# Package: ErrorTracer (via r-universe)

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**Type** Package

**Title** Bayesian Error Propagation and Forecast Uncertainty Decomposition

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**Description** Provides a full pipeline from regularized or standard regression models (elastic net, linear models, generalized linear models, random forests) to informed Bayesian priors, structured forecast uncertainty decomposition (parameter / environmental / residual, plus a temporal component when the model carries an autocorrelation term), and forecast shelf life analysis (the quantification of when a forecast becomes uninformative). Designed for ecological and genomic forecasting with climate or environmental covariates. Methods build on Bürkner (2017) <doi:10.18637/jss.v080.i01> for Bayesian regression via 'Stan', Friedman, Hastie, and Tibshirani (2010) <doi:10.18637/jss.v033.i01> for elastic net regularization, Wright and Ziegler (2017) <doi:10.18637/jss.v077.i01> for random forests, and Vehtari, Gelman, and Gabry (2017) <doi:10.1007/s11222-016-9696-4> for leave-one-out cross-validation.

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`decompose_uncertainty` *Extract or recompute uncertainty decomposition*

## Description

Returns a `data.frame` with the uncertainty decomposition stored inside an `et_prediction` object:

**param_var** Variance of the posterior linear predictor — captures uncertainty in fitted regression coefficients.

**env_var** Variance arising from measurement or prediction uncertainty in the predictor values (estimated via perturbation in `et_predict`). A genuine sub-share of `total_var` (see below), not an add-on. Zero when `env_noise = NULL`.

**residual_var** Posterior mean of $\sigma^2$ (or its family-specific analogue) — biological process noise, unmeasured drivers, and drift. For autocorrelation models this is the *innovation* variance, not the stationary marginal variance; the autocorrelated accumulation is reported separately in `temporal_var`. For a non-identity link it is evaluated at the *perturbed* mean, $E_s[V(\mu^{\text{env}})]$, because that is the mean the predictive draws are generated at; it therefore depends on `env_noise` through the variance function. For Gaussian, $V(\mu) = \sigma^2$ is independent of the mean and the distinction does not arise.

**temporal_var** (Only present when the model formula contains an autocorrelation term such as `ar()`, `ma()`, `arma()`, `cosy()`, `unstr()`, `sar()`, or `car()`.) Variance attributable to residual temporal or spatial dependence beyond the named channels, computed as the signed remainder `total_var - (param_var + env_var + residual_var)`. This captures the AR/MA/ARMA innovation accumulation that a single-innovation `residual_var` cannot represent. It is **signed**: a negative value means autocorrelated errors *reduce* predictive variance relative to the independent-innovation baseline, which is a real possibility for a covariance term. Being a remainder, it also absorbs Monte Carlo error from the other channels, so read a `temporal_var` of the same order as `v_env_mcse` as noise.

**closure_gap** (Only present for iid models.) `total_var - (param_var + env_var + residual_var)`: how far the named channels fall short of the measured posterior predictive variance. It is Monte Carlo error for a correctly specified iid model, of the order of `v_env_mcse`. A systematically large value means a channel is mis-estimated.

**total_var** Total predictive variance: the **sampled variance of the environmentally inclusive posterior predictive draws**, which is the distribution the reported credible interval is drawn from. The driver perturbation is applied *before* the predictive draw, so `env_var` is a genuine share of this total.

## Usage

```
decompose_uncertainty(predictions, ...)
```

## Arguments

| | |
|---|---|
| `predictions` | An `et_prediction` object from `et_predict`, or an `et_prediction_list` (grouped). |
| `...` | Unused. |

### Details

Changed in 1.4.0. `total_var` used to be *defined* as the sum of the other components, which made the shares reconcile to 100% by construction and made `env_var` an add-on to a predictive variance that did not contain it. It is now measured, and the sum is recovered as a *result*: the channels add up to `total_var` exactly for autocorrelation models (where `temporal_var` is the remainder) and up to Monte Carlo error for iid models (reported as `closure_gap`). `param_var`, `env_var` and `residual_var` remain non-negative; `temporal_var` and `closure_gap` are signed.

### Value

A `data.frame` with columns `obs_id`, `param_var`, `env_var`, `residual_var`, `total_var` (plus `temporal_var` for autocorrelation models or `closure_gap` for iid ones, and a leading `group` column for grouped predictions).

### Examples

```
set.seed(1)
df  <- data.frame(y = rnorm(20), x1 = rnorm(20))
fit <- et_fit(y ~ x1, data = df,
              chains = 1, iter = 500, warmup = 250,
              cores = 1, refresh = 0)
new_df <- data.frame(x1 = rnorm(5))
pred   <- et_predict(fit, newdata = new_df,
                     env_noise = list(x1 = 0.2),
                     n_draws = 200, n_perturb = 50)
decomp <- decompose_uncertainty(pred)
head(decomp)
```

---

## `et_calibrate` *Assess calibration of posterior predictive intervals*

---

### Description

Computes observed coverage probability at multiple nominal CI levels. A well-calibrated Bayesian model should produce 90% CIs that contain the true value 90% of the time, etc.

### Usage

```
et_calibrate(predictions, observed, response_col = NULL, ci_levels = NULL, ...)
```

### Arguments

| | |
|---|---|
| `predictions` | An `et_prediction` or `et_prediction_list`. |
| `observed` | A `data.frame` with true response values. Must have the same number of rows as `predictions$newdata` (rows are matched positionally) and a column with the true response values. |

| | |
|---|---|
| response_col | Character. Name of the response column in observed. Defaults to the left-hand side of the model formula if it can be inferred, otherwise must be specified. |
| ci_levels | Numeric vector. CI levels to assess. Defaults to all levels present in the et_prediction object. |
| ... | Unused. |

## Value

A data.frame with columns:

**ci_level** Nominal CI level.

**nominal** Same as ci_level.

**observed_coverage** Fraction of true values falling inside the CI.

**n_obs** Number of observations used.

**calibration_error** Signed difference: observed - nominal. Positive = over-coverage (CIs too wide / conservative). Negative = under-coverage (CIs too narrow / overconfident).

**sharpness** Mean CI width across observations. Sharpness and calibration are complementary: a model can be calibrated but useless if sharpness is poor (very wide CIs).

For grouped predictions, a group column is prepended.

## Examples

```
set.seed(1)
df  <- data.frame(y = rnorm(20), x1 = rnorm(20))
fit <- et_fit(y ~ x1, data = df,
              chains = 1, iter = 500, warmup = 250,
              cores = 1, refresh = 0)
valid_df <- data.frame(y = rnorm(5), x1 = rnorm(5))
pred <- et_predict(fit, newdata = valid_df,
                   n_draws = 200, n_perturb = 50)
cal <- et_calibrate(pred, observed = valid_df, response_col = "y")
print(cal)
```

---

# et_diagnose *Diagnose a fitted ErrorTracer model*

---

## Description

Computes Rhat, effective sample size ratios, divergent transitions, and leave-one-out cross-validation (LOO-CV) for a fitted et_model.

## Usage

```
et_diagnose(model, loo = TRUE, ...)
```

### Arguments

| | |
|---|---|
| model | An et_model or et_model_list. |
| loo | Logical. Whether to run LOO-CV (can be slow; default TRUE). |
| ... | Unused. |

### Value

A list with elements:

**convergence** List: rhat_max, rhat_all_ok, neff_min, neff_all_ok, n_divergences.

**loo** List or NULL: elpd_loo, p_loo, looic, n_bad_pareto_k, loo_object.

**summary** Printed summary from brms::summary().

For et_model_list, a named list of per-group diagnostic lists plus an aggregated summary data.frame.

---

## et_fit *Fit a Bayesian regression model with informed priors*

---

### Description

Wraps brms::brm() and attaches the prior specification, training data reference, and configuration for downstream uncertainty decomposition. Pass priors from extract_priors to use regularized-model coefficients to set the prior scale (and, with shrinkage = "estimate", the prior mean); omit it for default (weakly informative) priors.

