Example R notebook

Loading packages

The very first thing that you would like to do is loading the required R libraries. Lets check whether you have successfully installed all the packages.

```
library(tidyverse)
```

```
## -- Attaching packages --------------------------------------- tidyverse 1.2.1 --
```

```
## v ggplot2 3.2.1     v purrr   0.3.2
## v tibble  2.1.3     v dplyr   0.8.3
## v tidyr   1.0.0     v stringr 1.4.0
## v readr   1.3.1     v forcats 0.4.0
```

```
## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
```

```
library(emmeans)
library(brms)
```

```
## Loading required package: Rcpp
```

```
## Registered S3 method overwritten by 'xts':
##   method     from
##   as.zoo.xts zoo
```

```
## Loading 'brms' package (version 2.10.0). Useful instructions
## can be found by typing help('brms'). A more detailed introduction
## to the package is available through vignette('brms_overview').
```

```
library(tidybayes)
library(bayestestR)
```

```
##
## Attaching package: 'bayestestR'
```

```
## The following object is masked from 'package:tidybayes':
##
##     hdi
```

You will probably see some start message, and several warnings. If you don't see any errors, then with 99% you are probably fine with this step.

Obtaining the dataset.

Most of the datasets will be availabe through the course online repository (or some other repositories). Lets try to get the example dataset.

```
library(foreign)
crime_data <- read.dta("https://stats.idre.ucla.edu/stat/data/crime.dta")
```

Initial lookup at the data

There are several ways to look at the dataset. Lets try a simple `glimpse`.

```
crime_data %>%
  glimpse()
```

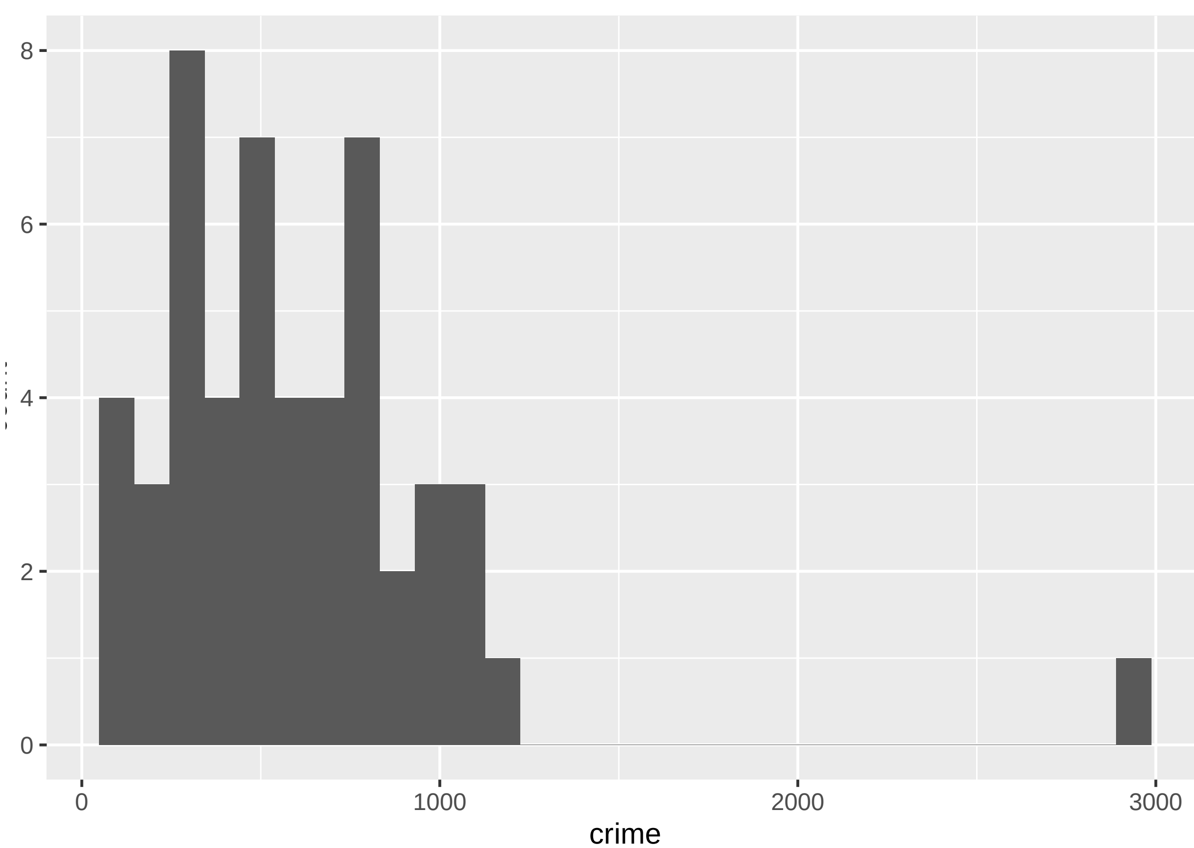
```
## Observations: 51
## Variables: 9
## $ sid      <dbl> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16...
## $ state    <chr> "ak", "al", "ar", "az", "ca", "co", "ct", "de", "fl",...
## $ crime    <int> 761, 780, 593, 715, 1078, 567, 456, 686, 1206, 723, 2...
## $ murder   <dbl> 9.0, 11.6, 10.2, 8.6, 13.1, 5.8, 6.3, 5.0, 8.9, 11.4,...
## $ pctmetro <dbl> 41.8, 67.4, 44.7, 84.7, 96.7, 81.8, 95.7, 82.7, 93.0,...
## $ pctwhite <dbl> 75.2, 73.5, 82.9, 88.6, 79.3, 92.5, 89.0, 79.4, 83.5,...
## $ pcths    <dbl> 86.6, 66.9, 66.3, 78.7, 76.2, 84.4, 79.2, 77.5, 74.4,...
## $ poverty  <dbl> 9.1, 17.4, 20.0, 15.4, 18.2, 9.9, 8.5, 10.2, 17.8, 13...
## $ single   <dbl> 14.3, 11.5, 10.7, 12.1, 12.5, 12.1, 10.1, 11.4, 10.6,...
```

