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Paste the URL (now in the clipboard) between the quotes in the command source("")

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You summarize the data by group with the command aggregate(y, by=list(as.factor(onewayanoval\$x)), summary)

To run the ANOVA and save the results in a data structure called aov1, enter $aov1=aov(y \sim as.factor(x))$

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The aov function produces an output structure very similar to the lm function that we used for regression.

Among other things, it contains the following numeric arrays:

- fitted.values contains what our model sees as the "signal" component of the data
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Notice that there are only three values (one for each group), and within a group every observation has the same "signal" value.

Now recall the data summary by group, aggregate(y, by=list(as.factor(onewayanoval\$x)), summary)

Notice that the group means (in the x. Mean column) match the fitted values for that group.

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Recall that in the output for the regression model (from lm), we could see the coefficients of the linear model, but with aov we don't see them. It is customary not to show the coefficients for an ANOVA model, because they can be very confusing.

Nonetheless, aov does produce estimated coefficients and it is instructive to examine them.

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First recall that our linear model for the one-way ANOVA with three levels of the factor is:

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Remember that the x_{1i} value is one if this subject is in group 1, and zero if they are not. x_{2i} and x_{3i} are definined in similar fashion.

Here's the confusing part. If we display the coefficients by entering aov1\$coefficients, there are coefficients for the intercept, for x_{2i} , and for x_{3i} , but not for x_{1i} . Why is x_{1i} missing?

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We can see the reason if we think of this as a linear algebra problem. The "ordinary least squares" techniques are sometimes called **projection** methods because the estimated "signal" is, geometrically speaking, the projection of y into the vector space spanned by the columns of the design matrix.

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Things get confusing if the columns of the design matrix are not linearly independent. In this case, we must choose a linearly independent set or **basis** for the space spanned by the columns of x.

The software does this for us automatically, so we don't have to give much thought to it, but it is crucial to understanding what the coefficients mean.

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In the one-way ANOVA with three levels of the factor, the design matrix has four columns, one for μ which is all ones, and one for each of x_{1i}, x_{2i} , and x_{3i} . However, there are only three linearly independent columns.

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In this example, we can choose a basis for the design matrix X by discarding any one of the four columns. The estimated "signal" will be the same regardless of which one we discard.

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In this case, the software decided to discard the column associated with group 1.

With the column for group 1 discarded, the fitted values for the three groups are:

• Group 1:
$$E(Y) = \mu$$

• Group 2:
$$E(Y) = \mu + \beta_2$$

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Notice that the corresponding "signal" value for each group, which is always E(Y) for that group, matches the group means we obtained with aggregate(y, by=list(as.factor(onewayanoval\$x)), summary)

This will always be the case for the one-way ANOVA regardless of which column we discard to get our basis.

We will look at one more example to see what happens if we choose a different basis. We can force R to discard the first column of the design matrix, the column of all ones corresponding to the coefficient μ , by specifying a "no intercept" model.

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Now list the coefficients of the model with aovni\$coefficients and notice that now they correspond to the three levels of the factor and match the group means.

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Now list the coefficients of the model with aovni\$coefficients and notice that now they correspond to the three levels of the factor and match the group means.

Finally, enter aovni\$fitted.values to confirm that the "signal" part of the model is still the mean for each group.