Package ‘embed’

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Title Extra Recipes for Encoding Predictors

Version 0.2.0

Description Predictors can be converted to one or more numeric representations using a variety of methods. Effect encodings using simple generalized linear models <arXiv:1611.09477> or nonlinear models <arXiv:1604.06737> can be used. There are also functions for dimension reduction and other approaches.

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BugReports https://github.com/tidymodels/embed/issues

Depends R (>= 3.4), recipes (>= 0.1.17)

Imports glue, dplyr, generics (>= 0.1.0), keras, lifecycle, purrr, rlang (>= 0.4.10), rsample, stats, tensorflow, tibble, tidyr, utils, uwot, withr

Suggests covr, ggplot2, irlba, knitr, lme4, modeldata, rmarkdown, rpart, rstanarm, testthat (>= 3.0.0), VBsparsePCA, xgboost

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NeedsCompilation no

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add_woe                  Add WoE in a data frame

Description

A tidyverse friendly way to plug WoE versions of a set of predictor variables against a given binary outcome.

Usage

add_woe(.data, outcome, ..., dictionary = NULL, prefix = "woe")

Arguments

- .data: A tbl. The data.frame to plug the new woe version columns.
- outcome: The bare name of the outcome variable.
- ...: Bare names of predictor variables, passed as you would pass variables to dplyr::select(). This means that you can use all the helpers like starts_with() and matches().
- dictionary: A tbl. If NULL the function will build a dictionary with those variables passed to .... You can pass a custom dictionary too, see dictionary() for details.
- prefix: A character string that will be the prefix to the resulting new variables.

Details

You can pass a custom dictionary to add_woe(). It must have the exactly the same structure of the output of dictionary(). One easy way to do this is to tweak a output returned from it.
**dictionary**

**Value**

A tibble with the original columns of .data plus the woe columns wanted.

**Examples**

```r
mtcars %>% add_woe("am", cyl, gear:carb)
```

---

**dictionary**

**Weight of evidence dictionary**

**Description**

Builds the woe dictionary of a set of predictor variables upon a given binary outcome. Convenient to make a woe version of the given set of predictor variables and also to allow one to tweak some woe values by hand.

**Usage**

```r
dictionary(.data, outcome, ..., Laplace = 1e-06)
```

**Arguments**

- `.data` A tbl. The data.frame where the variables come from.
- `outcome` The bare name of the outcome variable with exactly 2 distinct values.
- `...` bare names of predictor variables or selectors accepted by dplyr::select().
- `Laplace` Default to 1e-6. The pseudocount parameter of the Laplace Smoothing estimator. Value to avoid -Inf/Inf from predictor category with only one outcome class. Set to 0 to allow Inf/-Inf.

**Details**

You can pass a custom dictionary to step_woe(). It must have the exactly the same structure of the output of `dictionary()`. One easy way to do this is by tweaking an output returned from it.

**Value**

a tibble with summaries and woe for every given predictor variable stacked up.

**References**

Examples

mtcars %>% dictionary("am", cyl, gear:carb)

is_tf_available  Test to see if tensorflow is available

Description

Test to see if tensorflow is available

Usage

is_tf_available()

Value

A logical

Examples

is_tf_available()

solubility  Compound solubility data

Description

Compound solubility data

Details

Tetko et al. (2001) and Huuskonen (2000) investigated a set of compounds with corresponding experimental solubility values using complex sets of descriptors. They used linear regression and neural network models to estimate the relationship between chemical structure and solubility. For our analyses, we will use 1267 compounds and a set of more understandable descriptors that fall into one of three groups: 208 binary "fingerprints" that indicate the presence or absence of a particular chemical sub-structure, 16 count descriptors (such as the number of bonds or the number of Bromine atoms) and 4 continuous descriptors (such as molecular weight or surface area).

Value

solubility  a data frame
Source


Examples

data(solubility)
str(solubility)

---

**step_discretize_cart**  *Discretize numeric variables with CART*

**Description**

*step_discretize_cart* creates a *specification* of a recipe step that will discretize numeric data (e.g. integers or doubles) into bins in a supervised way using a CART model.

**Usage**

```r
step_discretize_cart(
  recipe,
  ..., role = NA,
  trained = FALSE,
  outcome = NULL,
  cost_complexity = 0.01,
  tree_depth = 10,
  min_n = 20,
  rules = NULL,
  skip = FALSE,
  id = rand_id("discretize_cart")
)
```

**Arguments**

- **recipe**  
  A recipe object. The step will be added to the sequence of operations for this recipe.

- **...**  
  One or more selector functions to choose which variables are affected by the step. See *selections()* for more details.

- **role**  
  Defaults to "predictor".

- **trained**  
  A logical to indicate if the quantities for preprocessing have been estimated.
outcome  A call to \texttt{vars} to specify which variable is used as the outcome to train CART models in order to discretize explanatory variables.

cost\_complexity  The regularization parameter. Any split that does not decrease the overall lack of fit by a factor of cost\_complexity is not attempted. Corresponds to \texttt{cp} in \texttt{rpart::rpart()}. Defaults to 0.01.

tree\_depth  The \textit{maximum} depth in the final tree. Corresponds to \texttt{maxdepth} in \texttt{rpart::rpart()}. Defaults to 10.

min\_n  The number of data points in a node required to continue splitting. Corresponds to \texttt{minsplit} in \texttt{rpart::rpart()}. Defaults to 20.

rules  The splitting rules of the best CART tree to retain for each variable. If length zero, splitting could not be used on that column.

skip  A logical. Should the step be skipped when the recipe is baked by \texttt{recipes::bake()}? While all operations are baked when \texttt{recipes::prep()} is run, some operations may not be able to be conducted on new data (e.g., processing the outcome variable(s)). Care should be taken when using \texttt{skip = TRUE} as it may affect the computations for subsequent operations.

id  A character string that is unique to this step to identify it.