Plotting some of the distributions.

We are interested in the crime level through states. Lets plot a simple histogram.

```
crime_data %>%
  ggplot(aes(crime)) +
  geom_histogram()
```

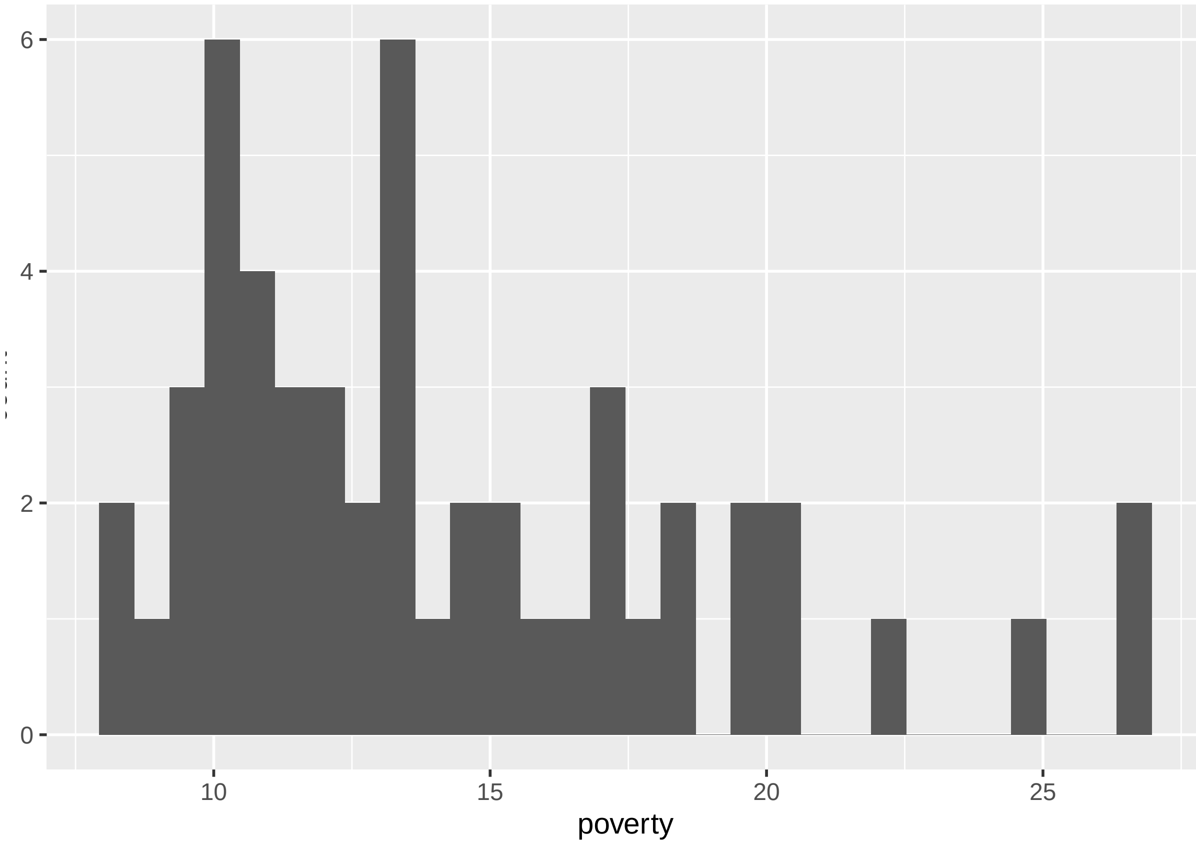
```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