### Usage

```
et_fit(
  formula,
  data,
  priors = NULL,
  chains = 4L,
  iter = 2000L,
  warmup = floor(iter/2),
  cores = min(chains, parallel::detectCores()),
  seed = 42L,
  adapt_delta = 0.95,
  max_treedepth = 12L,
  grouping = NULL,
  eiv = NULL,
  ar_prior = c("weakly_informative", "stationary", "flat"),
  silent = 2L,
  ...
)
```

## Arguments

| | |
|---|---|
| formula | An R formula, e.g.\ response ~ . or y ~ x1 + x2. |
| data | A data.frame with all predictors and the response. |
| priors | An et_prior_spec object from extract_priors, or a brmsprior object, or NULL for brms defaults. |
| chains | Integer. Number of MCMC chains (default 4). |
| iter | Integer. Total iterations per chain, including warmup (default 2000). |
| warmup | Integer. Warmup iterations per chain (default floor(iter / 2)). |
| cores | Integer. Parallel cores (default min(chains, parallel::detectCores())). |
| seed | Integer. Random seed for reproducibility (default 42). |
| adapt_delta | Numeric. Target acceptance probability for HMC (default 0.95). |
| max_treedepth | Integer. Maximum tree depth (default 12). |
| grouping | Character. Name of a column in data to use for grouping. If non-NULL, one model is fitted per unique group value and an et_model_list is returned. |
| eiv | Optional errors-in-variables specification. A named list / vector mapping predictor names to either a scalar SD or a vector of per-row SDs (length nrow(data)). For each entry, the formula term for that predictor is rewritten as brms::me(pred, se_pred) (an auxiliary se_<pred> column is appended to data), so the posterior reflects measurement error in the predictor as well as coefficient uncertainty. The beta posteriors widen accordingly, which partially absorbs what ErrorTracer's downstream env_var component would otherwise report. When eiv is supplied together with an et_prior_spec from extract_priors, the informed priors are *dropped* because they target class = "b" terms and me() terms live under class = "bsp"; brms defaults are used instead (and a warning is logged). |
| ar_prior | Character. Prior on autocorrelation parameters (class = "ar" / "ma") when the formula carries an ar() / ma() / arma() term. brms's own default is *flat and unbounded*, which on a short series lets the posterior straddle the unit root; the k-step forecast variance $\sigma^2(1-\phi^{2k})/(1-\phi^2)$ then diverges, and temporal_var and shelf_life become uninterpretable. Options:<br>"weakly_informative" (default) normal(0, 0.5) — about 95% of the prior mass lies inside $(-1, 1)$, but the parameter is not hard-bounded, so a genuinely non-stationary series can still say so.<br>"stationary" The same prior truncated to $(-1, 1)$. For AR(1) this is exactly the stationarity region; for higher orders it is necessary but not sufficient, and a warning says so.<br>"flat" brms's unbounded default.<br>A prior the caller supplies for these classes is never overridden. Regardless of the setting, et_fit() warns after fitting when more than 5% of the posterior sits at $\|\phi\| \geq 1$. |
| silent | Integer passed to brms::brm() (default 2, no Stan output). |
| ... | Additional arguments passed to brms::brm(). |

### Value

An `et_model` object (or an `et_model_list` if `grouping` is specified).

### Scope and limitations

`et_fit()` is deliberately a **thin wrapper around** `brms`: the formula, family, and any autocorrelation term (`ar()`/`ma()`/ `arma()`/...) are passed straight through, so ErrorTracer inherits `brms`'s modelling scope and its Stan back-end. The added value is the prior pipeline, the structured uncertainty decomposition, forecast skill / shelf life, and calibration diagnostics — not new model classes.

Two boundaries to keep in mind:

- **Hierarchical / random-effects models** fit through the formula (`y ~ x + (x | group)`) and are decomposed correctly, with the in-sample / out-of-sample distinction handled explicitly. Predicting for a group the fit has *seen* uses that group's estimated effect: the effect is a parameter, its posterior uncertainty is part of `param_var`, and there is no separate group channel (conditioning on a known group *reduces* predictive variance relative to the population level). Predicting for a *new* level integrates over the group-level distribution and adds a `group_var` channel carrying the between-group variance; `et_predict` detects new levels automatically. The `grouping` argument here is a *separate* device: it fits one independent model per group (no pooling), not a single multilevel model.
- **Convergence is your responsibility.** `et_fit()` emits a warning on high Rhat or divergent transitions, but you should inspect `et_diagnose` before predicting; the defaults (`iter = 2000`, 4 chains) are a starting point, not a guarantee.

### Examples

```
set.seed(1)
df  <- data.frame(y = rnorm(20), x1 = rnorm(20), x2 = rnorm(20))
ps  <- extract_priors(lm(y ~ x1 + x2, data = df))
fit <- et_fit(y ~ x1 + x2, data = df, priors = ps,
              chains = 1, iter = 500, warmup = 250,
              cores = 1, refresh = 0)
print(fit)
```

---

## et_pit *Probability integral transform (PIT) for calibration diagnostics*

---

### Description

Computes the probability integral transform of held-out observations under the (reported) posterior predictive distribution — the same distribution the credible intervals and `et_calibrate` coverage are built from, including environmental uncertainty when it was folded in. For a well-calibrated model the PIT values are $\mathrm{Uniform}(0, 1)$. Systematic departures diagnose *how* the model is miscalibrated, which interval coverage alone cannot: a **U-shape** means the predictive is too narrow (overconfident), a central **hump** means it is too wide (underconfident), and a **slope / shift** means it is biased. Visualise with `et_plot_pit` (a PIT / rank histogram).

### Usage

```
et_pit(predictions, observed, response_col = NULL, randomize = TRUE, ...)
```

### Arguments

| | |
|---|---|
| predictions | An et_prediction or et_prediction_list. |
| observed | A data.frame of true responses, positionally matched to predictions$newdata (and containing the grouping column for a grouped prediction). |
| response_col | Character. Response column name; inferred from the model formula when NULL. |
| randomize | Logical. Use the *randomized* PIT (default TRUE), which spreads the probability mass at ties so the values are uniform under calibration for **discrete** predictions (counts, binary). It is a no-op for continuous predictions, where exact ties have probability ~0. Set FALSE for the non-randomized $P(Y \leq y)$. |
| ... | Unused. |

### Value

A data.frame with columns obs_id and pit (plus a leading group column for grouped predictions).

### See Also

et_plot_pit, et_calibrate

---

## et_plot_calibration *Plot calibration: observed vs nominal coverage*

---

### Description

A well-calibrated model produces points along the 1:1 diagonal. Points above the diagonal indicate over-coverage (conservative); below indicates under-coverage (anti-conservative).

### Usage

```
et_plot_calibration(cal, group_col = NULL)
```

### Arguments

| | |
|---|---|
| cal | A data.frame from et_calibrate. |
| group_col | Optional character. Name of a column in cal that identifies sub-groups (e.g.\ "species", "cluster_id"). When NULL (default), et_plot_calibration uses the group column if present; otherwise it auto-detects any single non-canonical column with more than one unique value and treats it as the grouping. Set to NA to force a single un-grouped series. |

### Value

A ggplot2 object.

## et_plot_coefficients *Forest plot of regression coefficients*

### Description

Compares Bayesian posterior estimates (95% CI) with the regularized coefficient values used as prior means (shown as crosses).

### Usage

```
et_plot_coefficients(model)
```

### Arguments

| | |
|---|---|
| model | An et_model or et_model_list. |

### Value

A ggplot2 object.

## et_plot_decomposition *Plot uncertainty decomposition*

### Description

Produces a stacked bar chart showing the relative contributions of parameter, environmental, and residual variance for each observation, plus a fourth temporal-autocorrelation component when present in decomp (see decompose_uncertainty).

### Usage

```
et_plot_decomposition(decomp, proportional = TRUE, group_col = NULL)
```

### Arguments

| | |
|---|---|
| decomp | A data.frame from decompose_uncertainty or directly the $decomposition slot of an et_prediction. |
| proportional | Logical. If TRUE (default), each component is shown as a share of total_var (the measured predictive variance). Shares therefore sum to 1 exactly for autocorrelation models and to within Monte Carlo error for iid ones, where the shortfall is the closure_gap column. If FALSE, raw variances are shown. Because temporal_var is signed, a negative component is drawn below the zero line rather than silently clamped. |

group_col — Character. Optional name of a grouping column in decomp (present for grouped predictions). One bar is drawn per group: the components are summed over the group's observations and divided by the summed total_var, so the bar still sums to 1. That is a variance-weighted share, equal to mean(component) / mean(total_var), and it is the quantity to quote alongside the figure. It is not the mean of the per-observation shares, which would weight a low-variance lead equally with a high-variance one; for an autocorrelation model, where predictive variance grows with lead time, the two can differ by tens of percentage points.

