Contrast Model
The contrast model is the easiest to interpret because it is a standard linear model. Since we only have factor variables in our model, there are two ways of making interpretations. First, if we want to predict the amount of contrast that a patient will be given, we need to identify the levels of each variable that are associated with that patient. Then we add up the model estimates from those factors, and that gives us the amount of contrast we would expect that patient to get. For example, suppose we have a male patient age 30, with a BMI of 45, who was admitted to the ICU and had a CT using a DS type scanner. Our prediction for the amount of contrast that this patient would receive is

$$67.332(\text{intercept}) + 4.162(\text{male}) + 19.476(\text{age 18-35}) + 16.443(\text{BMI 40+}) + 2.480(\text{ICU}) - 9.316(\text{DS}) = 100.577$$

units of contrast. If the factor associated with a patient is the default used in the model (e.g. female), then we do not add any value to our prediction because the associated value with a default factor is 0.

More interestingly, we can use these model estimates to directly compare factor levels within the same variable. To do this, we simply take the difference between the two model estimates. Let's look at the age variable. We can say that we expect patients between 18-35 years of age to receive 19.476 more units of contrast than patients under 18. Since under 18 is the default level of the variable, we just use the model estimate because $19.476 - 0 = 19.476$. To compare 18-35 and over 35 year old patients, we say that patients between 18-35 years of age are expected to receive 0.899 units more contrast than patients over 35. It is important to note that we cannot say patients will receive X units more contrast, but we can say that patients are expected to receive or are associated with X units more contrast.

Effective Dosage Model
The radiation model is slightly more difficult to interpret because the amount of radiation was modeled on the logarithmic scale. The process of interpretation is identical to the contrast model, but we add one step to reverse the logarithmic transformation.

Suppose we want to predict the amount of radiation a patient will receive. As with the contrast model, we add up the coefficients associated with each factor variable. Then, we exponentiate this sum to go from a logarithmic prediction to a linear one. This sounds somewhat complicated, but let me give an example. Let's use the same patient as above (male, 30 years old, BMI of 45, admitted to the ICU, and scanned on a DS scanner). For this patient, we add up all the factor estimates just like before:

$$0.472(\text{intercept}) + 0.227(\text{male}) + 0.611(\text{age 18-35}) + 1.156(\text{BMI 40+}) + 0(\text{ICU}) - 0.205(DS) = 2.261$$

Now, we exponentiate this sum to get the expected dosage of radiation:

$$\exp(2.261) = 9.593$$

millisieverts of radiation. Here we add a 0 for the ICU factor because it is the default in the model.

The tricky part of log-transformed variables is when comparing two factor levels of the same variable. Here, we cannot simply take the difference between the two estimates. Instead, to compare two levels of the same variable we exponentiate both estimates and divide them. This gives us a ratio or percentage increase in expected effective dose. Let's compare 18-35 year old patients with patients over 35. We take the two estimates (.611 for 18-35, .624 for ¿35) and then use the ratio of their exponentiation:

$$\exp(.611)/\exp(.624) = 0.987$$

This tells us that patients between 18-35 are expected to receive 98.7% of the radiation that patients over 35 receive, a decrease of 1.3%. To see a bigger difference, we expect that patients scanned using the 64SSwoIR scanner will receive 119% more radiation than patients scanned using a DS scanner. As with the previous example, we get this number by taking $\exp(.582)/\exp(-.203) = 2.192 == 119.2\%$ increase

Positivity Model

The most difficult to interpret out of the three models is the positivity model, because it is not a simple linear model. For a logistic model, we are trying to predict a binary outcome (1 = PE detected, 0 = no PE). In this case, we cannot talk about a Y increase in positivity because that doesn't make sense for a binary result. Instead, we can talk about the probability of having a positive CT scan. Here the calculation is similar to the effective dosage model but the interpretation will be a little different.

Let's use our example patient again (male, 30 years old, BMI of 45, admitted to the ICU, and scanned on a DS scanner). For the positivity model, the only variables we care about are BMI and location, so we only need to use those two. First, we add up the model estimates for this patient and exponentiate:

$$\exp(-2.414(\text{intercept}) + 0.107(\text{BMI 40+}) + 0.543(\text{ICU})) = \exp(-1.764) = 0.171$$

This number is the odds that the given patient will have a positive result in the CT scan. To convert this into a probability, we take $\frac{\text{odds}}{1+\text{odds}}$. In this example we get

$$\frac{0.171}{1 + 0.171} = 0.146$$

Now we find that for a patient with a BMI over 40 that was admitted to the ICU, the probability of having a positive CT scan is 14.6%.

To compare two factors, we use the same technique as the effective dosage model. First we exponentiate the two model estimates and then take their ratio. Let's look at in-patients and out-patients. We compute

$$\frac{\exp(.295)}{\exp(-.147)} = \frac{1.343}{0.863} = 1.56$$

which tells us that the odds of an in-patient having a positive test result are 56% greater than the odds that an out-patient has a positive result. Again, our interpretation is in terms of odds ratios. However, when comparing two variables we do not need to transform the value any further. Odds ratios are commonly reported as the interpretation of logistic regression.