Reference categories for discrete predictors

A couple of questions and ideas were raised in class that needed a better answer than I could give in class. Here are a few notes about them.

Picking a reference category for discrete predictors

The problem can be illustrated by this simple regression model, using the kidiq data frame:

```
> library(arm)
> kidiq <- read.dta("child-iq/kidiq.dta",convert.underscore=TRUE)</pre>
> attach(kidiq)
> # mom.work takes the values
> #
> # 1 = did not work first 3 years of child's life
> # 2 = worked in 2nd or 3rd year of child's life
> # 3 = worked part time in first year of child's life
> # 4 = worked full time in first year of child's life
> work.factor <- as.factor(mom.work)</pre>
> # work.factor is a categorical version of mom.work, suitable
> # for one-way analysis of variance, for example...
> summary(fit1 <- lm(kid.score ~ work.factor))</pre>
> # ...
             Estimate Std. Error t value Pr(>|t|)
               82.000
                           2.305 35.568
                                            <2e-16 ***
(Intercept)
work.factor2
               3.854
                            3.095 1.245
                                            0.2137
work.factor3
                                            0.0013 **
               11.500
                            3.553
                                    3.237
work.factor4
                                    1.927
                5.210
                            2.704
                                            0.0547 .
> # ...
```

As you can see from the above R illustration, when you give R a factor it will drop the *first category in a factor* if necessary to make the model full-rank (estimable).

On the other hand, if there are no factors (e.g. you code dummies for the categories and enter them into the model by hand), then R will drops the *last regressor in the model* if necessary to make the model full-rank:

```
> summary(fit2 <- lm(kid.score ~ work.none +
+ work.23 + work.1p + work.1f))
> # ...
```

Coefficients: (1 not		defined because of			singularities)	
	Estimate	Std.	Error	t value	Pr(> t)	
(Intercept)	87.210		1.413	61.723	<2e-16	***
work.none	-5.210		2.704	-1.927	0.0547	
work.23	-1.356		2.502	-0.542	0.5882	
work.1p	6.290		3.050	2.062	0.0398	*
work.1f	NA		NA	NA	NA	
> #						

If you like working with factor variables directly, there is a command in R called relevel(), that can change which category R will drop (by making it be the first category in the factor:

```
> summary(fit3 <- lm(kid.score ~ relevel(work.factor,ref="4")))</pre>
> # ...
                                  Estimate Std. Error t value Pr(>|t|)
                                                                  <2e-16 ***
(Intercept)
                                    87.210
                                                 1.413
                                                        61.723
relevel(work.factor, ref = "4")1
                                    -5.210
                                                 2.704
                                                        -1.927
                                                                  0.0547 .
relevel(work.factor, ref = "4")2
                                    -1.356
                                                 2.502
                                                        -0.542
                                                                  0.5882
relevel(work.factor, ref = "4")3
                                     6.290
                                                 3.050
                                                                  0.0398 *
                                                         2.062
> # ...
> summary(fit3 <- lm(kid.score ~ relevel(work.factor,ref="2")))</pre>
> # ...
                                  Estimate Std. Error t value Pr(>|t|)
                                                 2.065
                                                        41.582
                                                                  <2e-16 ***
(Intercept)
                                    85.854
relevel(work.factor, ref = "2")1
                                                 3.095
                                    -3.854
                                                        -1.245
                                                                  0.2137
relevel(work.factor, ref = "2")3
                                     7.646
                                                 3.402
                                                         2.248
                                                                  0.0251 *
relevel(work.factor, ref = "2")4
                                     1.356
                                                 2.502
                                                         0.542
                                                                  0.5882
> # ...
```