## Value

A ggplot2 object.

---

# et_plot_forecast *Plot posterior predictive fan chart*

---

## Description

Overlays nested credible interval ribbons on the median forecast, with optional observed values for calibration assessment.

## Usage

```
et_plot_forecast(
  predictions,
  observed = NULL,
  response_col = NULL,
  time_col = NULL
)
```

## Arguments

| | |
|---|---|
| predictions | An et_prediction object. |
| observed | Optional data.frame with true response values. If provided, points are overlaid. |
| response_col | Character. Name of the response column in observed. |
| time_col | Character. Column in predictions$newdata used as the x-axis. Defaults to observation index. |

## Value

A ggplot2 object.

## et_plot_pit *Plot a PIT / rank histogram for calibration*

### Description

Histogram of the probability-integral-transform values from `et_pit`. Bars level with the dashed uniform reference line indicate calibration; a **U-shape** means overconfident (too-narrow) intervals, a central **hump** means underconfident (too-wide), and a **tilt** means bias. The shaded band is an approximate 95% consistency region for the bar heights under uniformity.

### Usage

```
et_plot_pit(pit, bins = 10L)
```

### Arguments

| | |
|---|---|
| `pit` | A `data.frame` from `et_pit` (a `pit` column, optionally `group`), or a bare numeric vector of PIT values. |
| `bins` | Integer. Number of histogram bins (default 10). |

### Value

A `ggplot` object.

### See Also

`et_pit`, `et_plot_calibration`

## et_plot_prior_posterior *Plot prior vs posterior distributions for model coefficients*

### Description

Overlays prior and posterior density for each predictor coefficient, visualising how much the data update the priors.

### Usage

```
et_plot_prior_posterior(model, max_preds = 8L, n_prior_draws = 4000L)
```

### Arguments

| | |
|---|---|
| `model` | An `et_model` object. |
| `max_preds` | Integer. Maximum number of predictors to show (default 8). Predictors are shown in the order they appear in the prior specification. |
| `n_prior_draws` | Integer. Number of random draws for the prior density (default 4000). |

### Value

A ggplot2 object.

---

`et_plot_sensitivity` *Plot a sensitivity profile*

---

### Description

Visualises the output of `et_sensitivity_profile`: for each noise grid point, shows how the **environmental share** of total variance and the **forecast horizon** respond. Observed horizons are drawn as solid points; projected horizons are hollow points; lower-bound rows are drawn as upward arrows at the last informative time.

### Usage

```
et_plot_sensitivity(sens, show = c("horizon", "env_share", "ratio"))
```

### Arguments

| | |
|---|---|
| `sens` | An `et_sensitivity` object from `et_sensitivity_profile`. |
| `show` | `"horizon"` (default) shows the shelf-life horizon; `"env_share"` shows `env_var / total_var`; `"ratio"` shows the mean CI width / plausible range. |

### Details

The x-axis is the noise fraction (when the grid was built from `fraction_grid`) or the grid step label otherwise. When both a numeric fraction and a descriptive label exist, the fraction is preferred for continuous x-positioning.

### Value

A ggplot2 object.

### See Also

`et_sensitivity_profile`

## et_plot_shelf_life *Plot forecast shelf life*

### Description

Shows how credible interval width grows over the forecast horizon and marks the threshold beyond which the forecast is uninformative.

### Usage

```
et_plot_shelf_life(sl, show_ratio = TRUE, max_ratio = NULL)
```

### Arguments

| | |
|---|---|
| sl | An et_shelf_life object from shelf_life. |
| show_ratio | Logical. If TRUE (default), plots the ratio (CI width / plausible range) rather than raw CI width. |
| max_ratio | Numeric. Optional upper limit for the y axis, applied as a zoom (coord_cartesian) rather than a filter, so nothing is dropped and a trace that exceeds it runs off the top of the panel. Use it when one series sits an order of magnitude above the rest and compresses them against the axis; say in the caption that the panel is capped. NULL (default) fits all of the data. |

### Value

A ggplot2 object.

## et_predict *Posterior prediction with uncertainty decomposition*

### Description

Generates posterior predictive draws for new observations, propagates environmental measurement uncertainty through the model, and computes credible intervals. The resulting et_prediction object is the input to decompose_uncertainty, shelf_life, and the plotting functions.

### Usage

```
et_predict(
  model,
  newdata,
  env_noise = NULL,
  env_cov = NULL,
  env_dist = NULL,
  env_ensemble = NULL,
```

```
  n_draws = 2000L,
  ci_levels = c(0.5, 0.8, 0.9, 0.95),
  n_perturb = NULL,
  n_env_draws = 1L,
  interval_type = c("predictive", "linpred"),
  include_env_in_ci = NULL,
  var_trim = 0,
  seed = NULL,
  ...
)
```

## Arguments

| | |
|---|---|
| `model` | An `et_model` or `et_model_list` object from `et_fit`. |
| `newdata` | A `data.frame` containing the predictor columns named in the model formula. For grouped models, must also contain the grouping column. |
| `env_noise` | Environmental measurement / prediction uncertainty. Can be:<br>• `NULL` (default): no environmental noise.<br>• A single numeric: applied as a fraction of each predictor's empirical SD in `newdata` (e.g.\ `0.1` means 10% noise, constant across all observations).<br>• A named `list` or named numeric vector with one scalar per predictor: constant absolute noise SD per predictor, e.g.\ `list(Tmean = 0.5, PPT = 10)`.<br>• A named `list` where each entry is a **numeric vector of length** `nrow(newdata)`: *time-varying* (per-row) noise SDs. Use this when predictor uncertainty grows with forecast horizon, e.g.\ from a GCM ensemble spread that increases over time: `list(Tmean = 0.30 + 0.01 * (years - base_year))`. Entries not supplied default to zero (no noise for that predictor). |
| `env_cov` | Correlation structure of the environmental noise. The *magnitudes* of the noise come from `env_noise`; `env_cov` supplies the *correlation* between predictors, so that a perturbation on row $i$ is drawn from $\mathcal{N}(0,\ D_i R D_i)$ with $D_i = \mathrm{diag}(\sigma_{i1}, \ldots, \sigma_{ip})$ and $R$ = the correlation matrix. One of:<br>• `NULL` (default): independent noise, $R = I$ — equivalent to ErrorTracer behaviour prior to this feature and the right choice when predictor measurement errors are genuinely independent (e.g.\ separate instruments on unrelated variables).<br>• `"empirical"`: compute the correlation of the predictor columns in the **training data** (`model$data`). Use this when predictor *errors* are expected to inherit the correlation structure of the predictors themselves — e.g.\ temperature and humidity that co-vary in the underlying climate system.<br>• `"newdata"`: compute the correlation of the predictor columns in `newdata`. Useful when the forecast window has a different covariance structure than training (e.g.\ scenario runs).<br>• A numeric $p \times p$ matrix with `dimnames` matching the model's predictors. Entries with an off-diagonal exceeding 1 are rescaled to a correlation matrix. Use this to supply an independent estimate of the *error* correlation structure (e.g.\ from a reanalysis product or a sensor covariance report). |

A correlation derived from training data is a working assumption: the structure of the *errors* is assumed to mirror the structure of the *values*. When this is implausible, pass a matrix directly.

`env_dist` Distributional form of the per-predictor noise. The `env_noise` SDs set the *magnitude* of the perturbation; `env_dist` sets its *shape*. For every distribution other than `"gaussian"`, the noise is calibrated so that (approximately) $E[\tilde{x}] = x$ and $\mathrm{Var}[\tilde{x}] = \sigma^2$, using a Gaussian copula to honour `env_cov`. One of:

- `NULL` (default): `"gaussian"` for every predictor — additive Gaussian noise, legacy behaviour.
- A single string (`"gaussian"`, `"lognormal"`, `"gamma"`, `"beta"`): applied to all predictors.
- A named list / character vector with one entry per predictor to override the default, e.g.\ `list(PPT = "gamma", tmax = "gaussian")`.