Details

\texttt{step_discretize_cart()} creates non-uniform bins from numerical variables by utilizing the information about the outcome variable and applying a CART model.

The best selection of buckets for each variable is selected using the standard cost-complexity pruning of CART, which makes this discretization method resistant to overfitting.

This step requires the \texttt{rpart} package. If not installed, the step will stop with a note about installing the package.

Note that the original data will be replaced with the new bins.

Value

An updated version of \texttt{recipe} with the new step added to the sequence of any existing operations.

Tidying

When you \texttt{tidy()} this step, a tibble with columns \texttt{terms} (the columns that is selected), \texttt{values} is returned.

See Also

\texttt{step\_discretize\_xgb()}, \texttt{recipes::recipe()}, \texttt{recipes::prep()}, \texttt{recipes::bake()}

Examples

```r
library(modeldata)
data(ad_data)
library(rsample)
```
step_discretize_xgb

split <- initial_split(ad_data, strata = "Class")
ad_data_tr <- training(split)
ad_data_te <- testing(split)
cart_rec <-
  recipe(Class ~ ., data = ad_data_tr) %>%
  step_discretize_cart(tau, age, p_tau, Ab_42, outcome = "Class", id = "cart splits")
cart_rec <- prep(cart_rec, training = ad_data_tr)

# The splits:
tidy(cart_rec, id = "cart splits")
bake(cart_rec, ad_data_te, tau)

step_discretize_xgb  Discretize numeric variables with XgBoost

Description

step_discretize_xgb creates a specification of a recipe step that will discretize numeric data (e.g. integers or doubles) into bins in a supervised way using an XgBoost model.

Usage

step_discretize_xgb(
  recipe,
  ..., role = NA, trained = FALSE, outcome = NULL, sample_val = 0.2,
  learn_rate = 0.3, num_breaks = 10, tree_depth = 1,
  min_n = 5, rules = NULL, skip = FALSE, id = rand_id("discretize_xgb")
)

Arguments

  recipe A recipe object. The step will be added to the sequence of operations for this recipe.
  ... One or more selector functions to choose which variables are affected by the step. See selections() for more details.
role Defaults to "predictor".
trained A logical to indicate if the quantities for preprocessing have been estimated.
outcome A call to `vars` to specify which variable is used as the outcome to train XgBoost models in order to discretize explanatory variables.
sample_val Share of data used for validation (with early stopping) of the learned splits (the rest is used for training). Defaults to 0.20.
learn_rate The rate at which the boosting algorithm adapts from iteration-to-iteration. Corresponds to `eta` in the `xgboost` package. Defaults to 0.3.
num_breaks The maximum number of discrete bins to bucket continuous features. Corresponds to `max_bin` in the `xgboost` package. Defaults to 10.
tree_depth The maximum depth of the tree (i.e. number of splits). Corresponds to `max_depth` in the `xgboost` package. Defaults to 1.
min_n The minimum number of instances needed to be in each node. Corresponds to `min_child_weight` in the `xgboost` package. Defaults to 5.
rules The splitting rules of the best XgBoost tree to retain for each variable.
skip A logical. Should the step be skipped when the recipe is baked by `recipes::bake()`? While all operations are baked when `recipes::prep()` is run, some operations may not be able to be conducted on new data (e.g. processing the outcome variable(s)). Care should be taken when using `skip = TRUE` as it may affect the computations for subsequent operations.
id A character string that is unique to this step to identify it.

Details

`step_discretize_xgb()` creates non-uniform bins from numerical variables by utilizing the information about the outcome variable and applying the xgboost model. It is advised to impute missing values before this step. This step is intended to be used particularly with linear models because thanks to creating non-uniform bins it becomes easier to learn non-linear patterns from the data.

The best selection of buckets for each variable is selected using an internal early stopping scheme implemented in the `xgboost` package, which makes this discretization method prone to overfitting.

The pre-defined values of the underlying xgboost learns good and reasonably complex results. However, if one wishes to tune them the recommended path would be to first start with changing the value of `num_breaks` to e.g.: 20 or 30. If that doesn’t give satisfactory results one could experiment with modifying the `tree_depth` or `min_n` parameters. Note that it is not recommended to tune `learn_rate` simultaneously with other parameters.

This step requires the `xgboost` package. If not installed, the step will stop with a note about installing the package.

Note that the original data will be replaced with the new bins.

Value

An updated version of `recipe` with the new step added to the sequence of any existing operations.
step_embed  

Encoding Factors into Multiple Columns  

Description  

step_embed creates a specification of a recipe step that will convert a nominal (i.e. factor) predictor into a set of scores derived from a tensorflow model via a word-embedding model. embed_control is a simple wrapper for setting default options.

Usage  

```r  
step_embed(  
  recipe,  
  ...,  
  role = "predictor",  
  trained = FALSE,  
  outcome = NULL,  
)  
```
predictors = NULL,
num_terms = 2,
hidden_units = 0,
options = embed_control(),
mapping = NULL,
history = NULL,
skip = FALSE,
id = rand_id("embed")
)

embed_control(
  loss = "mse",
  metrics = NULL,
  optimizer = "sgd",
  epochs = 20,
  validation_split = 0,
  batch_size = 32,
  verbose = 0,
  callbacks = NULL
)

Arguments

(recipe) A recipe object. The step will be added to the sequence of operations for this recipe.

(...) One or more selector functions to choose variables. For step_embed, this indicates the variables to be encoded into a numeric format. See recipes::selections() for more details. For the tidy method, these are not currently used.

(role) For model terms created by this step, what analysis role should they be assigned? By default, the function assumes that the embedding variables created will be used as predictors in a model.

(trained) A logical to indicate if the quantities for preprocessing have been estimated.

(outcome) A call to vars to specify which variable is used as the outcome in the neural network.

