

Extending lsmeans

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1 Introduction

Suppose you want to use `lsmeans` for some type of model that it doesn't (yet) support. Or, suppose you have developed a new package with a fancy model-fitting function, and you'd like it to work with `lsmeans`. What can you do? Well, there is hope because `lsmeans` is designed to be extended.

The first thing to do is to look at the help page for extending the package:

```
R> help("extending-lsmeans", package="lsmeans")
```

It gives details about the fact that you need to write two S3 methods, `recover.data` and `lsm.basis`, for the class of object that your model-fitting function returns. The `recover.data` method is needed to recreate the dataset so that the reference grid can be identified. The `lsm.basis` method then determines the linear functions needed to evaluate each point in the reference grid and to obtain associated information—such as the variance-covariance matrix—needed to do estimation and testing.

This vignette presents an example where suitable methods are developed, and discusses a few issues that arise.

2 Data example

The `MASS` package contains various functions that do robust or outlier-resistant model fitting. We will cobble together some `lsmeans` support for these. But first, let's create a suitable dataset (a simulated two-factor experiment) for testing.¹

```
R> fake = expand.grid(rep = 1:5, A = c("a1", "a2"), B = c("b1", "b2", "b3"))
R> fake$y = c(11.46, 12.93, 11.87, 11.01, 11.92, 17.80, 13.41, 13.96, 14.27, 15.82,
             23.14, 23.75, -2.09, 28.43, 23.01, 24.11, 25.51, 24.11, 23.95, 30.37,
             17.75, 18.28, 17.82, 18.52, 16.33, 20.58, 20.55, 20.77, 21.21, 20.10)
```

The y values were generated using predetermined means and Cauchy-distributed errors. There are some serious outliers in these data.

3 Supporting rlm

The `MASS` package provides an `rlm` function that fits robust-regression models using M estimation. We'll fit a model using the default settings for all tuning parameters:

¹I unapologetically use `=` as the assignment operator. It is good enough for C and Java, and supported by R.

```
R> library(MASS)
R> fake.rlm = rlm(y ~ A * B, data = fake)
R> library(lsmeans)
R> lsmeans(fake.rlm, ~B | A)
```

```
A = a1:
  B      lsmean      SE df asymp.LCL asymp.UCL
b1 11.83800 0.4774474 NA  10.90211  12.77389
b2 23.30000 0.4774474 NA  22.36411  24.23589
b3 17.80078 0.4774474 NA  16.86489  18.73667
```

```
A = a2:
  B      lsmean      SE df asymp.LCL asymp.UCL
b1 14.68344 0.4774474 NA  13.74755  15.61933
b2 24.71164 0.4774474 NA  23.77574  25.64753
b3 20.64200 0.4774474 NA  19.70611  21.57789
```

Confidence level used: 0.95

The first lesson to learn about extending `lsmeans` is that sometimes, it already works! It works here because `rlm` objects inherit from `lm`, which is supported by the `lsmeans` package, and `rlm` objects aren't enough different to create any problems.

4 Supporting `lqs` objects

The MASS resistant-regression functions `lqs`, `lmsreg`, and `ltsreg` are another story, however. They create `lqs` objects that are not extensions of any other class, and have other issues, including not even having a `vcov` method. So for these, we really do need to write new methods for `lqs` objects. First, let's fit a model.

```
R> fake.lts = ltsreg(y ~ A * B, data = fake)
```

4.1 The `recover.data` method

It is usually an easy matter to write a `recover.data` method. Look at the one for `lm` objects:

```
R> lsmeans:::recover.data.lm
```

```
function (object, ...)
{
  fcall = object$call
  recover.data(fcall, delete.response(terms(object)), object$na.action,
    ...)
}
<environment: namespace:lsmeans>
```

Note that all it does is obtain the `call` component and call the method for class `"call"`, with additional arguments for its `terms` component and `na.action`. It happens that we can access these attributes in exactly the same way as for `lm` objects; so, ...

```
R> recover.data.lqs = lsmeans::recover.data.lm
```

The trickier part is testing it, as it isn't clear that there is a required `data` argument.

```
R> rec.fake = recover.data(fake.lts, data = NULL)
R> head(rec.fake)
```

```
      A  B
1 a1 b1
2 a1 b1
3 a1 b1
4 a1 b1
5 a1 b1
6 a2 b1
```

Our recovered data excludes the response variable `y` (owing to the `delete.response` call), and this is fine.

By the way, the `data` argument is handed to `recover.data` if it is specified in the `ref.grid` or `lsmeans` call. It is needed to cover a desperate situation that occurs with certain kinds of models that are fitted by iteratively modifying the data. In those cases, the only way to recover the data is to for the user to give it explicitly, and `recover.data` just adds a few needed attributes to it.

