POSTERIOR SAMPLES ARE EVERYTHING!

- ML methods use estimated values for parameters for everything
  - $\mu = f(\hat{\theta})$
- Bayesian methods use the posterior distribution of the parameters for everything

```
> samples
# A tibble: 2,000 × 3
         a         b     sigma
   <dbl[1d]> <dbl[1d]> <dbl[1d]>
 1      115.     0.889      4.78
 2      109.     1.02       5.30
 3      112.     0.928      5.07
 4      111.     0.949      5.30
 5      111.     0.955      5.04
 6      115.     0.872      5.19
 7      109.     1.01       5.13
 8      117.     0.844      5.00
 9      115.     0.882      4.94
10      112.     0.939      4.95
# … with 1,990 more rows
```

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HOW TO GET POSTERIOR SAMPLES?

- There is no general method to find high probability regions in arbitrary probability distributions.
- This mean most models are fit using purely computational methods.
- For simple parameters spaces, we can do grid search or some brute force method to find high probability regions
- This breaks down quickly as the number of parameters increases