(predictors) An optional call to vars to specify any variables to be added as additional predictors in the neural network. These variables should be numeric and perhaps centered and scaled.

(num_terms) An integer for the number of resulting variables.

(hidden_units) An integer for the number of hidden units in a dense ReLu layer between the embedding and output later. Use a value of zero for no intermediate layer (see Details below).

(options) A list of options for the model fitting process.

(mapping) A list of tibble results that define the encoding. This is NULL until the step is trained by recipes::prep().

(history) A tibble with the convergence statistics for each term. This is NULL until the step is trained by recipes::prep().
**step_embed**

skip  A logical. Should the step be skipped when the recipe is baked by `recipes::bake()`?
While all operations are baked when `recipes::prep()` is run, some operations may not be able to be conducted on new data (e.g. processing the outcome variable(s)). Care should be taken when using skip = TRUE as it may affect the computations for subsequent operations.

id  A character string that is unique to this step to identify it.

optimizer, loss, metrics
Arguments to pass to `keras::compile()`

epochs, validation_split, batch_size, verbose, callbacks
Arguments to pass to `keras::fit()`

**Details**

Factor levels are initially assigned at random to the new variables and these variables are used in a neural network to optimize both the allocation of levels to new columns as well as estimating a model to predict the outcome. See Section 6.1.2 of Francois and Allaire (2018) for more details.

The new variables are mapped to the specific levels seen at the time of model training and an extra instance of the variables are used for new levels of the factor.

One model is created for each call to `step_embed`. All terms given to the step are estimated and encoded in the same model which would also contain predictors give in `predictors` (if any).

When the outcome is numeric, a linear activation function is used in the last layer while softmax is used for factor outcomes (with any number of levels).

For example, the keras code for a numeric outcome, one categorical predictor, and no hidden units used here would be

```r
keras_model_sequential() %>%
  layer_embedding(
    input_dim = num_factor_levels_x + 1,
    output_dim = num_terms,
    input_length = 1
  ) %>%
  layer_flatten() %>%
  layer_dense(units = 1, activation = "linear")
```

If a factor outcome is used and hidden units were requested, the code would be

```r
keras_model_sequential() %>%
  layer_embedding(
    input_dim = num_factor_levels_x + 1,
    output_dim = num_terms,
    input_length = 1
  ) %>%
  layer_flatten() %>%
  layer_dense(units = hidden_units, activation = "relu") %>%
  layer_dense(units = num_factor_levels_y, activation = "softmax")
```
Other variables specified by predictors are added as an additional dense layer after layer_flatten and before the hidden layer.

Also note that it may be difficult to obtain reproducible results using this step due to the nature of Tensorflow (see link in References).

tensorflow models cannot be run in parallel within the same session (via foreach or futures) or the parallel package. If using a recipes with this step with caret, avoid parallel processing.

**Value**

An updated version of recipe with the new step added to the sequence of existing steps (if any). For the tidy method, a tibble with columns terms (the selectors or variables for encoding), level (the factor levels), and several columns containing embed in the name.

**Tidying**

When you tidy() this step, a tibble with columns terms (the selectors or variables selected), levels (levels in variable), and a number of columns with embedding information are returned.

**References**

Francois C and Allaire JJ (2018) *Deep Learning with R*, Manning

"How can I obtain reproducible results using Keras during development?" [https://tinyurl.com/keras-repro](https://tinyurl.com/keras-repro)

"Concatenate Embeddings for Categorical Variables with Keras" [https://flovv.github.io/Embeddings_with_keras_part2/](https://flovv.github.io/Embeddings_with_keras_part2/)

**Examples**

```r
library(modeldata)

data(grants)

set.seed(1)
grants_other <- sample_n(grants_other, 500)

if (is_tf_available()) {
  rec <- recipe(class ~ num_ci + sponsor_code, data = grants_other) %>%
    step_embed(sponsor_code, outcome = vars(class),
               options = embed_control(epochs = 10))
}
```
step_feature_hash  Dummy Variables Creation via Feature Hashing

Description

[Soft-deprecated]

step_feature_hash is being deprecated in favor of textrecipes::step_dummy_hash(). This
function creates a specification of a recipe step that will convert nominal data (e.g. character or
factors) into one or more numeric binary columns using the levels of the original data.

Usage

step_feature_hash(
  recipe,
  ...,
  role = "predictor",
  trained = FALSE,
  num_hash = 2^6,
  preserve = deprecated(),
  columns = NULL,
  keep_original_cols = FALSE,
  skip = FALSE,
  id = rand_id("feature_hash")
)

Arguments

- **recipe**: A recipe object. The step will be added to the sequence of operations for this
  recipe.
- **...**: One or more selector functions to choose variables for this step. See selections() for more details.
- **role**: For model terms created by this step, what analysis role should they be assigned? By default, the new columns created by this step from the original variables will be used as predictors in a model.
- **trained**: A logical to indicate if the quantities for preprocessing have been estimated.
- **num_hash**: The number of resulting dummy variable columns.
- **preserve**: Use keep_original_cols instead to specify whether the selected column(s) should be retained in addition to the new dummy variables.
- **columns**: A character vector for the selected columns. This is NULL until the step is trained by recipes::prep().
- **keep_original_cols**: A logical to keep the original variables in the output. Defaults to FALSE.
skip A logical. Should the step be skipped when the recipe is baked by `bake()`? While all operations are baked when `prep()` is run, some operations may not be able to be conducted on new data (e.g. processing the outcome variable(s)). Care should be taken when using `skip = TRUE` as it may affect the computations for subsequent operations.

id A character string that is unique to this step to identify it.

Details

`step_feature_hash()` will create a set of binary dummy variables from a factor or character variable. The values themselves are used to determine which row that the dummy variable should be assigned (as opposed to having a specific column that the value will map to).

