```
# Notice that Average_age and Household_income do not seem to predict house prices
# Let's drop them in model2
model2 <- lm (House_price ~ Population + Crime, data = data)
anova(model2, model1)
```

```
> anova(model2, model1)
Analysis of Variance Table

Model 1: House_price ~ Population + Crime
Model 2: House_price ~ Population + Crime + Average_age + Household_income
  Res.Df        RSS Df Sum of Sq      F Pr(>F)
1    247 2.1666e+10
2    245 2.1622e+10  2  43401593 0.2459 0.7822
```

OK, so the models do not differ significantly by this test - we can use another measure of goodness-of-fit - AIC (Aikaike Information Criterion). AIC tells us how much information in our data is not captured by each model - lower values are better - can only be interpreted in a relative sense (i.e., comparing one model to another)…

```
> AIC(model1)
[1] 5290.354
> AIC(model2)
[1] 5286.855
```

We defined `model2` as having just two predictors - as `model2` has the lower AIC value (so more information in our data is explained by `model2` than by `model1`), we would be justified in selecting that as our ‘best’ model. AIC penalises models with increasing number of parameters (but not as much as BIC) so gives us a good trade-off of fitting our data and model complexity.