4.2 The `lsm.basis` method

The `lsm.basis` method has four required arguments:

```
R> args(lsmeans::lsm.basis.lm)
```

```
function (object, trms, xlev, grid, ...)
NULL
```

These are, respectively, the model object, its `terms` component (at least for the right-hand side of the model), a `list` of levels of the factors, and the grid of predictor combinations that specify the reference grid.

The function must obtain six things and return them in a named `list`. They are the matrix `X` of linear functions for each point in the reference grid, the regression coefficients `bhat`; the variance-covariance matrix `V`; a matrix `nbasis` for non-estimable functions; a function `dffun(k,dfargs)` for computing degrees of freedom for the linear function `sum(k*bhat)`; and a list `dfargs` of arguments to pass to `dffun`.

To write your own `lsm.basis` function, examining some of the existing methods can help; but the best resource is the `predict` method for the object in question, looking carefully to see what it does to predict values for a new set of predictors (e.g., `newdata` in `predict.lm`). Following this advice, let's take a look at it:

```
R> MASS::predict.lqs
```

```
function (object, newdata, na.action = na.pass, ...)
{
  if (missing(newdata))
    return(fitted(object))
}
```

```

Terms <- delete.response(terms(object))
m <- model.frame(Terms, newdata, na.action = na.action, xlev = object$xlevels)
if (!is.null(cl <- attr(Terms, "dataClasses")))
  .checkMFClasses(cl, m)
X <- model.matrix(Terms, m, contrasts = object$contrasts)
drop(X %*% object$coefficients)
}
<bytecode: 0x000000000c614c08>
<environment: namespace:MASS>

```

Based on this, here is a listing of an `lsm.basis` method for `lqs` objects:

```

1 R> lsm.basis.lqs = function(object, trms, xlev, grid, ...) {
2     m = model.frame(trms, grid, na.action = na.pass, xlev = xlev)
3     X = model.matrix(trms, m, contrasts.arg = object$contrasts)
4     bhat = coef(object)
5     Xmat = model.matrix(trms, data=object$model)
6     V = rev(object$scale)[1]^2 * solve(t(Xmat) %*% Xmat)
7     nbasis = matrix(NA)
8     dfargs = list(df = nrow(Xmat) - ncol(Xmat))
9     dffun = function(k, dfargs) dfargs$df
10    list(X=X, bhat=bhat, nbasis=nbasis, V=V, dffun=dffun, dfargs=dfargs)
11 }

```

Before explaining it, let's verify that it works:

```
R> lsmeans(fake.lts, ~ B | A)
```

A = a1:

B	lsmean	SE	df	lower.CL	upper.CL
b1	11.87278	0.2284451	24	11.40129	12.34427
b2	23.09278	0.2284451	24	22.62129	23.56427
b3	17.77278	0.2284451	24	17.30129	18.24427

A = a2:

B	lsmean	SE	df	lower.CL	upper.CL
b1	13.91278	0.2284451	24	13.44129	14.38427
b2	24.06278	0.2284451	24	23.59129	24.53427
b3	20.50278	0.2284451	24	20.03129	20.97427

Confidence level used: 0.95

Hooray! Note the results are comparable to those we had for `fake.rlm`, albeit the standard errors are quite a bit smaller.

4.3 Dissecting `lsm.basis.lqs`

Let's go through the listing of this method, by line numbers.

- 2-3: Construct the linear functions, **X**. This is a pretty standard two-step process: First obtain a model frame, **m**, for the grid of predictors, then pass it as data to **model.data** to create the associated design matrix. As promised, this code is essentially identical to what you find in **predict.lqs**.
- 4: Obtain the coefficients, **bhat**. Most model objects have a **coef** method.
- 5-6: Obtain the covariance matrix, **V**, of **bhat**. In many models, this can be obtained using the object's **vcov** method. But not in this case. Instead, I cobbled one together using what it would be for ordinary regression: $\hat{\sigma}^2(\mathbf{X}'\mathbf{X})^{-1}$, where **X** is the design matrix for the whole dataset (not the reference grid). Here, $\hat{\sigma}^2$ is obtained using the last element of the **scale** element of the object (depending on the method, there are one or two scale estimates). This probably under-estimates the variances and distorts the covariances, because robust estimators have some efficiency loss.
- 7: Compute the basis for non-estimable functions. This applies only when there is a possibility of rank deficiency in the model, and **lqs** methods cannot handle that. All linear functions are estimable, and we signal that by setting **nbasis** equal to a 1×1 matrix of **NA**. If rank deficiency were possible, **lsmeans** provides a fairly pain-free way to handle this—I would have coded:

```
R> nbasis = nonest.basis(Xmat)
```

There is a subtlety you need to know, though. Suppose the model is rank-deficient, so that the design matrix **X** has p columns but rank $r < p$. In that case, **bhat** should be of length p (not r), and there should be $p - r$ elements equal to **NA**, corresponding to columns of **X** that were excluded from the fit. Also, **X** should have all p columns. In other words, do not throw-out columns of **X** or their corresponding elements of **bhat**, as they are essential for assessing estimability. **V** should be $r \times r$, however: the covariance matrix for the non-excluded predictors.