Since this method does not rely on a pre-determined assignment of levels to columns, new factor levels can be added to the selected columns without issue. Missing values result in missing values for all of the hashed columns.

Note that the assignment of the levels to the hashing columns does not try to maximize the allocation. It is likely that multiple levels of the column will map to the same hashed columns (even with small data sets). Similarly, it is likely that some columns will have all zeros. A zero-variance filter (via `recipes::step_zv()`) is recommended for any recipe that uses hashed columns.

Value

An updated version of `recipe` with the new step added to the sequence of any existing operations.

Tidying

When you `tidy()` this step, a tibble with columns `terms` (the columns that is selected) is returned.

References


See Also

`recipes::step_dummy()`, `recipes::step_zv()`

Examples

data(grants, package = "modeldata")

if (is_tf_available()) {
  # This may take a while:
  rec <-
step_lencode_bayes

    recipe(class ~ sponsor_code, data = grants_other) %>%
    step_feature_hash(sponsor_code, num_hash = 2^6, keep_original_cols = TRUE) %>%
    prep()

    # How many of the 298 locations ended up in each hash column?
    results <-
        bake(rec, new_data = NULL, starts_with("sponsor_code")) %>%
        distinct()

        apply(results %>% select(-sponsor_code), 2, sum) %>%
        table()

step_lencode_bayes  
Supervised Factor Conversions into Linear Functions using Bayesian Likelihood Encodings

Description

step_lencode_bayes creates a specification of a recipe step that will convert a nominal (i.e. factor) predictor into a single set of scores derived from a generalized linear model estimated using Bayesian analysis.

Usage

step_lencode_bayes(
    recipe,
    ...,
    role = NA,
    trained = FALSE,
    outcome = NULL,
    options = list(seed = sample.int(10^5, 1)),
    verbose = FALSE,
    mapping = NULL,
    skip = FALSE,
    id = rand_id("lencode_bayes")
)

Arguments

    recipe  A recipe object. The step will be added to the sequence of operations for this recipe.
    ...     One or more selector functions to choose variables. For step_lencode_bayes, this indicates the variables to be encoded into a numeric format. See recipes::selections() for more details. For the tidy method, these are not currently used.
    role    Not used by this step since no new variables are created.
    trained A logical to indicate if the quantities for preprocessing have been estimated.
outcome A call to `vars` to specify which variable is used as the outcome in the generalized linear model. Only numeric and two-level factors are currently supported.

options A list of options to pass to `rstanarm::stan_glmer()`.

verbose A logical to control the default printing by `rstanarm::stan_glmer()`.

mapping A list of tibble results that define the encoding. This is NULL until the step is trained by `recipes::prep()`.

skip A logical. Should the step be skipped when the recipe is baked by `recipes::bake()`? While all operations are baked when `recipes::prep()` is run, some operations may not be able to be conducted on new data (e.g. processing the outcome variable(s)). Care should be taken when using `skip = TRUE` as it may affect the computations for subsequent operations.

id A character string that is unique to this step to identify it.

Details

For each factor predictor, a generalized linear model is fit to the outcome and the coefficients are returned as the encoding. These coefficients are on the linear predictor scale so, for factor outcomes, they are in log-odds units. The coefficients are created using a no intercept model and, when two factor outcomes are used, the log-odds reflect the event of interest being the first level of the factor.

For novel levels, a slightly trimmed average of the coefficients is returned.

A hierarchical generalized linear model is fit using `rstanarm::stan_glmer()` and no intercept via

```r
stan_glmer(outcome ~ (1 | predictor), data = data, ...) 
```

where the ... include the family argument (automatically set by the step, unless passed in by options) as well as any arguments given to the options argument to the step. Relevant options include chains, iter, cores, and arguments for the priors (see the links in the References below). `prior_intercept` is the argument that has the most effect on the amount of shrinkage.

Value

An updated version of `recipe` with the new step added to the sequence of existing steps (if any). For the tidy method, a tibble with columns `terms` (the selectors or variables for encoding), `level` (the factor levels), and `value` (the encodings).

Tidying

When you `tidy()` this step, a tibble with columns `terms` (the selectors or variables selected), `value` and `component` is returned.

References


"Hierarchical Partial Pooling for Repeated Binary Trials" https://tinyurl.com/stan-pooling
"Prior Distributions for ‘rstanarm’ Models" [https://tinyurl.com/stan-priors]
"Estimating Generalized (Non-)Linear Models with Group-Specific Terms with rstanarm" [https://tinyurl.com/stan-glm-grouped]

Examples

```r
library(recipes)
library(dplyr)
library(modeldata)

data(grants)
set.seed(1)
grants_other <- sample_n(grants_other, 500)

reencoded <- recipe(class ~ sponsor_code, data = grants_other) %>%
  step_lencode_bayes(sponsor_code, outcome = vars(class))
```

---

**step_lencode_glm**

**Supervised Factor Conversions into Linear Functions using Likelihood Encodings**

**Description**

*step_lencode_glm* creates a *specification* of a recipe step that will convert a nominal (i.e. factor) predictor into a single set of scores derived from a generalized linear model.

**Usage**

```r
step_lencode_glm(
  recipe,
  ..., role = NA,
  trained = FALSE,
  outcome = NULL,
  mapping = NULL,
  skip = FALSE,
  id = rand_id("lencode_glm")
)
```

**Arguments**

- `recipe` A recipe object. The step will be added to the sequence of operations for this recipe.
- `...` One or more selector functions to choose variables. For *step_lencode_glm*, this indicates the variables to be encoded into a numeric format. See `recipes::selections()` for more details. For the tidy method, these are not currently used.
role
A logical to indicate if the quantities for preprocessing have been estimated.

outcome
A call to \texttt{vars} to specify which variable is used as the outcome in the generalized linear model. Only numeric and two-level factors are currently supported.

mapping
A list of \texttt{tibble} results that define the encoding. This is \texttt{NULL} until the step is trained by \texttt{recipes::prep()}.

skip
A logical. Should the step be skipped when the recipe is baked by \texttt{recipes::bake()}? While all operations are baked when \texttt{recipes::prep()} is run, some operations may not be able to be conducted on new data (e.g. processing the outcome variable(s)). Care should be taken when using \texttt{skip = TRUE} as it may affect the computations for subsequent operations.

id
A character string that is unique to this step to identify it.