The distribution looks fine appart from a single outlier. Lets plot one the predictors of crime - poverty.

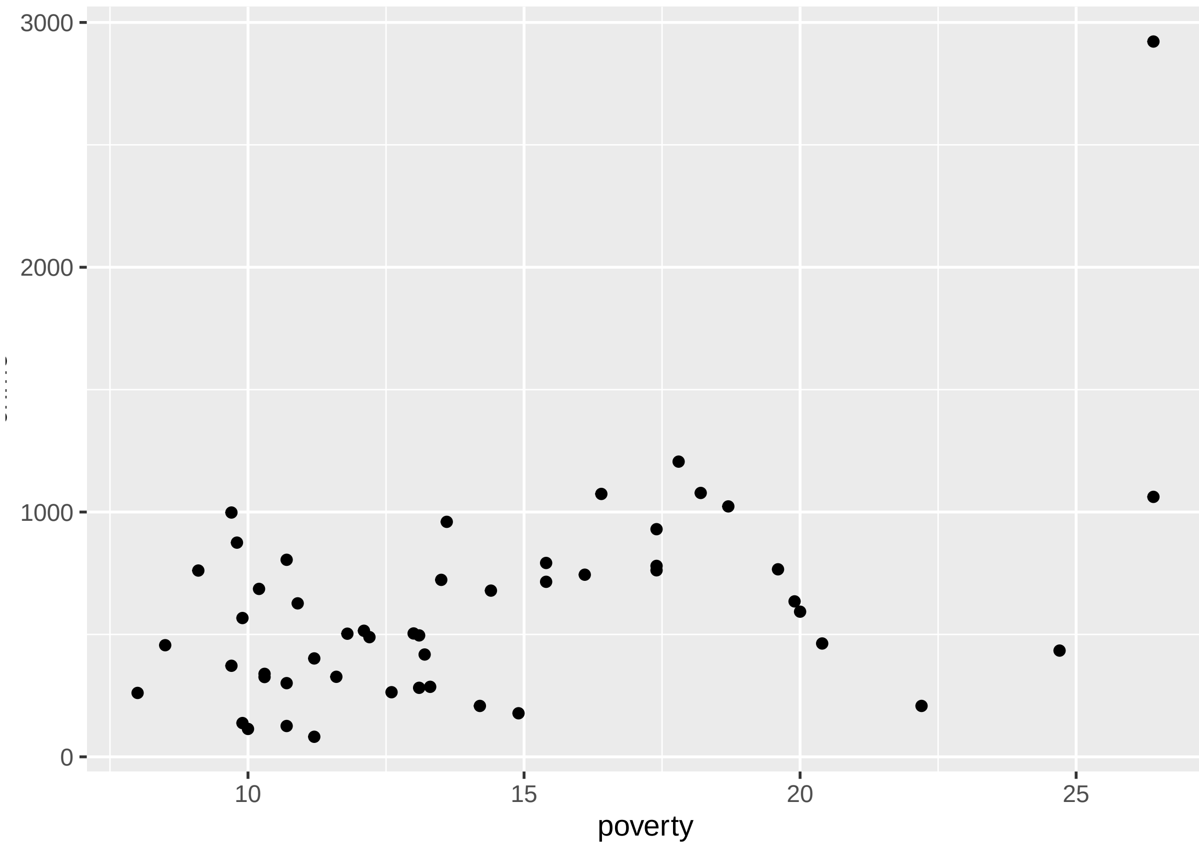
```
crime_data %>%
  ggplot(aes(poverty)) +
  geom_histogram()
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



