrf::hrf_gamma, params = list(shape = shape, rate = rate)
)

sframe <- fmrihrf::sampling_frame(blocklens = 200, TR = 1)
sbhm <- sbhm_build(
  library_spec = list(fun = gamma_fun, pgrid = param_grid, span = 32),
  r = 6, sframe = sframe, baseline = c(0, 0.5)
)

hrf_B <- sbhm_hrf(sbhm$B, sbhm$tgrid, sbhm$span)

## End(Not run)
```

---

sbhm_hrf	<i>Wrap a Learned Basis as an HRF (SBHM HRF)</i>
----------	--

---

### Description

Convert a shared time basis matrix  $B$  ( $T \times r$ ) into an `fmrihrf::HRF` object so it can be used directly in OASIS design construction. The HRF returns the  $r$  basis columns evaluated at arbitrary times by piecewise-linear interpolation on the provided time grid.

### Usage

```
sbhm_hrf(B, tgrid, span)
```

### Arguments

B	A numeric matrix ( $T \times r$ ) with orthonormal columns (shared basis).
tgrid	Numeric vector of length $T$ giving the global times (seconds) corresponding to the rows of $B$ .
span	Numeric HRF span passed to <code>fmrihrf::HRF()</code> metadata.

### Value

An `fmrihrf::HRF` object with `nbasis = ncol(B)`.

### Examples

```
## Not run:
  hrf_B <- sbhm_hrf(sbhm$B, sbhm$tgrid, sbhm$span)

## End(Not run)
```

---

sbhm_match	<i>Match Voxels to Library HRFs in Shared Basis (SBHM)</i>
------------	--

---

### Description

Given per-voxel aggregate coefficients `beta_bar` in the shared basis  $B$ , and library coordinates  $A$ , perform shape-only matching in a whitened, L2-normalized coefficient space (cosine similarity). Optionally apply a simple shrinkage of `beta_bar` towards a reference coordinate before matching, and an orientation fix.

**Usage**

```

sbhm_match(
  beta_bar,
  S,
  A,
  shrink = list(tau = 0, ref = NULL, snr = NULL),
  topK = 1,
  whiten = TRUE,
  sv_floor_rel = 1e-06,
  whiten_power = 1,
  orient_ref = TRUE
)

```

**Arguments**

beta_bar	Numeric matrix (r×V): per-voxel coefficients from a prepass GLM in the SBHM basis. Columns correspond to voxels.
S	Numeric vector (length r): singular values of the library SVD.
A	Numeric matrix (r×K): coordinates of library HRFs in SBHM basis.
shrink	List with optional shrinkage options: <ul style="list-style-type: none"> <li>• tau numeric &gt;=0: global strength (default 0, i.e., no shrinkage).</li> <li>• ref numeric length-r vector (alpha_ref) or NULL. If NULL, uses the mean of A columns. Shrinkage is: <math>\beta\_bar \leftarrow (1-\lambda)\beta\_bar + \lambda \text{ref}</math>.</li> <li>• snr optional numeric length-V estimates; if provided, per-voxel <math>\lambda_{\text{v}} = \tau / (\text{snr}_{\text{v}} + \tau)</math>. Otherwise <math>\lambda = \tau</math>.</li> </ul>
topK	Integer, return top-K scores/weights if >1 (default 1).
whiten	Logical, divide coefficients by S before normalization (default TRUE).
sv_floor_rel	Relative singular-value floor used when whiten=TRUE (default 1e-6).
whiten_power	Numeric in [0, 1] controlling whitening strength when whiten=TRUE. Uses division by $S^{\text{whiten\_power}}$ (1 = full whitening, 0.5 = partial whitening, 0 = no whitening). Default 1.
orient_ref	Logical, flip beta_bar columns when their dot with ref is negative before matching (default TRUE).

**Value**

A list with:

- idx length-V integer indices of best-matching library HRF (1..K)
- margin length-V numeric: score(top1) - score(top2)
- alpha\_hat r×V matrix: the selected library coordinates (unwhitened, unnormalized)
- scores optional K×V cosine score matrix (returned when topK > 1)
- weights optional top-K weights per voxel (when topK > 1)

**Examples**

```
## Not run:
set.seed(42)
r <- 4; K <- 12; V <- 3
A <- matrix(rnorm(r*K), r, K)
S <- seq(1, 0.2, length.out = r)
alpha2 <- A[,2]
beta_bar <- cbind(alpha2 + rnorm(r, sd = 0.1),
                  A[,7] + rnorm(r, sd = 0.1),
                  A[,10] + rnorm(r, sd = 0.1))
m <- sbhm_match(beta_bar, S, A)
m$idx

## End(Not run)
```

---

sbhm\_prepass

*SBHM Prepass: Aggregate Fit in Shared Basis*


---

**Description**

Compute per-voxel coefficients in the shared SBHM basis by fitting a single aggregate GLM with one regressor per basis column (trials summed), optionally residualizing by nuisances and prewhitening. This produces `beta_bar` ( $r \times V$ ) that you can feed to `sbhm_match()`.

**Usage**