Alternatively, if you have coded dummies for the categories yourself, you can just drop whichever level you don't want in the model:

```
> summary(fit4 <- lm(kid.score ~ work.none + work.1p + work.1f))</pre>
> # ...
            Estimate Std. Error t value Pr(>|t|)
              85.854
                                            <2e-16 ***
(Intercept)
                           2.065 41.582
work.none
              -3.854
                           3.095 -1.245
                                            0.2137
               7.646
                           3.402
                                   2.248
                                            0.0251 *
work.1p
work.1f
                           2.502
                                   0.542
                                            0.5882
               1.356
> # ...
```

The reference category

The category that is dropped becomes the "reference category" for interpreting the coefficients. This means that the intercept becomes the estimated effect for the *dropped* category, and the coefficients on the other

categories become deviations from this effect. For example, in the fit4 model above:

- The estimated effect for work.23 is the intercept, 85.854.
- The estimated effect for work.none is the sum of the intercept and this coefficient estimate: 85.854 + (-3.854) = 82.000.
- etc.

A difficulty with "reference categories" is that standard errors cannot always be read off the coefficient summary table. For example we do not know the SE for the effect of work.none, because it is a combination of the two SE's listed (2.065 and 3.095) together with some covariance between $\hat{\beta}_{intercept}$ and $\hat{\beta}_{work.none}$ in this model; that is, it depends on more entries of the variance-covariance matrix $(X^T X)^{-1} \hat{\sigma}^2$.

I generally prefer to omit the intercept, so that I get direct estimates of the effects of each category. In this case, the SE's listed in the coefficient table are exactly the SE's for the category effects, so there is no offstage magic with $(X^T X)^{-1} \hat{\sigma}^2$ to worry about:

```
> summary(fit5 <- lm(kid.score ~ work.none + work.23 + work.1p + work.1f - 1))</pre>
> # ...
          Estimate Std. Error t value Pr(>|t|)
work.none
             82.000
                          2.305
                                  35.57
                                           <2e-16 ***
work.23
             85.854
                          2.065
                                  41.58
                                           <2e-16 ***
work.1p
             93.500
                                           <2e-16 ***
                          2.703
                                  34.59
work.1f
             87.210
                                  61.72
                                           <2e-16 ***
                          1.413
> # ...
```

In some situations it does make sense to choose a reference category. In my experience there is always a *substantive, scientific* reason for choosing the reference category. For example, in the fit5 model above, as a matter of social science or education policy we may be directly interested in the difference in expected kid's score between moms who didn't work at all and moms who worked at various levels during the first three years of the child's life. In that case we should just drop work.none, because now the other estimated coefficients (and their SE's) directly estimate these differences:

```
> summary(fit6 <- lm(kid.score ~ work.23 + work.1p + work.1f))</pre>
> # ...
             Estimate Std. Error t value Pr(>|t|)
                                             <2e-16 ***
(Intercept)
               82.000
                            2.305
                                   35.568
work.23
                3.854
                            3.095
                                     1.245
                                             0.2137
work.1p
               11.500
                            3.553
                                     3.237
                                             0.0013 **
work.1f
                5.210
                            2.704
                                     1.927
                                             0.0547 .
> # ...
```

For example, the difference in expected child's score between mothers who work part time in the first year, vs mothers who don't work at all, is an additional 11.5 points, with an SE of 3.095; this is a statistically significant difference. On the other hand the difference in expected child's score between mothers who

work full time in years 2 and 3, vs mothers who don't work at all, is an additional 3.854 points; this is not statistically significantly different from 0 (we could not reject that hypothesis that kids from these two types of mothers have the same expected test scores).