Now lets plot crime against poverty.

```
crime_data %>%
  ggplot(aes(poverty, crime)) +
  geom_point()
```



Creating a simple Bayesian regression model.

Lets fit crime against poverty. This is your `Hello world!` to Bayesian modelling. Don't worry if you don't understand what you are doing or what is happening. This just a quick intro to get you the feeling of how we will work through the course.

```
fit <- brm(crime ~ poverty,
           data = crime_data,
           prior = prior(normal(0, 10), class = b))
```

```
## Compiling the C++ model
```

```
## Start sampling
```

```
##
## SAMPLING FOR MODEL '4666657389157456f312417abee138c4' NOW (CHAIN 1).
## Chain 1:
## Chain 1: Gradient evaluation took 7e-06 seconds
## Chain 1: 1000 transitions using 10 leapfrog steps per transition would take 0.07 seconds.
## Chain 1: Adjust your expectations accordingly!
## Chain 1:
## Chain 1:
## Chain 1: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 1: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 1: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 1: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 1: Iteration:  800 / 2000 [ 40%]  (Warmup)
```

```
## Chain 1: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 1: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 1: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 1: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 1: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 1: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 1: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 1:
## Chain 1:  Elapsed Time: 0.045868 seconds (Warm-up)
## Chain 1:                0.011356 seconds (Sampling)
## Chain 1:                0.057224 seconds (Total)
## Chain 1:
##
## SAMPLING FOR MODEL '4666657389157456f312417abee138c4' NOW (CHAIN 2).
## Chain 2:
## Chain 2: Gradient evaluation took 4e-06 seconds
## Chain 2: 1000 transitions using 10 leapfrog steps per transition would take 0.04 seconds.
## Chain 2: Adjust your expectations accordingly!
## Chain 2:
## Chain 2:
## Chain 2: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 2: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 2: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 2: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 2: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 2: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 2: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 2: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 2: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 2: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 2: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 2: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 2:
## Chain 2:  Elapsed Time: 0.064217 seconds (Warm-up)
## Chain 2:                0.011182 seconds (Sampling)
## Chain 2:                0.075399 seconds (Total)
## Chain 2:
##
## SAMPLING FOR MODEL '4666657389157456f312417abee138c4' NOW (CHAIN 3).
## Chain 3:
## Chain 3: Gradient evaluation took 4e-06 seconds
## Chain 3: 1000 transitions using 10 leapfrog steps per transition would take 0.04 seconds.
## Chain 3: Adjust your expectations accordingly!
## Chain 3:
## Chain 3:
## Chain 3: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 3: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 3: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 3: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 3: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 3: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 3: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 3: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 3: Iteration: 1400 / 2000 [ 70%]  (Sampling)
```

```
## Chain 3: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 3: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 3: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 3:
## Chain 3:  Elapsed Time: 0.047985 seconds (Warm-up)
## Chain 3:                0.011196 seconds (Sampling)
## Chain 3:                0.059181 seconds (Total)
## Chain 3:
##
## SAMPLING FOR MODEL '4666657389157456f312417abee138c4' NOW (CHAIN 4).
## Chain 4:
## Chain 4: Gradient evaluation took 4e-06 seconds
## Chain 4: 1000 transitions using 10 leapfrog steps per transition would take 0.04 seconds.
## Chain 4: Adjust your expectations accordingly!
## Chain 4:
## Chain 4:
## Chain 4: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 4: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 4: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 4: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 4: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 4: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 4: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 4: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 4: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 4: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 4: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 4: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 4:
## Chain 4:  Elapsed Time: 0.059005 seconds (Warm-up)
## Chain 4:                0.011122 seconds (Sampling)
## Chain 4:                0.070127 seconds (Total)
## Chain 4:
```