Distributions:

`"gaussian"` Additive normal noise ($\tilde{x} = x + \varepsilon, \varepsilon \sim N(0, \sigma^2)$). Appropriate for symmetric measurement error on a continuous, potentially negative scale (temperature, anomalies).

`"lognormal"` Multiplicative noise: $\log \tilde{x} \sim N(\log x - s^2/2,\ s^2)$ with $s^2 = \log(1 + (\sigma/x)^2)$. Preserves positivity; right-tail skewed. Natural for strictly positive continuous variables whose error scales with magnitude (e.g.\ enzyme activity, biomass). Rows with $x \leq 0$ are left unperturbed.

`"gamma"` $\tilde{x} \sim \mathrm{Gamma}(\mathrm{shape} = (x/\sigma)^2,\ \mathrm{rate} = x/\sigma^2)$. Positive support, right-skewed, analytic mean/variance match. Natural for precipitation, rates, and other non-negative continuous variables. Rows with $x \leq 0$ are left unperturbed.

`"beta"` $\tilde{x} \sim \mathrm{Beta}(\alpha, \beta)$ with $\alpha + \beta = x(1-x)/\sigma^2 - 1$. Support in $(0, 1)$; appropriate for proportions and probabilities (allele frequencies, presence rates). Rows with $x \notin (0, 1)$ or $\sigma^2 \geq x(1-x)$ are left unperturbed.

Correlation (`env_cov`) is applied to the latent standard-normal draws before the marginal quantile transform, so rank correlations are preserved across distributions.

`env_ensemble` Optional pathwise driver ensemble for forecasting under uncertain future covariates. A **named list**, one entry per uncertain driver predictor, where each entry is an $M \times H$ matrix of $M$ scenario trajectories over the $H = \mathrm{nrow}(\mathrm{newdata})$ forecast steps (rows are scenarios, columns are horizon steps). Unlike `env_noise` — which draws *independent* per-observation jitter that averages out and leaves the driver variance flat with lead time — each posterior draw here is paired with a whole *trajectory*, so the driver uncertainty is temporally coherent and **accumulates with lead time** as a real driver ensemble (e.g.\ CMIP members, or resampled climatology) fans out. Predictors absent from `env_ensemble` are held at their `newdata` values. When supplied, `env_ensemble` supersedes `env_noise` for the perturbation and is folded into the credible interval by default. This is the recommended way to build a genuine *reforecast* in which only information available at the issue date is used.

`n_draws` Integer. Number of posterior draws to use (default 2000; capped at the number of draws available in the fit).

`ci_levels` Numeric vector. Credible interval levels to compute (default `c(0.5, 0.8, 0.9, 0.95)`).

`n_perturb` Integer. Number of posterior draws used for the environmental perturbation step (default `n_draws`, i.e.\ every draw). Reducing it speeds up the perturbation at the cost of a smaller sample for *the whole env-inclusive budget*: the perturbed mean of draw $s$ must be paired with the residual of that same draw $s$, so when `n_perturb` < `n_draws` and environmental uncertainty is present, the predictive draws and every decomposition channel are computed on the first `n_perturb` draws rather than recycling the perturbation across all of them. Recycling would destroy $\mathrm{Cov}(\mu^{(s)}, y^{pp,(s)} - \mu^{(s)})$, which is substantially negative for an `ar()` fit and inflates the predictive variance (measured at up to 196x `env_var` on a near-unit-root series). Leave at the default unless the perturbation is the bottleneck.

`n_env_draws` Integer. Number of independent environmental perturbations averaged *per posterior draw* when estimating `env_var` (default `1`). Increasing this reduces Monte Carlo noise on the environmental-variance estimate at the cost of proportional computation. The decomposition always reports a Monte Carlo SE (`v_env_mcse`) alongside `env_var`; it decreases roughly like $1/\sqrt{n_env_draws \cdot n_perturb}$.

`interval_type` Character. Which draws to use when computing credible intervals:

- `"predictive"` (default): draws from `posterior_predict`, which include sigma (residual noise). Use this when forecasting **individual observations** — e.g. a single population's allele frequency, one site's ozone reading on a specific day.
- `"linpred"`: draws from `posterior_linpred`, which capture only parameter uncertainty (no sigma). Use this when forecasting the **mean response** — e.g. the expected ozone across many similar days, or mean delta f across replicate populations. These intervals are always narrower; they will undercover individual observations unless sigma is negligible.

The decomposition components and `posterior_predict` / `posterior_linpred` matrices are always computed regardless of this setting.

`include_env_in_ci`

Logical or `NULL`. Controls whether environmental (predictor) uncertainty is folded into the credible interval when `interval_type = "predictive"`. When `TRUE`, intervals are built from **environmentally inflated** draws in which the draws are generated at the env-perturbed mean. For a Gaussian identity link that is the location shift $\tilde{y} = \tilde{\mu} + (y^{pp} - \mu)$, which is exactly a draw from $N(\tilde{\mu}, \sigma^2)$ carrying that draw's own residual. For any other family the draw is taken from the response distribution *at* $\tilde{\mu}$, since the shift would keep the dispersion at $\mu$ while moving only the location (for a count model it also produced non-integer and negative draws). Models with a residual autocorrelation term keep the shift whatever the family, because $y^{pp} - \mu$ is what carries the `brms` forward iteration; such a fit reports a first-order approximation and says so. The interval variance is then param + env + residual, coherent with `total_var`. The default `NULL` means **auto**: env is folded in whenever the caller supplied non-zero `env_noise`, and omitted otherwise. Pass `FALSE` to force a parameter + residual interval even when `env_noise` is given — note that this makes the reported interval deliberately narrower than `total_var` implies, since `total_var` is always the variance of the env-inclusive draws.

`var_trim` Numeric in $[0, 0.5)$, default `0`. Winsorization applied when computing *every* variance channel of the decomposition: each column of draws is clipped to its [`var_trim`, $1 -$ `var_trim`] quantiles before `var()`. The default `0` is the plain sample variance, so the reported budget describes exactly the distribution the quantile credible interval is drawn from. A non-zero value trades that coherence for robustness against a heavy-tailed predictive distribution, and is applied uniformly across `param_var`, `env_var`, the posterior-predictive variance and hence `temporal_var` — never to one channel only, which would bias their differences. Winsorizing is **not** the right remedy for a near-unit-root autocorrelation posterior: it masks a diverging forecast variance rather than fixing it, and leaves the budget describing a different distribution from the interval. Prefer a stationarity-respecting prior at fit time (`et_fit(ar_prior = "stationary")`).

`seed` Integer or `NULL` (default). Seed for the random draws this function makes: the posterior-predictive draw and the driver perturbation of `env_noise` / `env_ensemble`. `NULL` takes the seed the model was fitted with (`model$config$seed`), so a prediction is reproducible from the model alone and two scripts that reach the same fit by different routes agree. The caller's random stream is saved and restored, so seeding here never disturbs anything downstream. Pass `NA` to keep the ambient stream and leave the draws free. For an `et_model_list` the seed is offset by group position, so the groups neither share a perturbation stream nor stop being reproducible.

`...` Passed to methods.

## Value

An `et_prediction` object (list) containing:

`posterior_predict` Matrix `[n_draws x n_obs]`: full posterior predictive draws (parameter + residual uncertainty).

`posterior_linpred` Matrix `[n_draws x n_obs]`: linear predictor draws on the **link scale** (parameter uncertainty only).

`lp_perturbed` Matrix `[n_perturb x n_obs]`: linear predictor on the link scale computed on environmentally perturbed inputs.

`sigma_draws` Numeric vector: posterior draws of sigma (`NA` for families without a sigma parameter, e.g.\ Binomial).

`credible_intervals` data.frame with columns `row_id`, `ci_level`, `lower`, `median`, `upper`, `width`.