```
sbhm_prepass(
  Y,
  sbhm,
  design_spec,
  Nuisance = NULL,
  prewhiten = NULL,
  ridge = list(mode = "fractional", lambda = 0.01, alpha_ref = NULL),
  data_fac = NULL
)
```

**Arguments**

<code>Y</code>	Numeric matrix $T \times V$ of fMRI time series.
<code>sbhm</code>	SBHM object from <code>sbhm_build()</code> (must contain <code>B</code> , <code>S</code> , <code>A</code> , <code>tgrid</code> , <code>span</code> ).
<code>design_spec</code>	List describing events (same shape as <code>oasis\$design_spec</code> ). Must contain <code>sframe</code> and <code>cond</code> with onsets (and optional <code>duration</code> , <code>amplitude</code> , <code>span</code> ). <code>cond\$hrf</code> is ignored and replaced with <code>sbhm_hrf</code> . Optional others (list of other conditions) will be aggregated as nuisances.
<code>Nuisance</code>	Optional $T \times P$ nuisance matrix (motion, drift, etc.).

prewhiten	Optional fmriAR prewhitening options (see ?lss). If provided, Y and design are prewhitened together.
ridge	Optional list for targeted ridge shrinkage in the prepass solve: <ul style="list-style-type: none"> <li>• mode: "fractional" (default) or "absolute". Fractional scales by mean(diag(G)).</li> <li>• lambda: nonnegative scalar (default 0.01 in fractional mode).</li> <li>• alpha_ref: r-vector to shrink towards (default zero vector).</li> </ul>
data_fac	Optional list for external factorization: scores (T×q), loadings (q×V). If provided, computes X'Y via (X'Scores) × Loadings. In this PR2 version, prewhitening is not applied when data_fac is used.

## Details

Notes:

- Aggregated per-basis regressors can be highly collinear, making  $G = A' A$  ill-conditioned. A small ridge is recommended for stability. The default uses fractional mode with  $\lambda = 0.01$  (scaled by  $\text{mean}(\text{diag}(G))$ ).
- When data\_fac is provided (factorized data path), prewhitening is skipped in this version; both dense and factorized paths perform nuisance residualization consistently.

## Value

List with:

- beta\_bar r×V aggregate coefficients
- A\_agg T×r aggregated per-basis design (after any residualization/whitening)
- G r×r crossprod of A\_agg
- diag list with K=r, ntrials, times, used\_prewhiten

## Examples

```
## Not run:
library(fmrihrf)
set.seed(1)
Tlen <- 120; V <- 5; r <- 4
sframe <- sampling_frame(blocklens = Tlen, TR = 1)
H <- cbind(exp(-seq(0, 30, length.out = Tlen)/4),
           exp(-seq(0, 30, length.out = Tlen)/6))
sbhm <- sbhm_build(library_H = H, r = r, sframe = sframe, normalize = TRUE)
onsets <- seq(5, 95, by = 10)
design_spec <- list(sframe = sframe, cond = list(onsets = onsets, duration = 0, span = 30))
hrf_B <- sbhm_hrf(sbhm$B, sbhm$grid, sbhm$span)
rr <- fmrihrf::regressor(onsets = onsets, hrf = hrf_B, duration = 0, span = 30, summate = FALSE)
X <- fmrihrf::evaluate(rr, grid = sbhm$grid, precision = 0.1, method = "conv")
betas_true <- matrix(rnorm(r), r)
Y <- matrix(rnorm(Tlen*V, sd = 0.5), Tlen, V)
Y[,1] <- Y[,1] + X %%% betas_true
pre <- sbhm_prepass(Y, sbhm, design_spec)
str(pre)
```

```
## End(Not run)
```

---

```
sbhm_project
```

```
Project Trial-wise SBHM Coefficients to Scalar Amplitudes
```

---

### Description

Given trial-wise coefficients in the shared basis ( $r \times n_{\text{trials}} \times V$ ) and the voxel-specific matched library coordinates  $\alpha_{\text{hat}}$  ( $r \times V$ ), compute scalar amplitudes per trial and voxel via least-squares projection:  $a = (\alpha' \beta) / (\alpha' \alpha)$ .

### Usage

```
sbhm_project(beta_rt, alpha_hat)
```

### Arguments

beta_rt	3D array of shape $r \times n_{\text{trials}} \times V$ containing per-trial coefficients in the SBHM basis (as returned by OASIS with $K=r$ , reshaped).
alpha_hat	Numeric matrix $r \times V$ of matched library coordinates per voxel (e.g., <code>sbhm_match()</code> \$alpha_hat). These should be in the same coordinate system as beta_rt (unwhitened, not L2-normalized) for interpretable amplitudes.

### Value

Numeric matrix  $n_{\text{trials}} \times V$  of scalar amplitudes.

### Examples

```
## Not run:
r <- nrow(alpha_hat)
ntrials <- nrow(beta_mat) / r
beta_rt <- array(beta_mat, dim = c(r, ntrials, ncol(beta_mat)))
amps <- sbhm_project(beta_rt, alpha_hat)