The most frequent category

It has been suggested to choose the category with the most observations as the reference category (i.e. drop it from the model), in order to have small SE's of the estimated regression coefficients. Here is a little simulated example to explore this idea —e (by the way, exploring modeling ideas is another excellent use of simulation!).

```
> X1 <- c(rep(0,90),rep(1,10))</pre>
> X2 <- c(rep(1,10),rep(0,90))</pre>
> X3 <- 1 - X1 - X2
> apply(cbind(X1,X2,X3),1,sum)
 > apply(cbind(X1,X2,X3),2,sum)
X1 X2 X3
10 10 80
> X.true <- cbind(X1,X2,X3)</pre>
> beta.true <- c(4,5,6)
> Y <- X.true %*% beta.true + rnorm(100)</pre>
> summary(orig.model <- lm(Y ~ X1 + X2 + X3 - 1))</pre>
> # ...
  Estimate Std. Error t value Pr(>|t|)
                           <2e-16 ***
X1 4.49687
            0.27758
                    16.20
X2 4.76452
            0.27758
                    17.16
                           <2e-16 ***
X3 6.04773
            0.09814
                    61.62
                           <2e-16 ***
> # ...
> summary(no.X1 <- lm(Y ~ X2 + X3))</pre>
> # ...
         Estimate Std. Error t value Pr(>|t|)
                                 < 2e-16 ***
(Intercept)
           4.4969
                    0.2776
                          16.200
X2
           0.2677
                    0.3926
                           0.682
                                   0.497
X3
           1.5509
                    0.2944
                           5.268 8.33e-07 ***
> # ...
```

```
> summary(no.X2 <- lm(Y ~ X1 + X3))</pre>
> # ...
            Estimate Std. Error t value Pr(>|t|)
(Intercept)
               4.7645
                          0.2776
                                  17.165
                                           < 2e-16 ***
              -0.2677
                          0.3926
                                   -0.682
                                              0.497
X1
X3
               1.2832
                          0.2944
                                    4.358 3.26e-05 ***
> # ...
> summary(no.X3 <- lm(Y ~ X1 + X2))</pre>
> # . . .
            Estimate Std. Error t value Pr(>|t|)
(Intercept)
             6.04773
                         0.09814
                                   61.624 < 2e-16 ***
             -1.55086
                         0.29442
                                  -5.268 8.33e-07 ***
X1
X2
             -1.28320
                         0.29442 -4.358 3.26e-05 ***
> # ...
```

It does appear that the SEs for model no.X3 are smaller than (or equal to) the SEs for models no.X1 and no.X2, but *one must keep in mind that different quantities are being estimated*. For example in no.X3 the coefficient for X1 -1.55086, and SE 0.29442, says that the effect of X1 is significantly different from the effect of X3. In model no.X2 the coefficient for X1 -0.2677, and SE 0.3926, says that the effect of X1 is *not* significantly different from the effect of X2.

Thus, we haven't actually improved the same SEs for the same estimated effects by dropping X3, rather we have generated SEs for different estimated effects. The SEs are not at all comparable.

Moreover, predicted values for a new data point have the same SEs under all three models (as the matrix algebra would tell us they must):

```
> unlist(predict(orig.model,data.frame(X1=1,X2=0,X3=0),se=T))
         fit.1
                        se.fit
                                           df residual.scale
     4.4968655
                    0.2775785
                                                    0.8777804
                                   97.0000000
> unlist(predict(no.X1,data.frame(X2=0,X3=0),se=T))
         fit.1
                        se.fit
                                           df residual.scale
     4.4968655
                    0.2775785
                                                    0.8777804
                                   97.0000000
> unlist(predict(no.X2,data.frame(X1=1,X3=0),se=T))
         fit.1
                        se.fit
                                           df residual.scale
     4.4968655
                     0.2775785
                                   97.0000000
                                                    0.8777804
> unlist(predict(no.X3,data.frame(X1=1,X2=0),se=T))
         fit.1
                        se.fit
                                           df residual.scale
     4.4968655
                    0.2775785
                                   97.0000000
                                                   0.8777804
```

My conclusion is that dropping a category to reduce SEs doesn't actually make sense, because the SEs are for estimating different things, and therefore the SEs cannot be compared.

It is far better, as suggested above, to choose a reference category to match the scientific questions you are asking. If there is no good substantive scientific reason for choosing a reference category, I suggest dropping the intercept instead, where possible.