`decomposition` data.frame with columns `obs_id`, `total_var`, `param_var`, `env_var`, `v_env_mcse`, `residual_var`, plus `temporal_var` for autocorrelation models or `closure_gap` for iid ones. All components are on the **response scale**. `total_var` is the **measured** variance of the env-inclusive predictive draws, not the sum of the channels; see `decompose_uncertainty`. `v_env_mcse` is the Monte Carlo SE of `env_var`. `residual_var` is per-observation for non-Gaussian families (e.g.\ Binomial: $E_s[\mu^{(s)}(1-\mu^{(s)})]$) and constant for Gaussian.

`newdata` The input `newdata`.

`model` Reference to the `et_model` used.

`env_cov` The $p \times p$ correlation matrix actually used for perturbation (identity for `env_cov = NULL`).

`env_dist` Named character vector mapping each predictor to the distribution actually used for its perturbation.

## See Also

decompose_uncertainty, shelf_life, et_calibrate

---

`et_priors_split` *Extract priors from data held out from the likelihood*

---

## Description

The standard workflow fits a regularized model and the Bayesian model on the *same* rows. Even with `shrinkage = "zero"`, which never reuses a point estimate as a prior mean, two things still cross over: the prior *scale* is set from those rows, and — more consequentially — when the first-stage model performs variable *selection*, the surviving predictor set is chosen using the same data that then forms the likelihood. Reported coverage is therefore conditional on that selection being correct, which is easy to satisfy in a simulation with orthogonal nuisance predictors and much less so in the correlated designs typical of real covariates.

## Usage

```
et_priors_split(data, prior_fun, prop = 0.5, seed = NULL, strata = NULL, ...)
```

## Arguments

| | |
|---|---|
| `data` | A `data.frame` containing both the first-stage predictors and the response. |
| `prior_fun` | A function taking a `data.frame` and returning a fitted model that `extract_priors` accepts (e.g.\ an `lm`/`glm`/`cv.glmnet` fit). |
| `prop` | Proportion of rows used for the **prior** stage (default `0.5`). The remainder is returned for the likelihood. |
| `seed` | Optional integer seed for the split, for reproducibility. |
| `strata` | Optional column name in `data`. When supplied the split is stratified within its levels, so each level is represented in both halves — important for grouped or seasonal designs where a naive split can leave a level entirely absent from one side. |
| `...` | Passed to `extract_priors` (e.g.\ `multiplier`, `min_sd`, `shrinkage`). |

## Details

`et_priors_split()` removes both by construction: the first-stage model is fitted on a random subset, and the rows returned for the Bayesian fit are its complement. Selection and likelihood then share no observations, so the posterior needs no post-selection caveat.

## Value

A list with:

**priors** The `et_priors` object from the prior-stage rows.

**fit_data** Rows to pass to `et_fit` — disjoint from the rows used to build the priors.

**prior_data** Rows used for the first stage, returned so the split is auditable rather than hidden.

**prop, n_prior, n_fit** The realised split.

### The trade-off, stated plainly

Splitting costs sample size. With `prop = 0.5` the likelihood sees half the data, so the posterior is genuinely wider — that width is honest rather than pessimistic, but at small $n$ the loss can dominate whatever the prior contributes. Splitting is worth it when selection stability is in doubt (many correlated candidate predictors) and not worth it when the predictor set is fixed a priori, where there is no selection to protect against and the full sample should go to the likelihood.

### See Also

`extract_priors` for the single-sample workflow.

### Examples

```
set.seed(1)
d <- data.frame(x1 = rnorm(80), x2 = rnorm(80))
d$y <- 1 + 2 * d$x1 + rnorm(80)
sp  <- et_priors_split(d, function(df) lm(y ~ x1 + x2, data = df), seed = 1)
fit <- et_fit(y ~ x1 + x2, data = sp$fit_data, priors = sp$priors,
              chains = 1, iter = 500, refresh = 0)
```

---

## et_sensitivity_profile

*Sensitivity profile of the environmental uncertainty component*

---

### Description

Sweeps a grid of noise magnitudes, re-runs `et_predict` for each, and summarises how the environmental variance component and the forecast shelf life respond. This turns the subjective choice of `env_noise` into an auditable *curve*: instead of reporting a single shelf life at one (often hand-picked) measurement-error level, the user sees how the horizon degrades as assumed noise grows.

### Usage

```
et_sensitivity_profile(
  model,
  newdata,
  response_scale,
  fraction_grid = NULL,
  absolute_grid = NULL,
  env_cov = NULL,
  env_dist = NULL,
  include_env_in_ci = TRUE,
  ci_level = 0.9,
  ci_levels = c(0.5, 0.8, 0.9, 0.95),
  threshold = 1,
  time_col = NULL,
```

```
  n_draws = 2000L,
  n_perturb = NULL,
  max_extrapolation_factor = 10,
  verbose = TRUE,
  plausible_range = NULL
)
```

## Arguments

| | |
|---|---|
| model | An et_model from et_fit. |
| newdata | data.frame passed to et_predict. |
| response_scale | Two-element numeric vector c(min, max), as in shelf_life. The effective range is diff(response_scale). |
| fraction_grid | Optional numeric vector of scalar noise fractions. |
| absolute_grid | Optional list of env_noise arguments (each a named list / vector). If supplied together with fraction_grid, fraction_grid is ignored. |
| env_cov, env_dist | Passed through to et_predict. |
| include_env_in_ci | Logical. If TRUE (default), credible intervals — and hence the shelf-life horizon — are computed from environmentally inflated draws (et_predict(..., include_env_in_ci = TRUE)). Set FALSE to see how env_var evolves while holding the CI fixed at parameter + residual. |
| ci_level | Numeric. Used for shelf life and CI width tracking (default 0.90). Must be in ci_levels. |
| ci_levels | Numeric vector of CI levels computed per iteration (default c(0.5, 0.8, 0.9, 0.95)). |
| threshold | Numeric. Shelf-life threshold (default 1.0). |
| time_col | Character. Optional time column for shelf life. |
| n_draws, n_perturb | Passed to et_predict. |
| max_extrapolation_factor | Passed to shelf_life. |
| verbose | Logical. If TRUE (default), logs each iteration. |
| plausible_range | Deprecated. Use response_scale instead. |

## Details

Three argument styles are supported for the grid:

- fraction_grid: scalar fractions of each predictor's SD in newdata. These are passed straight to the scalar form of et_predict's env_noise. Use this for an apples- to-apples sweep that scales all predictors together.

- `absolute_grid`: a `list` of named numeric lists / vectors; each list element becomes a single `env_noise` argument (so you can sweep absolute SDs for one predictor while holding others fixed).
- Neither supplied (`NULL`): a default log-spaced fraction grid `c(0, 0.01, 0.025, 0.05, 0.1, 0.2, 0.4, 0.8)` is used.

Each iteration calls `et_predict(..., env_noise = g)` then `shelf_life` and records:

- Mean parameter / environmental / residual / total variance across forecast observations.
- The horizon description (`"observed"`, `"projected"`, or `"lower_bound"`) and numeric horizon if any.
- Mean / max CI width / plausible-range ratio.

## Value

An `et_sensitivity` object: a `data.frame` with one row per grid point and columns

`grid_id` 1-indexed step.

`label` Short descriptor of the env_noise used (e.g.\ `"fraction = 0.05"`).

`fraction` Scalar fraction when applicable; `NA` for absolute-grid rows.

`param_var, env_var, residual_var, total_var` Mean across forecast observations.

`env_share` `env_var / total_var` — the fraction of total predictive variance attributable to predictor noise. `total_var` is the measured variance of the env-inclusive posterior predictive draws, so `env_var` is a genuine sub-share of it and this sits in $[0, 1]$ up to Monte Carlo error.

`ci_width_mean, ci_width_max` At `ci_level`.

`ratio_mean, ratio_max` CI width / plausible range.

`horizon_type` One of `"observed"`, `"projected"`, `"lower_bound"`.

`horizon` Numeric horizon (observed or projected) or `NA` for lower-bound rows.

`horizon_description` The long description returned by `shelf_life`.

The returned object carries the original call and `response_scale` as attributes for use by `et_plot_sensitivity`.