- 8-9: Obtain **dffun** and **dfargs**. This is a little awkward because it is designed to allow support for mixed models, where approximate methods may be used to obtain degrees of freedom. The function **dffun** is expected to have two arguments: **k**, the vector of coefficients of **bhat**, and **dfargs**, a list containing any additional arguments. In this case (and in many other models), the degrees of freedom are the same regardless of **k**. We put the required degrees of freedom in **dfargs** and write **dffun** so that it simply returns that value.
- 10: Return these results in a named list.

4.4 The “honest” version

Because of the inadequacies mentioned above for estimating the covariance matrix, then—lacking any better estimate—I think it’s probably better to set it and the degrees of freedom to **NAs**. We will still be able to get the LS means and contrasts thereof, but no standard errors or tests. With that in mind, here’s a replacement version:

```
R> lsm.basis.lqs = function(object, trms, xlev, grid, ...) {
  m = model.frame(trms, grid, na.action = na.pass, xlev = xlev)
  X = model.matrix(trms, m, contrasts.arg = object$contrasts)
  bhat = coef(object)
```

```

      V = diag(rep(NA, length(bhat)))
      nbasis = matrix(NA)
      dffun = function(k, dfargs) NA
      list(X=X, bhat=bhat, nbasis=nbasis, V=V, dffun=dffun, dfargs=list())
    }

```

And here is a test:

```
R> lsmeans(fake.lts, pairwise ~ B)
```

```
$lsmeans
```

B	lsmean	SE	df	asympt.LCL	asympt.UCL
b1	12.89278	NA	NA	NA	NA
b2	23.57778	NA	NA	NA	NA
b3	19.13778	NA	NA	NA	NA

Results are averaged over the levels of: A

Confidence level used: 0.95

```
$contrasts
```

contrast	estimate	SE	df	z.ratio	p.value
b1 - b2	-10.685	NA	NA	NA	NA
b1 - b3	-6.245	NA	NA	NA	NA
b2 - b3	4.440	NA	NA	NA	NA

Results are averaged over the levels of: A

P value adjustment: tukey method for a family of 3 means

5 Hook functions

Most linear models supported by `lsmeans` have straightforward structure: Regression coefficients, their covariance matrix, and a set of linear functions that define the reference grid. However, a few are more complex. An example is the `"clm"` class in the `ordinal` package, which allows a scale model in addition to the location model. When a scale model is used, the scale parameters are included in the model matrix, regression coefficients, and covariance matrix, and we can't just use the usual matrix operations to obtain estimates and standard errors. To facilitate using custom routines for these tasks, the `lsm.basis.clm` function includes, in its `misc` part, the names (as character constants) of two "hook" functions: `misc$estHook` has the name of the function to call when computing estimates, standard errors, and degrees of freedom (for the `summary` method); and `misc$vcovHook` has the name of the function to call to obtain the covariance matrix of the grid values (used by the `vcov` method). These functions are called in lieu of the usual built-in routines for these purposes, and return the appropriately sized matrices.

In addition, you may want to apply some form of special post-processing after the reference grid is constructed. To provide for this, give the name of your function to post-process the object in `misc$postGridHook`. Again, `"clm"` objects (as well as `"polr"` in the `MASS` package) serve as an example. They allow a `mode` specification that in two cases, calls for post-processing. The `"cum.prob"` mode uses the `regrid` function to transform the linear predictor to the cumulative-probability scale. And the `"prob"` mode performs this, as well as applying the contrasts necessary to difference the cumulative probabilities into the class probabilities.

6 Conclusions

It is relatively simple to write appropriate methods that work with `lsmeans` for model objects it does not support. I hope this vignette is helpful for understanding how. Furthermore, if you are the developer of a package that fits linear models, I encourage you to include `recover.data` and `lsm.basis` methods for those classes of objects, and to remember to export them in your `NAMESPACE` file as follows:

```
S3method(myobject, recover.data)
S3method(myobject, lsm.basis)
```