CH 11: Assumptions - Part I

Assumptions for Regression Models

The assumptions described in *Regression and Other Stories*, are more broad than many textbooks. In order of importance,

1. **Validity:**

2. **Representativeness:**

3. **Additivity and linearity:**

4. **Independence of Errors:**

5. **Equal Variance of Errors:**

6. **Normality of Errors:**

What if the assumptions are violated??

Plots of fitted model

For simple models with one continuous predictor and/or one categorical predictor, we have see how to fit the model with `geom_smooth`.

With additional covariates in the model this becomes more challenging. Consider the candy dataset and a model

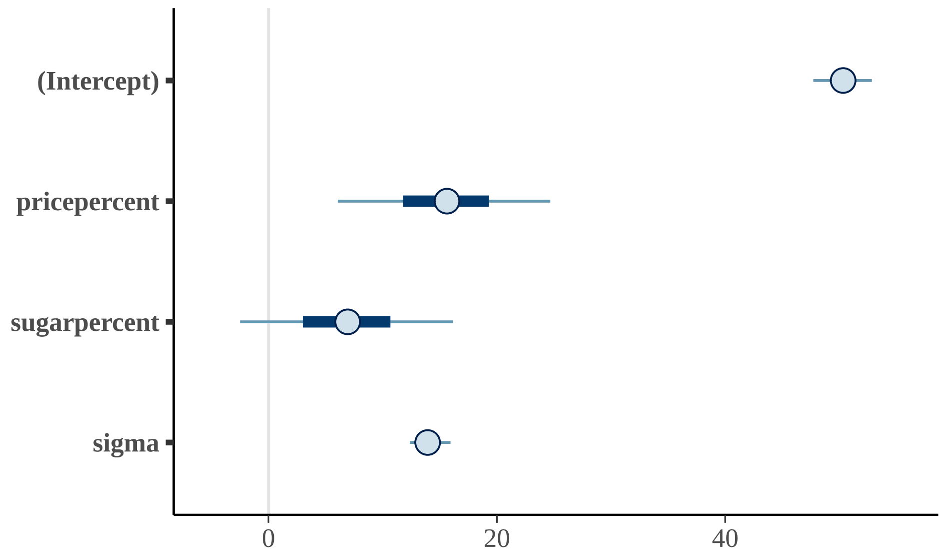
```
candy <- read_csv("https://math.montana.edu/ahoegh/teaching/stat446/candy-data.csv") %>%
  mutate(pricepercent = pricepercent - mean(pricepercent),
         sugarpercent = sugarpercent - mean(sugarpercent))
```

```
## Parsed with column specification:
## cols(
##   competitorname = col_character(),
##   chocolate = col_double(),
##   fruity = col_double(),
##   caramel = col_double(),
##   peanutyalmondy = col_double(),
##   nougat = col_double(),
##   crispedricewafer = col_double(),
##   hard = col_double(),
##   bar = col_double(),
##   pluribus = col_double(),
##   sugarpercent = col_double(),
##   pricepercent = col_double(),
##   winpercent = col_double()
## )
```

```
candy_model <- stan_glm(winpercent ~ pricepercent + sugarpercent, data = candy, refresh = 0)
print(candy_model)
```

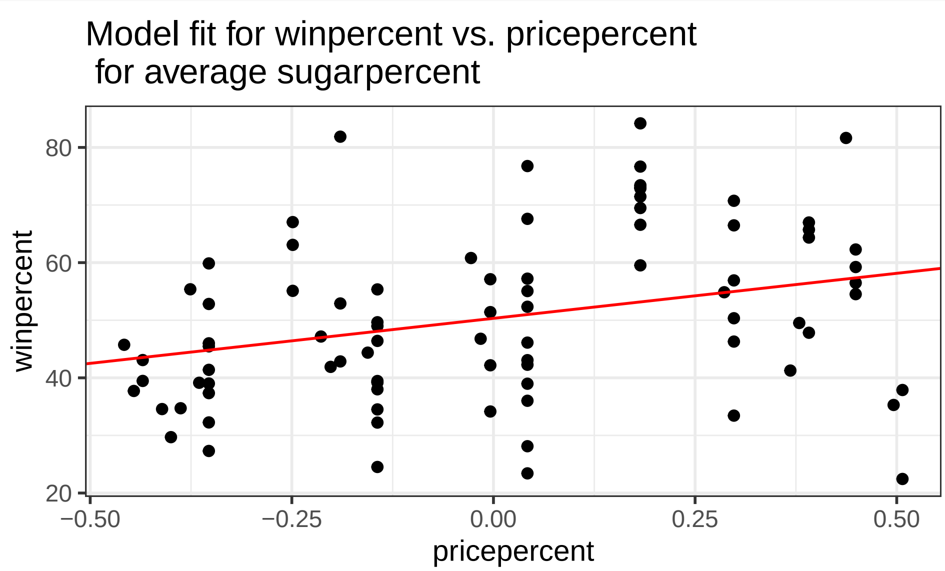
```
## stan_glm
##  family:       gaussian [identity]
##  formula:      winpercent ~ pricepercent + sugarpercent
##  observations: 85
##  predictors:   3
## ------
##              Median MAD_SD
## (Intercept)  50.3    1.5
## pricepercent 15.6    5.6
## sugarpercent  6.9    5.7
##
## Auxiliary parameter(s):
##       Median MAD_SD
## sigma 13.9    1.1
##
## ------
## * For help interpreting the printed output see ?print.stanreg
## * For info on the priors used see ?prior_summary.stanreg
```

```
plot(candy_model)
```