Details
For each factor predictor, a generalized linear model is fit to the outcome and the coefficients are returned as the encoding. These coefficients are on the linear predictor scale so, for factor outcomes, they are in log-odds units. The coefficients are created using a no intercept model and, when two factor outcomes are used, the log-odds reflect the event of interest being the first level of the factor. For novel levels, a slightly trimmed average of the coefficients is returned.

Value
An updated version of \texttt{recipe} with the new step added to the sequence of existing steps (if any). For the tidy method, a \texttt{tibble} with columns \texttt{terms} (the selectors or variables for encoding), \texttt{level} (the factor levels), and \texttt{value} (the encodings).

Tidying
When you \texttt{tidy()} this step, a \texttt{tibble} with columns \texttt{terms} (the selectors or variables selected), \texttt{value} and \texttt{component} is returned.

References

Examples
```r
library(recipes)
library(dplyr)
library(modeldata)

data(grants)
set.seed(1)
grants_other <- sample_n(grants_other, 500)
```
step_lencode_mixed

reencoded <- recipe(class ~ sponsor_code, data = grants_other) %>%
step_lencode_glm(sponsor_code, outcome = vars(class))

step_lencode_mixed  Supervised Factor Conversions into Linear Functions using Bayesian Likelihood Encodings

Description

step_lencode_mixed creates a specification of a recipe step that will convert a nominal (i.e. factor) predictor into a single set of scores derived from a generalized linear mixed model.

Usage

step_lencode_mixed(
  recipe,
  ..., role = NA,
  trained = FALSE,
  outcome = NULL,
  options = list(verb = 0),
  mapping = NULL,
  skip = FALSE,
  id = rand_id("lencode_mixed")
)

Arguments

  recipe A recipe object. The step will be added to the sequence of operations for this recipe.

  ... One or more selector functions to choose variables. For step_lencode_mixed, this indicates the variables to be encoded into a numeric format. See recipes::selections() for more details. For the tidy method, these are not currently used.

  role Not used by this step since no new variables are created.

  trained A logical to indicate if the quantities for preprocessing have been estimated.

  outcome A call to vars to specify which variable is used as the outcome in the generalized linear model. Only numeric and two-level factors are currently supported.

  options A list of options to pass to lme4::lmer() or lme4::glmer().

  mapping A list of tibble results that define the encoding. This is NULL until the step is trained by recipes::prep().

  skip A logical. Should the step be skipped when the recipe is baked by recipes::bake()? While all operations are baked when recipes::prep() is run, some operations may not be able to be conducted on new data (e.g. processing the outcome variable(s)). Care should be taken when using skip = TRUE as it may affect the computations for subsequent operations.
id

A character string that is unique to this step to identify it.

Details

For each factor predictor, a generalized linear model is fit to the outcome and the coefficients are returned as the encoding. These coefficients are on the linear predictor scale so, for factor outcomes, they are in log-odds units. The coefficients are created using a no intercept model and, when two factor outcomes are used, the log-odds reflect the event of interest being the first level of the factor.

For novel levels, a slightly trimmed average of the coefficients is returned.

A hierarchical generalized linear model is fit using `lme4::lmer()` or `lme4::glmer()`, depending on the nature of the outcome, and no intercept via

```r
lmer(outcome ~ 1 + (1 | predictor), data = data, ...)
```

where the ... include the family argument (automatically set by the step) as well as any arguments given to the options argument to the step. Relevant options include control and others.

Value

An updated version of recipe with the new step added to the sequence of existing steps (if any). For the tidy method, a tibble with columns terms (the selectors or variables for encoding), level (the factor levels), and value (the encodings).

Tidying

When you tidy() this step, a tibble with columns terms (the selectors or variables selected), value and component is returned.

References


Examples

```r
library(recipes)
library(dplyr)
library(modeldata)

data(grants)

set.seed(1)
grants_other <- sample_n(grants_other, 500)

reencoded <- recipe(class ~ sponsor_code, data = grants_other) %>%
  step_lencode_mixed(sponsor_code, outcome = vars(class))
```
**Description**

`step_pca_sparse()` creates a *specification* of a recipe step that will convert numeric data into one or more principal components that can have some zero coefficients.

**Usage**

```r
step_pca_sparse(
  recipe,
  ...,
  role = "predictor",
  trained = FALSE,
  num_comp = 5,
  predictor_prop = 1,
  options = list(),
  res = NULL,
  prefix = "PC",
  keep_original_cols = FALSE,
  skip = FALSE,
  id = rand_id("pca_sparse")
)
```

**Arguments**

- **recipe**  
  A recipe object. The step will be added to the sequence of operations for this recipe.

- **...**  
  One or more selector functions to choose which variables will be used to compute the components. See `selections()` for more details. For the tidy method, these are not currently used.

- **role**  
  For model terms created by this step, what analysis role should they be assigned? By default, the function assumes that the new principal component columns created by the original variables will be used as predictors in a model.

- **trained**  
  A logical to indicate if the quantities for preprocessing have been estimated.

- **num_comp**  
  The number of PCA components to retain as new predictors. If `num_comp` is greater than the number of columns or the number of possible components, a smaller value will be used.

- **predictor_prop**  
  The maximum number of original predictors that can have non-zero coefficients for each PCA component (via regularization).