## End(Not run)
```

---

stglmnet_options	<i>Construct stglmnet backend options</i>
------------------	---

---

## Description

Convenience constructor for the `stglmnet=` list accepted by `lss(method = "stglmnet")`. Unknown fields are allowed via `...` for forward compatibility.

## Usage

```
stglmnet_options(
  mode = c("cv", "fixed"),
  alpha = 0.2,
  lambda = NULL,
  overlap_strategy = c("none", "multiplicative", "additive", "hybrid", "threshold"),
  pool_to_mean = FALSE,
  pool_strength = 1,
  pool_mean_penalty = 0,
  whiten = c("inherit", "auto", "never", "always"),
  cv_folds = 5L,
  cv_type.measure = c("auto", "mse", "correlation", "reliability", "composite"),
  cv_select = c("optimal", "1se"),
  return_fit = FALSE,
  ...
)
```

## Arguments

<code>mode</code>	<code>"cv"</code> (default) selects lambda by internal cross-validation, while <code>"fixed"</code> uses the supplied lambda sequence or the smallest fitted lambda when no scalar is provided.
<code>alpha</code>	Elastic-net mixing parameter passed to <code>glmnet</code> .
<code>lambda</code>	Optional lambda sequence (or scalar in fixed mode).
<code>overlap_strategy</code>	Trial-overlap penalty mapping. One of <code>"none"</code> , <code>"multiplicative"</code> , <code>"additive"</code> , <code>"hybrid"</code> , or <code>"threshold"</code> .
<code>pool_to_mean</code>	Logical; reparameterize trial effects into a pooled mean plus orthogonal contrasts.
<code>pool_strength</code>	Penalty multiplier applied to pooled contrasts.
<code>pool_mean_penalty</code>	Penalty applied to the pooled mean coefficient.
<code>whiten</code>	One of <code>"inherit"</code> (default), <code>"auto"</code> , <code>"never"</code> , or <code>"always"</code> . <code>"inherit"</code> uses the top-level <code>prewhiten=</code> argument only.
<code>cv_folds</code>	Number of folds used when <code>mode = "cv"</code> .

<code>cv_type.measure</code>	Cross-validation objective.
<code>cv_select</code>	Lambda selection rule in CV mode. "optimal" uses the best-scoring lambda, "1se" applies the one-standard-error rule.
<code>return_fit</code>	Logical; when TRUE, <code>lss(method="stglmnet")</code> returns a list containing beta, fit metadata, and the selected lambda.
<code>...</code>	Additional backend options.

**Value**

A list with class "fmrilss\_stglmnet\_options".

**Examples**

```
stglmnet_options(mode = "fixed", lambda = 0.05, alpha = 0.5)
```

---

VoxelHRF

*VoxelHRF object*


---

**Description**

Simple list-based S3 class returned by `estimate_voxel_hrf` containing voxel-wise HRF basis coefficients and related metadata.

**Value**

No value itself. This topic documents the structure returned by `estimate_voxel_hrf()`.

**Examples**

```
## Not run:
Y <- matrix(rnorm(100), 50, 2)
events <- data.frame(onset = c(5, 25), duration = 1, condition = "A")
basis <- fmrihrf::HRF_SPMG1
est <- estimate_voxel_hrf(Y, events, basis)
class(est)

## End(Not run)
```

# Index

benchmark\_mixed\_solve, 3

calculate\_recovery\_metrics, 4  
compare\_hrf\_recovery, 4  
create\_lwu\_grid, 5

estimate\_voxel\_hrf, 6

fit\_oasis\_grid, 7  
fmrilss\_options, 8

generate\_lwu\_data, 8  
generate\_rapid\_design, 9

item\_build\_design, 10  
item\_compute\_u, 11  
item\_cv, 13  
item\_fit, 14  
item\_from\_lsa, 15  
item\_predict, 17  
item\_slice\_fold, 17

lsa, 18  
lss, 19, 27–30  
lss\_beta\_cpp, 24  
lss\_cpp\_optimized, 25  
lss\_design, 26  
lss\_fit\_wrappers, 29  
lss\_naive, 29  
lss\_naive\_fit, 31  
lss\_optimized, 32  
lss\_optimized\_fit, 33  
lss\_sbhm, 34  
lss\_sbhm\_design, 36  
lss\_sbhm\_design(), 35  
lss\_with\_hrf, 38  
LSSBeta, 38, 39

mixed\_precompute, 40  
mixed\_solve, 40  
mixed\_solve\_cpp (mixed\_solve), 40

mixed\_solve\_optimized, 42

oasis\_options, 20, 27, 43

plot\_hrf\_comparison, 44  
prewhiten\_options, 20, 21, 27, 45  
project\_confounds, 46  
project\_confounds\_cpp, 47

sbhm\_build, 48  
sbhm\_hrf, 50  
sbhm\_match, 50  
sbhm\_match(), 35  
sbhm\_prepass, 52  
sbhm\_prepass(), 35  
sbhm\_project, 54  
stglnet\_options, 20, 55

VoxelHRF, 6, 38, 56