## See Also

`et_predict`, `shelf_life`, `et_plot_sensitivity`

`et_shelf_life_pool` *Pool forecast shelf lives across multiple forecast origins*

## Description

A shelf life read off a *single* forecast origin is a property of that training window as much as of the system: it inherits whatever was idiosyncratic about the final training years. Established practice in ecological forecast evaluation is to issue forecasts repeatedly from rolling origins and summarise skill indexed by **both** origin and lead time (Dietze 2017; Thomas et al. 2020; Petchey et al. 2015). This function does the pooling half of that: given the horizons obtained at several origins, it returns a horizon with an interval rather than a point.

## Usage

```
et_shelf_life_pool(horizons, conf_level = 0.95)
```

## Arguments

| | |
|---|---|
| `horizons` | Either a list of `et_shelf_life` objects (one per forecast origin, in any order), or a `data.frame` with columns `lead` (numeric horizon in lead time) and `censored` (logical, `TRUE` when the forecast was still informative at the last available lead). A `group` column, when present, is summarised separately. |
| `conf_level` | Confidence level for the Kaplan–Meier interval on the median horizon (default `0.95`). |

## Value

A `data.frame`, one row per group (or a single row when ungrouped), with columns:

**group** Group label, when supplied.

**n_origins** Number of forecast origins contributing.

**n_observed** Origins at which the horizon was reached in-window.

**n_censored** Origins right-censored (still informative at the end).

**median_lead** Pooled horizon in lead time. `NA` when every origin is censored — which is itself a result: the forecast never became uninformative from any origin.

**lower, upper** Confidence bounds on the median.

**min_lead, max_lead** Range of the observed horizons.

**method** `"kaplan-meier"` or `"median (uncensored only)"`.

## Why censoring matters

Later origins have fewer lead times available, so a long horizon may not be observed before the data run out — the forecast is still informative at the last available lead. That is **right-censoring**, not a missing value. Dropping those origins would bias the pooled horizon downward (only the short horizons survive), and treating the last lead as the horizon would bias it downward too. Both are

avoided by treating the pooled horizon as a time-to-event problem and estimating it with Kaplan–Meier, which uses the censored origins as the partial information they are.

When **survival** is available the median horizon and its confidence interval come from `survival::survfit()`. Otherwise the function falls back to the median of the observed horizons and says so in the `method` field — a fallback that is biased low whenever anything is censored, which is why the interval is reported as `NA` there.

## References

Dietze, M. C. (2017) Prediction in ecology: a first-principles framework. *Ecological Applications* 27:2048–2060.

Petchey, O. L. *et al.* (2015) The ecological forecast horizon, and examples of its uses and determinants. *Ecology Letters* 18:597–611.

## See Also

`shelf_life` for the single-origin horizon.

## Examples

```
# Horizons from five origins; the last was censored.
h <- data.frame(lead     = c(2, 3, 2, 3, 5),
                censored = c(FALSE, FALSE, FALSE, FALSE, TRUE))
et_shelf_life_pool(h)
```

---

`et_sim` *Simulated allele-frequency-change dataset for ErrorTracer tutorials*

---

## Description

A named list containing training data, forecast predictors, validation responses, and ground-truth parameters for two synthetic SNP clusters (A and B) at a hypothetical mountain plant site. The dataset is designed to exercise every step of the ErrorTracer pipeline and to support parameter-recovery validation (true coefficients are known).

## Usage

```
et_sim
```

## Format

A named `list` with seven elements:

`train data.frame` with 100 rows and 6 columns (2 clusters × 50 training years, 1970–2019):

**year** Integer. Calendar year.

**cluster_id** Character. SNP cluster identifier: `"A"` or `"B"`.

**Tmean** Numeric. Standardised mean growing-season temperature (original unit: °C; standardised using training-period mean and SD).

**PPT** Numeric. Standardised total growing-season precipitation (original unit: mm).

**SWE** Numeric. Standardised peak snow water equivalent (original unit: mm).

**z_diff** Numeric. Simulated allele-frequency change on the arcsin-sqrt scale ($\arcsin(\sqrt{f})$ transformation). This transformation is unbounded and has no fixed $[-1, 1]$ constraint; the plausible range should be derived from the training data or from the theoretical bounds ($[0, \pi/2]$\ on the arcsin scale).

`forecast` `data.frame` with 30 rows and 5 columns (2 clusters × 15 forecast years, 2020–2034). Same columns as `train` except `z_diff` is absent — these are the prediction targets. Predictors are standardised using the training-period statistics stored in `standardization`.

`validation` `data.frame` with 30 rows and 3 columns (`year`, `cluster_id`, `z_diff`). True response values for the forecast period; used with `et_calibrate` to assess posterior predictive coverage.

`true_params` Named `list` with one element per cluster. Each element is a named numeric vector of the true data-generating parameters: `intercept`, `Tmean`, `PPT`, `SWE`, and `sigma` (residual SD).

**Cluster A** `intercept` = `0.00`, `Tmean` = `0.50`, `PPT` = `-0.30`, `SWE` = `0.20`, `sigma` = `0.30`

**Cluster B** `intercept` = `0.10`, `Tmean` = `0.30`, `PPT` = `-0.20`, `SWE` = `-0.25`, `sigma` = `0.35`

`env_noise` Named `list`. Suggested per-predictor environmental noise SDs (on the standardised scale) for use with the `env_noise` argument of `et_predict`: `Tmean` = `0.30`, `PPT` = `0.20`, `SWE` = `0.15`.

`standardization` Named `list` with one element per predictor. Each element is a named numeric vector `c(mean = ..., sd = ...)` giving the training-period statistics used to standardise the data. Needed if you wish to back-transform predictions to the original (unstandardised) scale with `unstandardize`.

`description` Character string. Human-readable description of the dataset and how it was generated.

## Details

The climate time series are simulated as AR(1) processes with a warming trend in `Tmean` (+0.015 °C yr$^{-1}$, cumulating to ~0.30 SD above the training mean over the 15-year forecast window). `SWE` is generated with a weak dependence on `Tmean` (negative coupling) and `PPT` (positive coupling) plus a dominant independent noise component, so that the three predictors have only mild pairwise correlation ($|R| < 0.2$ on the training subset). This makes all regression coefficients reliably identifiable in a single replicate. All predictors are standardised using training-period statistics only.

In addition to the three real climate predictors, the dataset includes ten independent standardised nuisance predictors `d1`, ..., `d10` with zero true effect on the response. They give the regularized-prior extraction step a real selection job: cv.glmnet (alpha = 0.5) is expected to identify the three real predictors and shrink the ten dummies toward zero. Without them, regularization on three well-identified predictors merely biases the true coefficients without selecting anything.

Responses are generated from a linear model with Gaussian noise:

$$z_diff_t = \alpha + \beta_1 Tmean_t + \beta_2 PPT_t + \beta_3 SWE_t + \varepsilon_t, \quad \varepsilon_t \sim \mathcal{N}(0, \sigma^2)$$

The true parameters are stored in `et_sim$true_params` for parameter-recovery validation.

The dataset was generated with `set.seed(111)`. The full generation script is at `data-raw/generate_et_sim.R`.

## Source

Generated by `data-raw/generate_et_sim.R` with `set.seed(111)`.

## Examples

```
data(et_sim)

# Inspect structure
str(et_sim, max.level = 2)

# Training data
head(et_sim$train)

# True parameters for cluster A
et_sim$true_params$A

# Suggested noise SDs for et_predict()
et_sim$env_noise
```

---

`et_skill_score` *Null-model-relative forecast skill (CRPS)*

---

## Description

Scores a forecast against a null model with the continuous ranked probability score (CRPS) and returns the per-lead-time skill, $1 - \mathrm{CRPS}_{\mathrm{model}}/\mathrm{CRPS}_{\mathrm{null}}$ (positive when the model beats the null). This is the accuracy-relative counterpart to `shelf_life`'s precision criterion; report both. The **forecast limit** — the first lead time beginning a sustained run of non-skillful periods — is attached as an attribute.