- One option is to plot the response against each predictor holding the other continuous predictors constant and setting levels of categorical predictors.

```
candy %>%
  ggplot(aes(y = winpercent, x = pricepercent)) +
  geom_point() +
  geom_abline(intercept = candy_model$coefficients['(Intercept)'],
              slope = candy_model$coefficients['pricepercent'],
              color = 'red') +
  labs(title = 'Model fit for winpercent vs. pricepercent \n for average sugarpercent') +
  theme_bw()
```

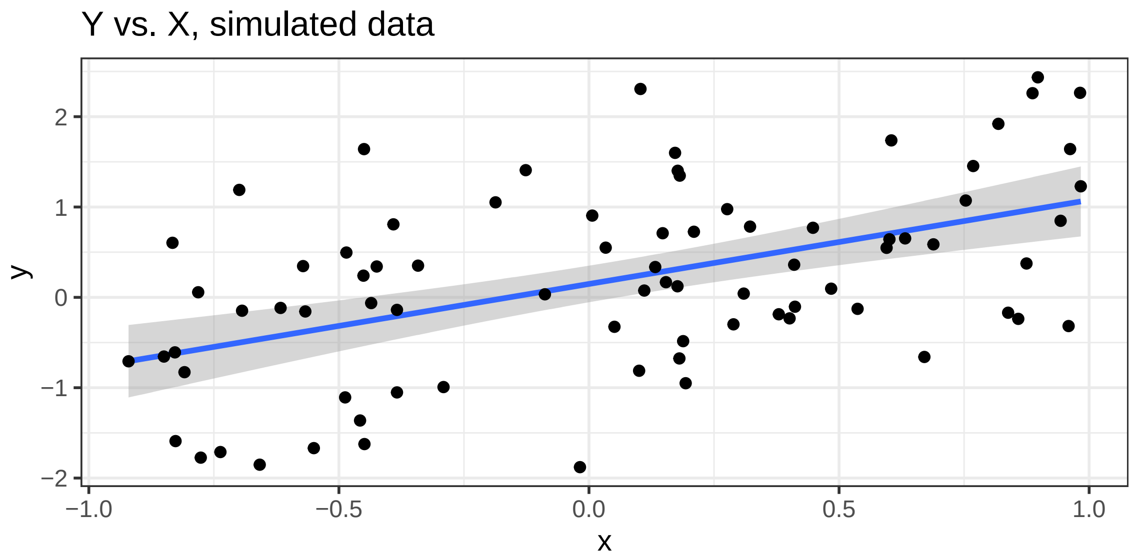


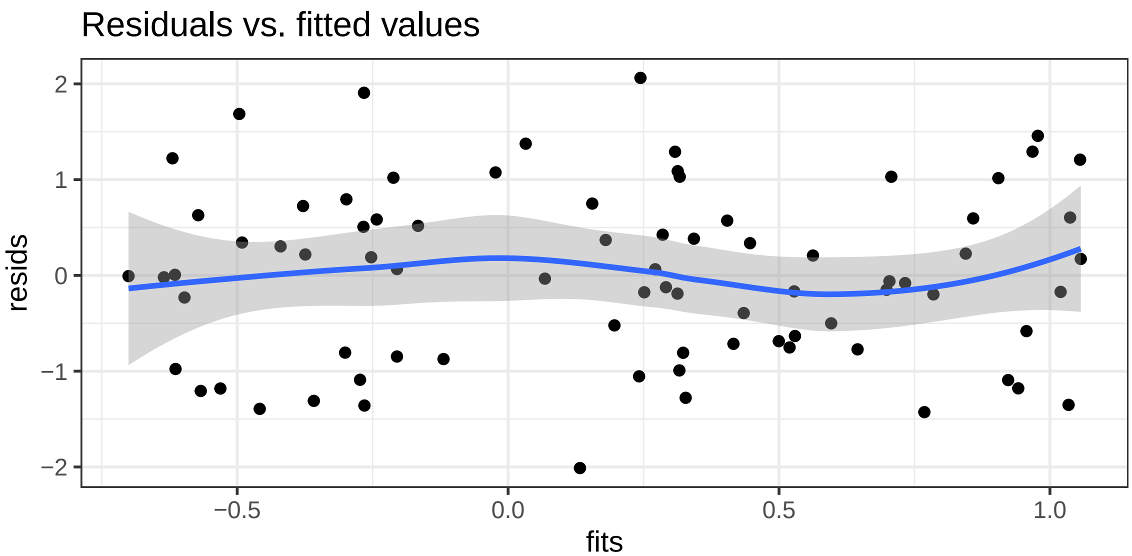
Residual Plots

Model fit can also be evaluated looking at residuals plots.

These plots should result in absence of patterns.

Residual Plots from Fake Data It is not always obvious (at least initially) what residual plots should look like and what variations could be expected when the model is indeed true.





It can also be useful to create a panel of figures to explore residuals vs. each covariate.