- **options**  
  A list of options to the default method for `irlba::ssvd()`.

- **res**  
  The rotation matrix once this preprocessing step has been trained by `prep()`.

- **prefix**  
  A character string that will be the prefix to the resulting new variables. See notes below.
**step_pca_sparse**

`keep_original_cols`  
A logical to keep the original variables in the output. Defaults to FALSE.

`skip`  
A logical. Should the step be skipped when the recipe is baked by `recipes::bake()`? While all operations are baked when `recipes::prep()` is run, some operations may not be able to be conducted on new data (e.g. processing the outcome variable(s)). Care should be taken when using `skip = TRUE` as it may affect the computations for subsequent operations.

`id`  
A character string that is unique to this step to identify it.

**Details**

The `irlba` package is required for this step. If it is not installed, the user will be prompted to do so when the step is defined. The `irlba::ssvd()` function is used to encourage sparsity; that documentation has details about this method.

The argument `num_comp` controls the number of components that will be retained (per default the original variables that are used to derive the components are removed from the data). The new components will have names that begin with `prefix` and a sequence of numbers. The variable names are padded with zeros. For example, if `num_comp < 10`, their names will be `PC1 - PC9`. If `num_comp = 101`, the names would be `PC001 - PC101`.

**Value**

An updated version of `recipe` with the new step added to the sequence of existing steps (if any). For the `tidy` method, a tibble with columns `terms` (the selectors or variables selected), `value` (the loading), and `component`.

**Tidying**

When you `tidy()` this step, a tibble with columns `terms` (the selectors or variables selected), `value` and `component` is returned.

**See Also**

`step_pca_sparse_bayes()`

**Examples**

```r
library(recipes)
library(ggplot2)

data(ad_data, package = "modeldata")

ad_rec <-
  recipe(Class ~ ., data = ad_data) %>%
  step_zv(all_predictors()) %>%
  step_YeoJohnson(all_numeric_predictors()) %>%
  step_normalize(all_numeric_predictors()) %>%
  step_pca_sparse(
    all_numeric_predictors(),
    predictor_prop = 0.75,
```
step_pca_sparse_bayes

num_comp = 3,  
id = "sparse pca"

%>%
prep()

tidy(ad_rec, id = "sparse pca") %>%
mutate(value = ifelse(value == 0, NA, value)) %>%
ggplot(aes(x = component, y = terms, fill = value)) +
  geom_tile() +
  scale_fill_gradient2() +
  theme(axis.text.y = element_blank())

---

**step_pca_sparse_bayes**  *Sparse Bayesian PCA Signal Extraction*

**Description**

`step_pca_sparse_bayes()` creates a specification of a recipe step that will convert numeric data into one or more principal components that can have some zero coefficients.

**Usage**

```r
step_pca_sparse_bayes(
  recipe, 
  ..., 
  role = "predictor", 
  trained = FALSE, 
  num_comp = 5, 
  prior_slab_dispersion = 1, 
  prior_mixture_threshold = 0.1, 
  options = list(), 
  res = NULL, 
  prefix = "PC", 
  keep_original_cols = FALSE, 
  skip = FALSE, 
  id = rand_id("pca_sparse_bayes")
)
```

**Arguments**

- `recipe`: A recipe object. The step will be added to the sequence of operations for this recipe.
- `...`: One or more selector functions to choose which variables will be used to compute the components. See `selections()` for more details. For the tidy method, these are not currently used.
- `role`: For model terms created by this step, what analysis role should they be assigned? By default, the function assumes that the new principal component columns created by the original variables will be used as predictors in a model.
trained
A logical to indicate if the quantities for preprocessing have been estimated.

num_comp
The number of PCA components to retain as new predictors. If num_comp is greater than the number of columns or the number of possible components, a smaller value will be used. A value of zero indicates that PCA will not be used on the data.

prior_slab_dispersion
This value is proportional to the dispersion (or scale) parameter for the slab portion of the prior. Smaller values result in an increase in zero coefficients.

prior_mixture_threshold
The parameter that defines the trade-off between the spike and slab components of the prior. Increasing this parameter increases the number of zero coefficients.

options
A list of options to the default method for \texttt{VBsparsePCA::VBsparsePCA()}.

res
The rotation matrix once this preprocessing step has been trained by \texttt{prep()}.

prefix
A character string that will be the prefix to the resulting new variables. See notes below.

keep_original_cols
A logical to keep the original variables in the output. Defaults to \texttt{FALSE}.

skip
A logical. Should the step be skipped when the recipe is baked by \texttt{recipes::bake()}? While all operations are baked when \texttt{recipes::prep()} is run, some operations may not be able to be conducted on new data (e.g. processing the outcome variable(s)). Care should be taken when using \texttt{skip = TRUE} as it may affect the computations for subsequent operations.

id
A character string that is unique to this step to identify it.

Details

The \texttt{VBsparsePCA} package is required for this step. If it is not installed, the user will be prompted to do so when the step is defined.

A spike-and-slab prior is a mixture of two priors. One (the "spike") has all of its mass at zero and represents a variable that has no contribution to the PCA coefficients. The other prior is a broader distribution that reflects the coefficient distribution of variables that do affect the PCA analysis. This is the "slab". The narrower the slab, the more likely that a coefficient will be zero (or are regularized to be closer to zero). The mixture of these two priors is governed by a mixing parameter, which itself has a prior distribution and a hyper-parameter prior.

PCA coefficients and their resulting scores are unique only up to the sign. This step will attempt to make the sign of the components more consistent from run-to-run. However, the sparsity constraint may interfere with this goal.

The argument num_comp controls the number of components that will be retained (per default the original variables that are used to derive the components are removed from the data). The new components will have names that begin with prefix and a sequence of numbers. The variable names are padded with zeros. For example, if num_comp < 10, their names will be PC1 - PC9. If num_comp = 101, the names would be PC001 - PC101.
Value

An updated version of recipe with the new step added to the sequence of existing steps (if any). For the tidy method, a tibble with columns terms (the selectors or variables selected), value (the loading), and component.