## Usage

```
et_skill_score(
  predictions,
  observed,
  response_col = NULL,
  time_col = NULL,
  null = c("climatology", "random_walk"),
  climatology = NULL,
  rw_sd = NULL,
  rw_start = NULL,
  min_run = 2L,
  ...
)
```

### Arguments

| | |
|---|---|
| predictions | An et_prediction or et_prediction_list. |
| observed | A data.frame of true responses positionally matched to predictions$newdata (with the grouping column for grouped input). |
| response_col | Character. Response column name; inferred from the model formula when NULL. |
| time_col | Character. Optional time column in newdata used for the time axis (lead time otherwise defaults to the row index). |
| null | Character. The null model: "climatology" (default; the unconditional response distribution) or "random_walk" (persistence: the last observed value carried forward with variance growing linearly with lead time). |
| climatology | Optional numeric vector giving the climatological reference distribution. Defaults to the training response values. |
| rw_sd, rw_start | Optional random-walk per-step innovation SD and start value. Default to sd(diff(train_response)) and the last training response, respectively. |
| min_run | Integer. Number of *consecutive* non-skillful periods required before the forecast limit is declared (default 2). Skill near zero crosses by chance, and a bare first-crossing rule (min_run = 1, the previous behaviour) promotes a lone dip to a horizon — the same failure mode shelf_life guards against. Isolated dips are still reported via n_below / first_below. |
| ... | Unused. |

### Value

A data.frame with columns obs_id, time, crps_model, crps_null, skill, and skillful (skill > 0); a leading group column for grouped input. The attribute "forecast_limit" holds a list with the null-relative horizon, its type ("observed" or "lower_bound"), and the diagnostics n_below, first_below and min_run; or is per-group for grouped input.

### See Also

shelf_life, et_calibrate

---

## et_sobol *Global (Sobol) variance-based sensitivity of the predictive mean*

---

### Description

An optional, order-independent alternative to the additive budget from decompose_uncertainty. Decomposes the variance of the response-scale predictive mean $\mu = g^{-1}(\eta)$ into first-order **parameter** and **environmental** (driver) Sobol indices plus their **interaction**, by independently resampling the parameter draws and the predictor perturbations (Saltelli 2010 first-order; Jansen total-order). Unlike the sequential additive split, this is insensitive to the order in which factors are added and makes any parameter×driver interaction explicit — the general case a non-linear link or correlated drivers can produce.

### Usage

```
et_sobol(predictions, n_sobol = 1024L, seed = NULL, ...)
```

### Arguments

| | |
|---|---|
| predictions | An et_prediction that was produced with non-zero env_noise (the environmental factor needs a perturbation scale). |
| n_sobol | Integer. Base sample size for the Sobol estimator (default 1024). Total model evaluations per observation are 4 * n_sobol. |
| seed | Optional integer for reproducible sampling. |
| ... | Unused. |

### Value

A data.frame with one row per forecast observation:

**obs_id** Observation index.

**S_param, S_env** First-order Sobol indices (fraction of the predictive-mean variance from parameters / drivers alone).

**ST_param, ST_env** Total-order indices (including interactions).

**interaction** 1 - S_param - S_env: the share of predictive-mean variance attributable to the parameter×driver interaction.

**var_mu** Variance of the predictive mean (the quantity being decomposed).

**residual_var** Mean within-draw family variance (the irreducible part; var_mu + residual_var approximates the total predictive variance).

### See Also

decompose_uncertainty (the default additive budget).

---

## et_theme *Minimal ggplot2 theme for ErrorTracer plots*

---

### Description

Minimal ggplot2 theme for ErrorTracer plots

### Usage

```
et_theme(base_size = 12)
```

### Arguments

| | |
|---|---|
| base_size | Base font size (default 12). |

### Value

A ggplot2 theme object.

`extract_priors` *Extract brms prior specification from a regularized or standard regression model*

## Description

Converts a fitted model object into a `brms` prior specification suitable for `et_fit`. The regularized or standard fit sets the *scale* of each coefficient's prior (its SD); the `shrinkage` argument controls the prior *mean*. With the default `shrinkage = "zero"` the priors are centred at zero — a regularizing (ridge-style) prior whose width is informed by the fit but whose location carries no reused point estimate. With `shrinkage = "estimate"` the coefficient estimates are used as informative prior means, so the Bayesian model starts close to the regularized solution.

## Usage

```
extract_priors(
  model,
  multiplier = 2,
  min_sd = 0.1,
  shrinkage = c("zero", "estimate"),
  intercept_prior_sd = NULL,
  sigma_prior_scale = 1,
  ...
)

## S3 method for class 'lm'
extract_priors(
  model,
  multiplier = 2,
  min_sd = 0.1,
  shrinkage = c("zero", "estimate"),
  intercept_prior_sd = NULL,
  sigma_prior_scale = 1,
  ...
)

## S3 method for class 'glm'
extract_priors(
  model,
  multiplier = 2,
  min_sd = 0.1,
  shrinkage = c("zero", "estimate"),
  intercept_prior_sd = NULL,
  sigma_prior_scale = 1,
  ...
)
```

```
## S3 method for class 'cv.glmnet'
extract_priors(
  model,
  multiplier = 2,
  min_sd = 0.1,
  shrinkage = c("zero", "estimate"),
  intercept_prior_sd = NULL,
  sigma_prior_scale = 1,
  lambda = "lambda.min",
  ...
)

## S3 method for class 'glmnet'
extract_priors(
  model,
  multiplier = 2,
  min_sd = 0.1,
  shrinkage = c("zero", "estimate"),
  intercept_prior_sd = NULL,
  sigma_prior_scale = 1,
  s = 1L,
  ...
)

## S3 method for class 'ranger'
extract_priors(
  model,
  multiplier = 2,
  min_sd = 0.1,
  shrinkage = c("zero", "estimate"),
  intercept_prior_sd = NULL,
  sigma_prior_scale = 1,
  ...
)
```

## Arguments

| | |
|---|---|
| `model` | A fitted model. Supported classes:<br>• `cv.glmnet` / `glmnet` — elastic net / lasso<br>• `lm` — ordinary least squares<br>• `glm` — generalized linear model<br>• `ranger` — random forest (importance-scaled flat priors) |
| `multiplier` | Numeric scalar. Prior SD is set to `multiplier * \|coef\|` (for signed-coefficient methods) or `multiplier * importance_normalised` (for ranger). Default 2.0. |
| `min_sd` | Numeric scalar. Minimum prior SD to avoid degenerate (spike) priors on near-zero coefficients. Default 0.1. |
| `shrinkage` | Character. Sets the prior *mean*: `"zero"` (default) centres every coefficient prior at 0 (a regularizing prior with a data-informed scale but no reused location); |

"estimate" uses the fitted coefficient as the prior mean (informative, but reuses the data — see the double-use note above). For ranger the mean is always 0 (no signed coefficients), so shrinkage has no effect.

intercept_prior_sd
: Optional prior SD for the intercept term. The default NULL emits *no* explicit intercept prior and lets brms pick its data-aware default (student_t(3, median(y), mad(y))). If you supply a numeric value, the prior becomes normal(0, intercept_prior_sd) — this is only appropriate when the response has been centred (or nearly so) before fitting, since brms's class = "Intercept" refers to the intercept at the centre of the predictors, whose posterior mean equals E[y] there. Supplying a small intercept_prior_sd for an uncentred response will pull the intercept toward zero and cripple the fit.

sigma_prior_scale
: Scale parameter for the half-Cauchy prior on the residual SD sigma. Default 1.0.

...
: Additional arguments passed to methods.

lambda
: Which lambda to extract coefficients from when the model is a cv.glmnet object. Either "lambda.min" (default) or "lambda.1se".

s
: Index (integer) or value of lambda to extract coefficients at when the model is a plain glmnet object. Defaults to the first lambda (smallest regularisation).

## Details

**The** ranger **path is experimental.** Random-forest permutation importance has no sign and no natural scale in the units of a GLM coefficient, so the mapping used here — priors centred at zero with SD set to multiplier * importance_normalised (importance normalised to [min_sd, 1]; only variables with positive importance retained) — is a heuristic, not a calibrated correspondence. It is offered for exploratory feature screening only; for a principled prior prefer glmnet/ lm/glm, whose coefficients are on the model's scale. A signed importance (e.g. from SHAP values) would be needed to inform the prior mean.

