Additional advice on figures for Homework 3.

The figures for Homework 3 are admittedly a challenge. For Question 3 you are asked to construct the figures that display the gmc_texp x popteach_c interaction and the gmc_mean_pop_t x popteach_c interaction. The basic display should show the relationship of peer-rated popularity as a function of teacher-rated popularity (popteach_c). In one figure, use separate lines to illustrate how teacher experience (gmc_texp) alters that relationship. In another figure, use separate lines to illustrate how class mean teacher popularity ratings (gmc_mean_pop_t) alters that relationship.
To make these figures most accurate you need to make several adjustments.

1. The relationship between peer-rated popularity and teacher-rated popularity is illustrated by predicting peer-rated popularity for "low" and "high" teacher-rated popularity. "Low" and "high" are defined by locations one standard deviation below and above the mean for teacher-rated popularity, respectively. But, that standard deviation needs to be obtained with care. Teacher-rated popularity could itself be affected by class differences, so the best way to get the standard deviation is to use popteach_c as the outcome in an unconditional model:

   ```
   Pop_Teach_Fit <- lmer(Pop_Data$popteach_c~1 + (1|class),data=Pop_Data)
   ```

   and then get the standard deviation as follows:

   ```
   SD_TP <- sigma(Pop_Teach_Fit)
   ```

2. Separate lines for levels of teacher experience are defined in a similar way. That is, "low" and "high" experience are one standard deviation below and above the mean for teacher experience, respectively. Because teacher experience does not vary within classroom, we can simply get the standard deviation with SD_TE <- sd(gmc_texp).

3. Now the tricky part. The teacher popularity ratings for a particular classroom might be affected by the experience of the teacher (or the mean teacher-rated popularity of the class). If so, then we need to shift the line for a particular level of teacher experience (for example, "low") in the horizontal direction to account for that relationship. For example, if teachers with low experience tend to rate their students higher in popularity on average, then we would shift the line showing the relationship of peer-rated popularity to teacher-rated popularity by an amount that reflects the relationship between experience and teacher-rated popularity. So, first we need to determine the relationship between teacher experience and teacher-rated popularity. For the other figure you will need the relationship between gmc_mean_pop_t and teacher-rated popularity, so we will get that here as well:

   ```
   Pop_Teach_Fit_2 <- lmer(Pop_Data$popteach~1 + gmc_texp + gmc_mean_pop_t +
   (1|class),data=Pop_Data)
   ```

   The fixed effects from this model indicate the relationship between teacher experience and teacher-rated popularity, and, the relationship between classroom mean teacher-rated popularity and teacher-rated popularity. With both in the equation, we get their unique relationships. In combination with the standard deviations, we can now determine by how much we need to shift the teacher-rated popularity lines. We do this by multiplying the standard deviation value by the corresponding fixed effect. The fixed effect tells us by how much teacher-rated popularity increases or decreases with a one-unit increase in, for example, teacher experience. But, we don't want a one-unit increase or decrease; we want a standard deviation increase or decrease:

```
TE_Inc_1 <- SD_TE*fixef(Pop_Teach_Fit_2)[2]
```

The value, TE_Inc_1, is the amount by which teacher-rated popularity would be expected to move with a one-standard deviation change in teacher experience.

4. So, to create the relevant data for prediction, we need to define "low" and "high" values for teacher-rated popularity by using both the standard deviation for teacher-rated popularity but also the shift that accounts for the relationship between teacher experience (or classroom mean teacher-rated popularity) and teacher-rated popularity:

```
predict_data_Low <- with(Pop_Data,data.frame(class=1,
        popteach_c=seq(from=-TE_Inc_1-SD_TP,to=-TE_Inc_1+SD_TP,by=SD_TP),
        gmc_texp=-SD_TE,
        gmc_mean_pop_t=mean(Pop_Data$gmc_mean_pop_t)))
```

Looks complicated, but here is what is happening. First, consider the sequence of values for popteach_c. We want this to range from a standard deviation below the mean to a standard deviation above the mean. That is reflected by SD_TP. But, because these data are for a teacher with low experience, we shift the popteach_c values by an amount equal to –TE_Inc_1. The value for gmc_texp is set to –SD_TE because these data are for a teacher with "low" experience. We are not including variation in gmc_mean_pop_t in this figure, so we set gmc_mean_pop_t to its mean.

Similarly we would create the data for a teacher with "high" experience as follows:

```
predict_data_High <- with(Pop_Data,data.frame(class=1,
        popteach_c=seq(from=TE_Inc_1-SD_TP,to=TE_Inc_1+SD_TP,by=SD_TP),
        gmc_texp=SD_TE,
        gmc_mean_pop_t=mean(Pop_Data$gmc_mean_pop_t)))
```

We follow a similar procedure for the other figure, but substitute the increment that corresponds to a one standard deviation change in gmc_mean_pop_t and average over teacher experience instead:

```
SD_MTP <- sd(Pop_Data$gmc_mean_pop_t)

TP_Inc_1 <- SD_MTP*fixef(Pop_Teach_Fit_2)[3]

predict_data_Low <- with(Pop_Data,data.frame(class=1,
        popteach_c=seq(from=-TP_Inc_1-SD_TP,to=-TP_Inc_1+SD_TP,by=SD_TP),
        gmc_texp=mean(gmc_texp),
        gmc_mean_pop_t=-SD_MTP))
```