Tidying

When you tidy() this step, a tibble with columns terms (the selectors or variables selected), value and component is returned.

References


See Also

step_pca_sparse()

Examples

library(recipes)
library(ggplot2)
data(ad_data, package = "modeldata")
ad_rec <-
  recipe(Class ~ ., data = ad_data) %>%
  step_zv(all_predictors()) %>%
  step_YeoJohnson(all_numeric_predictors()) %>%
  step_normalize(all_numeric_predictors()) %>%
  step_pca_sparse_bayes(
    all_numeric_predictors(),
    prior_mixture_threshold = 0.95,
    prior_slab_dispersion = 0.05,
    num_comp = 3,
    id = "sparse bayesian pca"
  ) %>%
  prep()

tidy(ad_rec, id = "sparse bayesian pca") %>%
  mutate(value = ifelse(value == 0, NA, value)) %>%
  ggplot(aes(x = component, y = terms, fill = value)) +
  geom_tile() +
  scale_fill_gradient2() +
  theme(axis.text.y = element_blank())
Description

step_umap creates a specification of a recipe step that will project a set of features into a smaller space.

Usage

step_umap(
  recipe,
  ...,
  role = "predictor",
  trained = FALSE,
  outcome = NULL,
  neighbors = 15,
  num_comp = 2,
  min_dist = 0.01,
  learn_rate = 1,
  epochs = NULL,
  options = list(verbose = FALSE, n_threads = 1),
  seed = sample(10^5, 2),
  prefix = "UMAP",
  keep_original_cols = FALSE,
  retain = deprecated(),
  object = NULL,
  skip = FALSE,
  id = rand_id("umap")
)

Arguments

recipe A recipe object. The step will be added to the sequence of operations for this recipe.

... One or more selector functions to choose variables for this step. See selections() for more details.

role For model terms created by this step, what analysis role should they be assigned? By default, the new columns created by this step from the original variables will be used as predictors in a model.

trained A logical to indicate if the quantities for preprocessing have been estimated.

outcome A call to vars to specify which variable is used as the outcome in the encoding process (if any).
step_umap

neighbors
An integer for the number of nearest neighbors used to construct the target simplicial set. If neighbors is greater than the number of data points, the smaller value is used.

num_comp
An integer for the number of UMAP components. If num_comp is greater than the number of selected columns minus one, the smaller value is used.

min_dist
The effective minimum distance between embedded points.

learn_rate
Positive number of the learning rate for the optimization process.

epochs
Number of iterations for the neighbor optimization. See uwot::umap() for more details.

options
A list of options to pass to uwot::umap(). The arguments X, n_neighbors, n_components, min_dist, n_epochs, ret_model, and learning_rate should not be passed here. By default, verbose and n_threads are set.

seed
Two integers to control the random numbers used by the numerical methods. The default pulls from the main session’s stream of numbers and will give reproducible results if the seed is set prior to calling prep() or bake().

prefix
A character string for the prefix of the resulting new variables. See notes below.

keep_original_cols
A logical to keep the original variables in the output. Defaults to FALSE.

retain
Use keep_original_cols instead to specify whether the original predictors should be retained along with the new embedding variables.

object
An object that defines the encoding. This is NULL until the step is trained by recipes::prep().

skip
A logical. Should the step be skipped when the recipe is baked by bake()? While all operations are baked when prep() is run, some operations may not be able to be conducted on new data (e.g. processing the outcome variable(s)). Care should be taken when using skip = TRUE as it may affect the computations for subsequent operations.

id
A character string that is unique to this step to identify it.

Details

UMAP, short for Uniform Manifold Approximation and Projection, is a nonlinear dimension reduction technique that finds local, low-dimensional representations of the data. It can be run unsupervised or supervised with different types of outcome data (e.g. numeric, factor, etc). The new components will have names that begin with prefix and a sequence of numbers. The variable names are padded with zeros. For example, if num_comp < 10, their names will be UMAP1 - UMAP9. If num_comp = 101, the names would be UMAP001 - UMAP101.

Value

An updated version of recipe with the new step added to the sequence of any existing operations.

Tidying

When you tidy() this step, a tibble with columns terms (the selectors or variables selected) is returned.
References

Examples
library(recipes)
library(ggplot2)

split <- seq.int(1, 150, by = 9)
tr <- iris[-split, ]
te <- iris[split, ]

set.seed(11)
supervised <-
  recipe(Species ~ ., data = tr) %>%
  step_center(all_predictors()) %>%
  step_scale(all_predictors()) %>%
  step_umap(all_predictors(), outcome = vars(Species), num_comp = 2) %>%
  prep(training = tr)

theme_set(theme_bw())
bake(supervised, new_data = te, Species, starts_with("umap")) %>%
  ggplot(aes(x = UMAP1, y = UMAP2, col = Species)) +
  geom_point(alpha = .5)

step_woe  Weight of evidence transformation

Description
step_woe creates a specification of a recipe step that will transform nominal data into its numerical transformation based on weights of evidence against a binary outcome.