## Value

An et_prior_spec list containing:

prior A brmsprior object for use in brms::brm().

pred_names Character vector of included predictor names.

coefs Named numeric vector of regularized coefficients (NULL for ranger, which uses importance instead).

method Character: the dispatch method used.

multiplier, min_sd Settings echo.

## Prior/likelihood double use

Centring the priors on the coefficient *estimates* (shrinkage = "estimate") and then refitting the Bayesian model on the *same* data uses those data twice — once to locate the prior mean and once through the likelihood — which can make posteriors overconfident, especially at small $n$.

The default shrinkage = "zero" avoids this by not reusing the estimated location: only the prior scale is data-informed, which is a standard weakly-informative device. If you use shrinkage = "estimate", check calibration with et_calibrate, or build the priors on data held out from the likelihood fit.

## Examples

```
fit_lm <- lm(mpg ~ wt + hp + cyl, data = mtcars)
ps <- extract_priors(fit_lm, multiplier = 2, min_sd = 0.1)
print(ps)
```

---

shelf_life *Compute the forecast shelf life*

---

## Description

Quantifies *when* a forecast becomes uninformative by comparing the width of credible intervals to a response scale. A forecast is uninformative when its CI width exceeds threshold * response_scale.

## Usage

```
shelf_life(
  predictions,
  response_scale = NULL,
  ci_level = 0.9,
  threshold = 1,
  time_col = NULL,
  skill = NULL,
  min_slope_for_projection = 1e-04,
  max_extrapolation_factor = 10,
  min_run = 2L,
  projection_alpha = 0.05,
  ...,
  plausible_range = NULL
)
```

## Arguments

| | |
|---|---|
| predictions | An et_prediction or et_prediction_list. |
| response_scale | Numeric vector of length 2 (c(min, max)) giving the response scale used as the denominator in the CI-width / range ratio. Supply a biologically motivated interval when one exists. When NULL (default), the observed range of the **training response** is used as a documented, reproducible default (with an informational message) instead of an arbitrary number. The effective range is diff(response_scale). |
| ci_level | Numeric. The credible interval level to use (default 0.90). Must be present in the et_prediction object. |

`threshold` Numeric. CI width / response scale above which the forecast is uninformative (default 1.0).

`time_col` Character. Optional column in `predictions$newdata` to use as the time axis. If `NULL`, observation index is used.

`skill` Optional skill gate. A `data.frame` returned by `et_skill_score` (positionally matched to the forecast rows; its `skillful` column is used) or a bare logical vector. When supplied, a forecast period is `informative` only if it is both precise *and* skillful, so a precise-but-biased forecast does not pass. When `NULL` (default) the precision criterion is used alone.

`min_slope_for_projection`
Numeric. Minimum linear slope (of ratio vs.\ time) required to attempt extrapolation when all periods are informative. Below this value the shelf life is reported as a lower bound only. Default `1e-4`.

`max_extrapolation_factor`
Numeric. Cap on how far the linear projection may reach beyond the observed window. If the projected crossing time exceeds `max(time) + max_extrapolation_factor * (max(time) - min(time))`, the result is reported as a lower bound instead of a projection. Set to `Inf` to disable the cap. Default `10`.

`min_run` Integer. Number of *consecutive* uninformative periods required before the threshold counts as crossed (default `2`). Guards against a single noisy period manufacturing a horizon when the ratio hovers near `threshold`. Set `min_run = 1` to recover the pre-1.3.1 first-exceedance behaviour; raise it for noisier series.

`projection_alpha`
Numeric. Significance level for the one-sided test that the fitted ratio-vs-time slope is positive (default `0.05`). A slope can clear `min_slope_for_projection` while being statistically indistinguishable from flat; extrapolating it yields a confident-looking crossing time whose interval may span centuries and include the past. When the slope fails this test the result is reported as a lower bound instead of a projection. Set to `1` to disable the test and recover the pre-1.3.1 behaviour.

`...` Unused.

`plausible_range`
Deprecated. Use `response_scale` instead.

## Details

Shelf life is a **precision** criterion on the response scale — a deliberate *complement* to accuracy-relative forecast limits (Petchey et al. 2015; Wesselkamp et al. 2025), not a replacement. It answers "when do the error bars get too wide to act on?", whereas a forecast limit answers "when does the model stop beating a null?". Because a forecast can be precise yet biased, pass a `skill` table from `et_skill_score` to **gate** the shelf life on skill: a period then counts as informative only if it is both precise *and* beats the null model. This couples the two views and prevents a precise-but-biased forecast from silently passing.

The function operates in three modes depending on the available data and whether the uninformative threshold is crossed within the forecast window:

**Observed** The threshold is crossed within the forecast/validation window *and the crossing persists*. The shelf life is the first time point beginning a run of `min_run` consecutive periods with `ratio >= threshold`. Requiring persistence matters: when the ratio hovers near `threshold` without trending, a single noisy period can exceed it by chance, and the first-exceedance rule used before ErrorTracer 1.3.1 would report that excursion as a horizon. Isolated exceedances are now reported in the horizon diagnostics (`n_exceedances`, `first_exceedance`) instead of being promoted to a crossing.

**Projected** No sustained crossing occurs in-window but the CI/range ratio is trending upward *detectably* — the fitted slope must exceed `min_slope_for_projection` **and** be significantly positive at `projection_alpha`. A linear trend is extrapolated to estimate when the threshold would be reached. The projected crossing time $t^* = (\tau - a)/b$ (where $\tau$ is the threshold, $a$ the fitted intercept, $b$ the fitted slope) is reported together with a standard error `se_t_star` derived via the delta method.

**Lower bound** No sustained crossing and no trend distinguishable from flat (or a projection beyond the extrapolation cap). The shelf life is reported as a lower bound: `> last observed time`. This is the honest outcome for a forecast whose precision simply does not degrade in-window.

The intended workflow is:

1. Fit the model (`et_fit`).
2. Predict on held-out data or a future time window (`et_predict`).
3. Call `shelf_life()` on those predictions.
4. If the threshold is not crossed in the held-out window, the *projected* mode extrapolates the horizon automatically.

## Value

An `et_shelf_life` object (a `data.frame`) with columns:

**obs_id** Observation index.

**time** Time axis value.

**ci_width** Width of the credible interval at `ci_level`.

**plausible_range** Effective response scale (scalar diff).

**ratio** CI width / response scale.

**informative** Logical; `TRUE` when ratio < threshold.

For grouped predictions a `group` column is prepended. The object carries three attributes that drive `print()`:

`horizon` Named list with elements `value`, `type` (`"observed"`, `"projected"`, or `"lower_bound"`), `last_informative`, `description`, (for projected) `se_t_star`, and the exceedance diagnostics `n_exceedances`, `frac_exceedance`, `first_exceedance` and `min_run`. Comparing `first_exceedance` with `value` shows whether the reported horizon rests on a persistent crossing or whether isolated excursions preceded it.

`horizon_by_group` For grouped objects: named list of per-group horizon lists.

`threshold` The threshold value used.

## Examples

```
set.seed(1)
df  <- data.frame(y = rnorm(20), year = 2001:2020, x1 = rnorm(20))
fit <- et_fit(y ~ x1, data = df,
              chains = 1, iter = 500, warmup = 250,
              cores = 1, refresh = 0)
new_df <- data.frame(x1 = rnorm(10), year = 2021:2030)
pred   <- et_predict(fit, newdata = new_df,
                     n_draws = 200, n_perturb = 50)
sl <- shelf_life(pred,
                 response_scale            = range(df$y),
                 ci_level                  = 0.90,
                 threshold                 = 1.0,
                 time_col                  = "year",
                 max_extrapolation_factor  = 10)
print(sl)
```

---

# standardize *Standardize a numeric vector (mean-centre, unit-variance)*

---

## Description

Standardize a numeric vector (mean-centre, unit-variance)

## Usage

```
standardize(x)
```

## Arguments

| | |
|---|---|
| x | Numeric vector. |

## Value

Standardized numeric vector. Returns zeros if variance is zero.

---

# unstandardize *Reverse standardization*

---

## Description

Reverse standardization

## Usage

```
unstandardize(z, mu, s)
```

## Arguments

| | |
|---|---|
| z | Standardized values. |
| mu | Original mean. |
| s | Original standard deviation. |

## Value

Values on the original scale.

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