Summarising our results

Lets summarise our results.

```
fit
```

```
##  Family: gaussian
##   Links: mu = identity; sigma = identity
## Formula: crime ~ poverty
##    Data: crime_data (Number of observations: 51)
## Samples: 4 chains, each with iter = 2000; warmup = 1000; thin = 1;
##          total post-warmup samples = 4000
##
## Population-Level Effects:
##           Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## Intercept   337.42    130.27    80.94   589.86 1.00     3476     3234
## poverty      19.13      8.19     2.98    34.68 1.00     3295     2970
##
## Family Specific Parameters:
##       Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
```

```
## sigma   409.03     44.19   334.57   504.71 1.00     2889     2636
##
## Samples were drawn using sampling(NUTS). For each parameter, Eff.Sample
## is a crude measure of effective sample size, and Rhat is the potential
## scale reduction factor on split chains (at convergence, Rhat = 1).
```

It seems like poverty is positively and reliably associated with crime level (at the state level).

Plotting our posterior.

Lets see to what extent the obtained posterior distribution supports positive association.

```r
pd_fit <- p_direction(fit)
plot(pd_fit)
```

Plotting posterior against prior

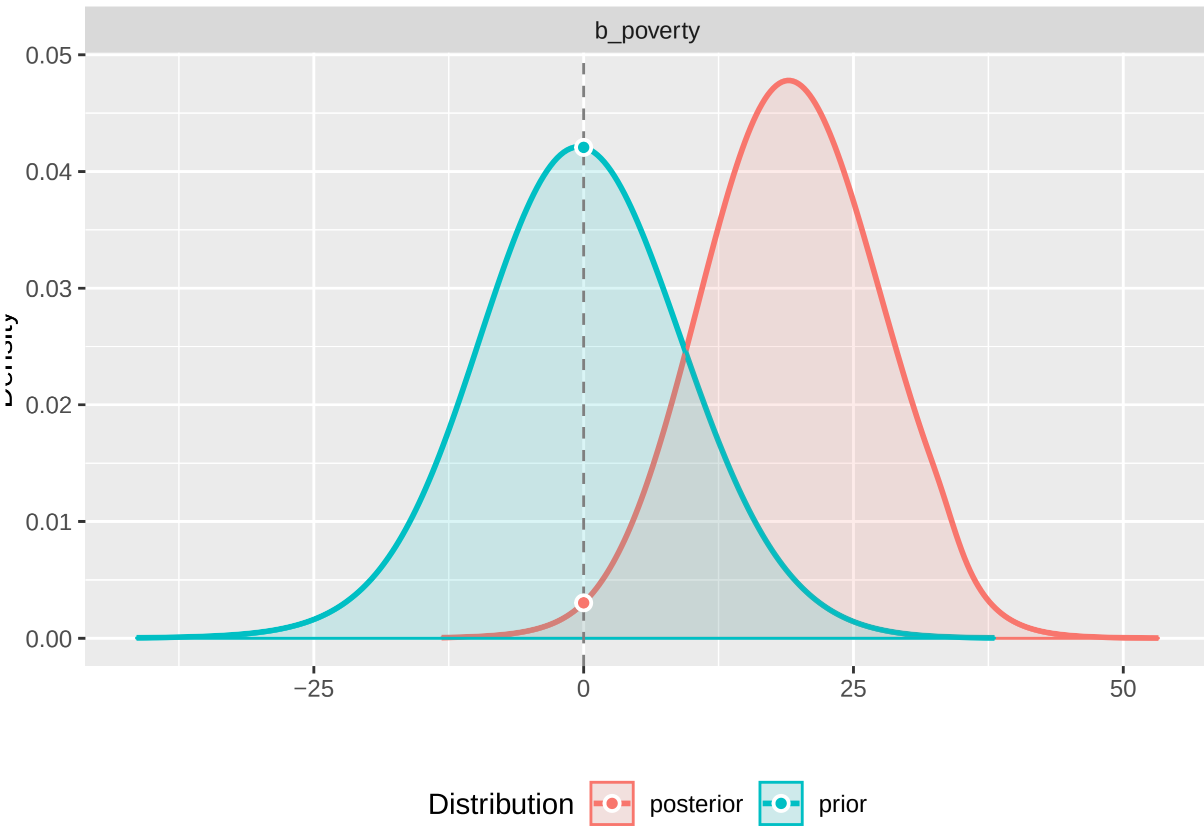
Now lets compare posterior distribution to prior distribution.

```r
bf_fit <- bayesfactor_parameters(fit)
```

```
## Computation of Bayes factors: sampling priors, please wait...
```

```
## Loading required namespace: logspline
```