Usage
step_woe(
  recipe,
  ...,
  role = "predictor",
  outcome,
  trained = FALSE,
  dictionary = NULL,
  Laplace = 1e-06,
  prefix = "woe",
  skip = FALSE,
)
### Arguments

- **recipe**: A recipe object. The step will be added to the sequence of operations for this recipe.
- **...**: One or more selector functions to choose which variables will be used to compute the components. See `selections()` for more details. For the tidy method, these are not currently used.
- **role**: For model terms created by this step, what analysis role should they be assigned? By default, the function assumes that the new woe components columns created by the original variables will be used as predictors in a model.
- **outcome**: The bare name of the binary outcome encased in `vars()`.
- **trained**: A logical to indicate if the quantities for preprocessing have been estimated.
- **dictionary**: A tbl. A map of levels and woe values. It must have the same layout than the output returned from `dictionary()`. If ‘NULL’ the function will build a dictionary with those variables passed to .... See `dictionary()` for details.
- **Laplace**: The Laplace smoothing parameter. A value usually applied to avoid \(-\infty/\infty\) results. The default is 1e-6. Also known as 'pseudocount' parameter of the Laplace smoothing technique.
- **prefix**: A character string that will be the prefix to the resulting new variables. See notes below.
- **skip**: A logical. Should the step be skipped when the recipe is baked by `recipes::bake()`? While all operations are baked when `recipes::prep()` is run, some operations may not be able to be conducted on new data (e.g. processing the outcome variable(s)). Care should be taken when using `skip = TRUE` as it may affect the computations for subsequent operations.
- **id**: A character string that is unique to this step to identify it.

### Details

WoE is a transformation of a group of variables that produces a new set of features. The formula is

$$woe_c = \log((P(X = c|Y = 1))/(P(X = c|Y = 0)))$$

where \(c\) goes from 1 to \(C\) levels of a given nominal predictor variable \(X\).

These components are designed to transform nominal variables into numerical ones with the property that the order and magnitude reflects the association with a binary outcome. To apply it on numerical predictors, it is advisable to discretize the variables prior to running WoE. Here, each variable will be binarized to have woe associated later. This can achieved by using `step_discretize()`.

The argument `Laplace` is an small quantity added to the proportions of 1’s and 0’s with the goal to avoid \(\log(p/0)\) or \(\log(0/p)\) results. The numerical woe versions will have names that begin with `woe_` followed by the respective original name of the variables. See Good (1985).
One can pass a custom dictionary tibble to `step_woe()`. It must have the same structure of the output from `dictionary()` (see examples). If not provided it will be created automatically. The role of this tibble is to store the map between the levels of nominal predictor to its woe values. You may want to tweak this object with the goal to fix the orders between the levels of one given predictor. One easy way to do this is by tweaking an output returned from `dictionary()`.

**Value**

An updated version of `recipe` with the new step added to the sequence of existing steps (if any). For the tidy method, a tibble with the woe dictionary used to map categories with woe values.

**Tidying**

When you `tidy()` this step, a tibble with columns `terms` (the selectors or variables selected), `value`, `n_tot`, `n_bad`, `n_good`, `p_bad`, `p_good`, `woe` and `outcome` is returned. See `dictionary()` for more information.

**References**


**Examples**

```r
library(modeldata)
data("credit_data")

set.seed(111)
in_training <- sample(1:nrow(credit_data), 2000)

credit_tr <- credit_data[in_training,]
credit_te <- credit_data[-in_training,]

rec <- recipe(Status ~ ., data = credit_tr) %>%
  step_woe(Job, Home, outcome = vars(Status))

woe_models <- prep(rec, training = credit_tr)

# the encoding:
bake(woe_models, new_data = credit_te %>% slice(1:5), starts_with("woe"))

# the original data
credit_te %>%
  slice(1:5) %>%
  dplyr::select(Job, Home)

# the details:
tidy(woe_models, number = 1)

# Example of custom dictionary + tweaking
# custom dictionary
```
woe_dict_custom <- credit_tr %>% dictionary(Job, Home, outcome = "Status")
woe_dict_custom[4, "woe"] <- 1.23 # tweak

# passing custom dict to step_woe()
rec_custom <- recipe(Status ~ ., data = credit_tr) %>%
  step_woe(Job, Home, outcome = vars(Status), dictionary = woe_dict_custom) %>%
  prep()

rec_custom_baked <- bake(rec_custom, new_data = credit_te)
rec_custom_baked %>%
dplyr::filter(woe_Job == 1.23) %>%
  head()

tidy.step_lencode_bayes

Tidy the Result of a Recipe

Description

tidy will return a data frame that contains information regarding a recipe or operation within the recipe (when a tidy method for the operation exists). See recipes::tidy.recipe for more information.

Usage

## S3 method for class 'step_lencode_bayes'
tidy(x, ...)

## S3 method for class 'step_discretize_cart'
tidy(x, ...)

## S3 method for class 'step_discretize_xgb'
tidy(x, ...)

## S3 method for class 'step_lencode_glm'
tidy(x, ...)

## S3 method for class 'step_feature_hash'
tidy(x, ...)

## S3 method for class 'step_lencode_mixed'
tidy(x, ...)

## S3 method for class 'step_pca_sparse'
tidy(x, ...)

## S3 method for class 'step_pca_sparse_bayes'
tidy(x, ...)
## S3 method for class 'step_embed'
tidy(x, ...)

## S3 method for class 'step_umap'
tidy(x, ...)

## S3 method for class 'step_woe'
tidy(x, ...)

### Arguments

- **x**
  - A `step_woe` object.
- **...**
  - Not currently used.

### woe_table

Crosstable with woe between a binary outcome and a predictor variable.

### Description

Calculates some summaries and the WoE (Weight of Evidence) between a binary outcome and a given predictor variable. Used to build the dictionary.

### Usage

```r
woe_table(predictor, outcome, Laplace = 1e-06)
```

### Arguments

- **predictor**
  - A atomic vector, usually with few distinct values.
- **outcome**
  - The dependent variable. A atomic vector with exactly 2 distinct values.
- **Laplace**
  - The pseudocount parameter of the Laplace Smoothing estimator. Default to 1e-6. Value to avoid -Inf/Inf from predictor category with only one outcome class. Set to 0 to allow Inf/-Inf.

### Value

A tibble with counts, proportions and woe. Warning: woe can possibly be -Inf. Use 'Laplace' arg to avoid that.

### References


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