Other ways of fitting the linear model

lm() function for linear models

$$y_i \sim N(\mu_i, \sigma)$$

$$\mu_i = \alpha + \beta x_i$$

```
> df <- data.frame(growth = c(12, 10, 8, 11, 6, 7, 2, 3, 3),
                   tannin = c(0, 1, 2, 3, 4, 5, 6, 7, 8))
> df$tannin = scale(df$tannin, scale = FALSE)
> df$growth = scale(df$growth, scale = FALSE)

> ols_fit = lm(growth ~ tannin, data = df)
> precis(ols_fit)
             mean   sd  5.5% 94.5%
(Intercept)  0.00 0.56 -0.90  0.90
tannin      -1.22 0.22 -1.57 -0.87
```

α (Intercept)

β tannin

Other ways of fitting the linear model

stan_glm() function for linear models and priors!

$$y_i \sim N(\mu_i, \sigma)$$

$$\mu_i = \alpha + \beta x_i$$

And some standard priors...

```
> sglm_fit = stan_glm(growth ~ tannin, data = df, cores = 4)

> summary(sglm_fit, probs = c(0.025, 0.975))[, 1:7]
                      mean        mcse        sd       2.5%      97.5% n_eff
(Intercept) α  -0.01069275 0.015974907 0.6971944  -1.403377  1.3696905  1905
tannin      β  -1.21608408 0.005609107 0.2482728  -1.716820 -0.7229236  1959
sigma           1.98129172 0.016244872 0.6447948   1.145132  3.5859302  1575
mean_PPD       -0.01273309 0.020249189 0.9958192  -2.030730  2.0076369  2418
log-posterior -23.56539992 0.046443876 1.4480299 -27.365501 -21.9264227   972
                  Rhat
(Intercept)   1.000676
tannin        1.001776
sigma         1.000847
mean_PPD      1.000271
log-posterior 1.003540
```