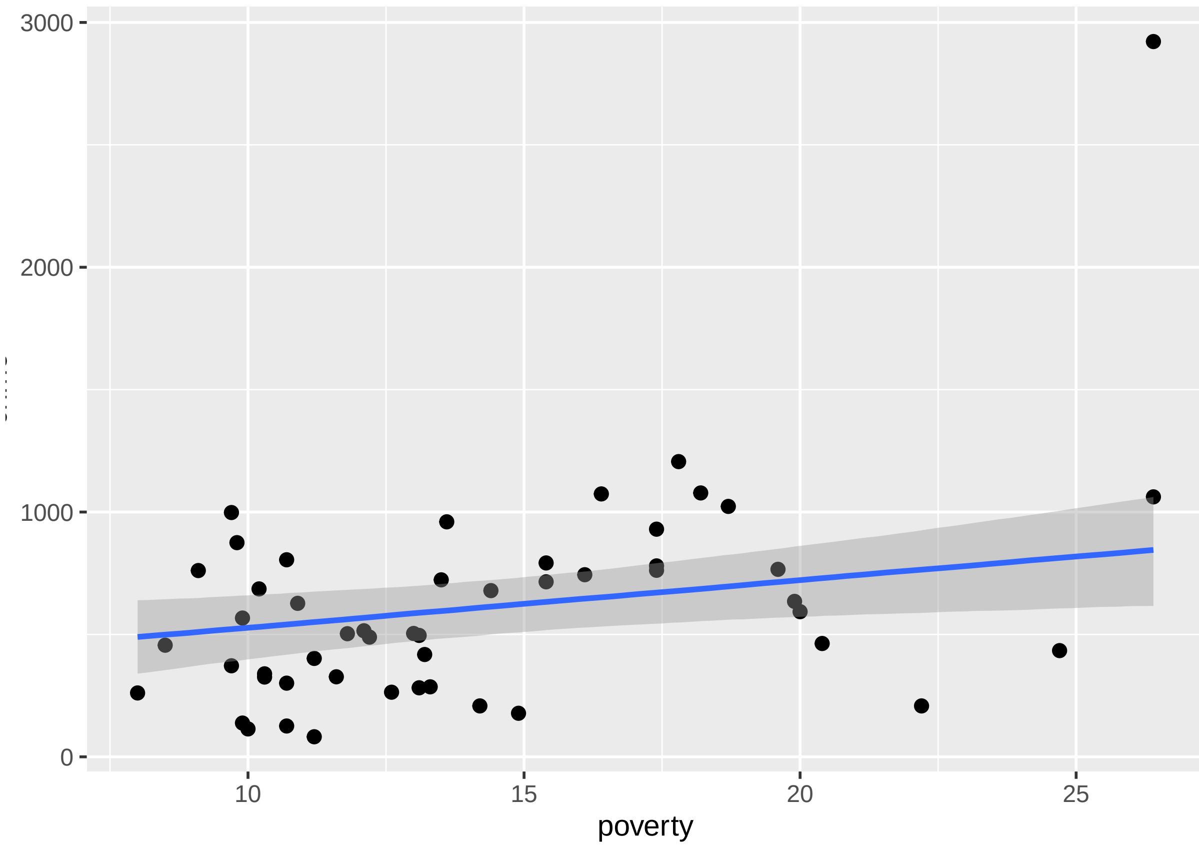
```r
plot(bf_fit)
```



Plotting predictions against data

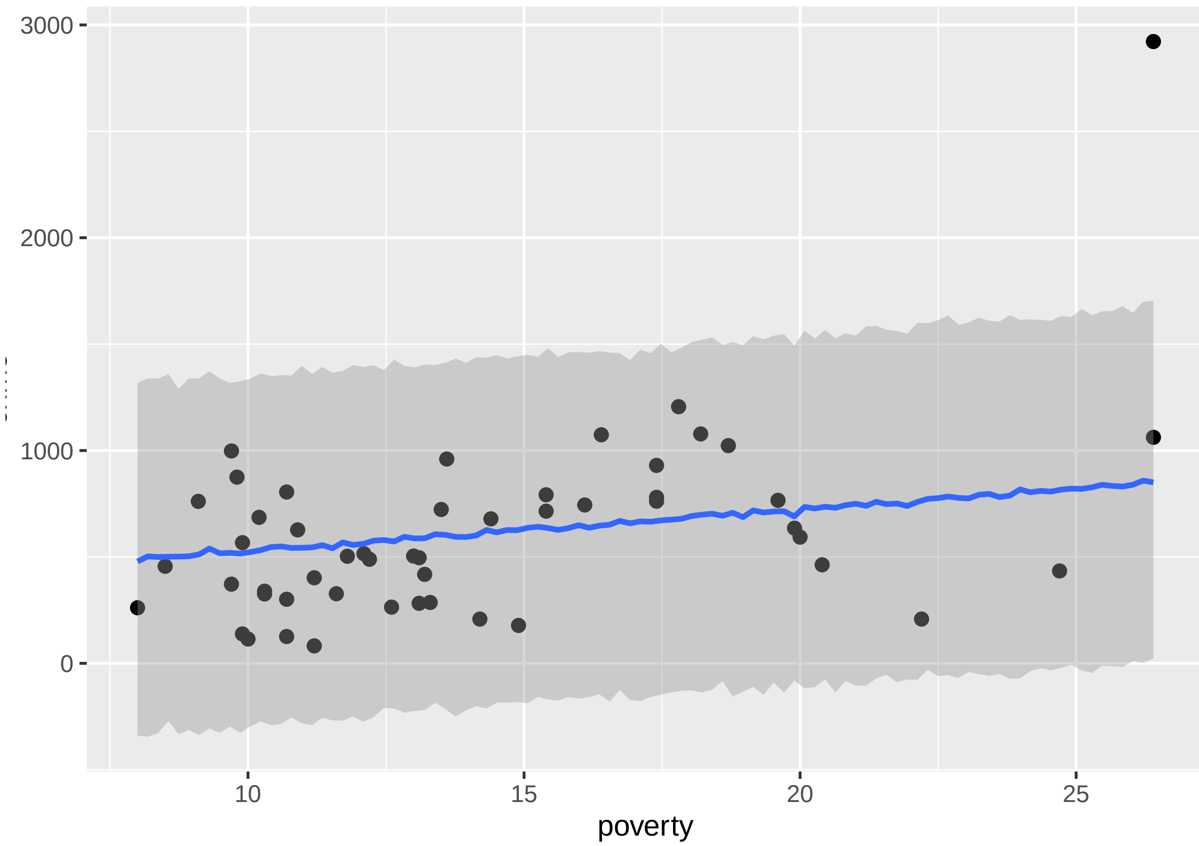
Now lets plot the fitted regression line against the collected data.

```r
marginal_effects(fit, effects = "poverty") %>%
  plot(points = T)
```



If you would like to fit predicted crime level given the poverty level it is also quite simple.

```
marginal_effects(fit, effects = "poverty", method = "predict") %>%
  plot(points = T)
```



If you find the code in this notebook hard to follow, DON'T PANIC. It will get easier with time. I would also recommend you to go through some online tutorials. For example Hadley Wickham's R for Data Science.