

# Simple CFR approach

Here is the basic model. We are interested in estimating the CFR among confirmed cases,  $\rho$ . Presume that the time from confirmation to report of death (censoring at recovery) follows an exponential distribution:

$$\Pr(Y_i < t) = F(t; \lambda_1)$$

Where  $Y_i$  is the time from confirmation to death for person  $i$ .

Moreover, the time from confirmation to death or recovery (composite outcome) follows an exponential distribution:

$$\Pr(T_i < t) = G(t; \lambda)$$

Where  $T_i$  is the time from confirmation to death or recovery for person  $i$ .

To ease application of the above models to our dataset, which is organized by calendar date, we will assume both time to death and time to the composite outcome follow an exponential distribution with a constant hazard function,  $\lambda_1$  and  $\lambda$ , respectively, for now.

Let  $d_{jv}$  be the number of reported deaths in location  $j$  and calendar date  $v$ . Based on the above:

$$E(d_{jv}) = \sum_{k=0}^v n_{jk} \lambda_1$$

where  $n_{jv}$  is the number in the risk set on that day (i.e., cumulative number of confirmed cases reported on day  $v$  minus the cumulative number of deaths on that day and the cumulative number of people recovered).

In addition,

$$E(n_{jv}) = c_{jv} - \sum_{k=0}^{v-1} n_{jk} \lambda$$

where  $n_{jv}$  is the number in the risk set on that day (i.e., cumulative number of confirmed cases reported on day  $v$  minus the cumulative number of deaths on that day and the cumulative number of people recovered).

Finally

$$\rho = \int_0^\infty \hat{\lambda}_1 [1 - \hat{G}(t)] dt = \int_0^\infty \hat{\lambda}_1 e^{-\hat{\lambda} t} dt$$

.

First, define the stan model.

```
data {
  int <lower=0> T; //the number of time steps included
  int <lower=0> L; //the number of locations we have data from

  real <lower=0> c[T,L]; // cumulative number of confirmed cases reported on each day.
  real <lower=0> r[T,L]; // cumulative number of recovered cases reported on each day.
  int <lower=0> d[T,L]; // cumulative number of deaths reported on each day.
  int <lower=0> n[T,L]; //number of currently infected people on each day.
  int <lower = 0> V; // max infection duration (we should be able to get rid of this)
}

parameters {
  real <lower=0> lambda1; //parameter for time to death distribution
  real <lower=0> lambda; // parameter for time to death or recovery distribution
```

```

}

transformed parameters {
  real <lower=0> expected_deaths[T,L]; // cumulative # deaths BY time T
  real <lower=0> expected_riskset[T,L]; // # infected at time T
  real <lower=0> expected_exit[T,L]; // cumulative # those who have exited due to death or recovery BY

  //this can be made more efficient...but for now./
  for (j in 1:L) {
    for (t in 1:T) {
      expected_deaths[t,j] = 0.0001;
      expected_exit[t,j] = 0.0001;
      for (k in 1:t) {
        expected_exit[k,j] += n[k,j] * lambda;
        expected_deaths[k,j] += n[k,j] * lambda1;
      }
      expected_riskset[t,j] = c[t,j] - expected_exit[t,j];
      //expected_recovered[t,j] = (expected_exit[t,j] - expected_deaths[t,j]);
    }
  }
}

model {

  //definitely can be made more efficient.
  for (j in 1:L) {
    for (t in 1:T) {
      //target+=poisson_lpmf(d[t,j]|expected_deaths[t,j]) + poisson_lpmf(n[t,j]|expected_riskset[t,j]);
      target+=poisson_lpmf(d[t,j]|expected_deaths[t,j]) + poisson_lpmf(n[t,j]|expected_riskset[t,j]);
    }
  }
  // print(target());
}

//generated quantities {
//real <lower = 0, upper = 1> rho;
// for (v in 1:V){
//   rho += exp(loglambda1) * exp(-exp(loglambda) * v);
//   rho += lambda1 * exp(-lambda * v);
// }
//print(rho);
//rho = integrate_1d(getft, 0, positive_infinity(), {lambda1, lambda}, t);

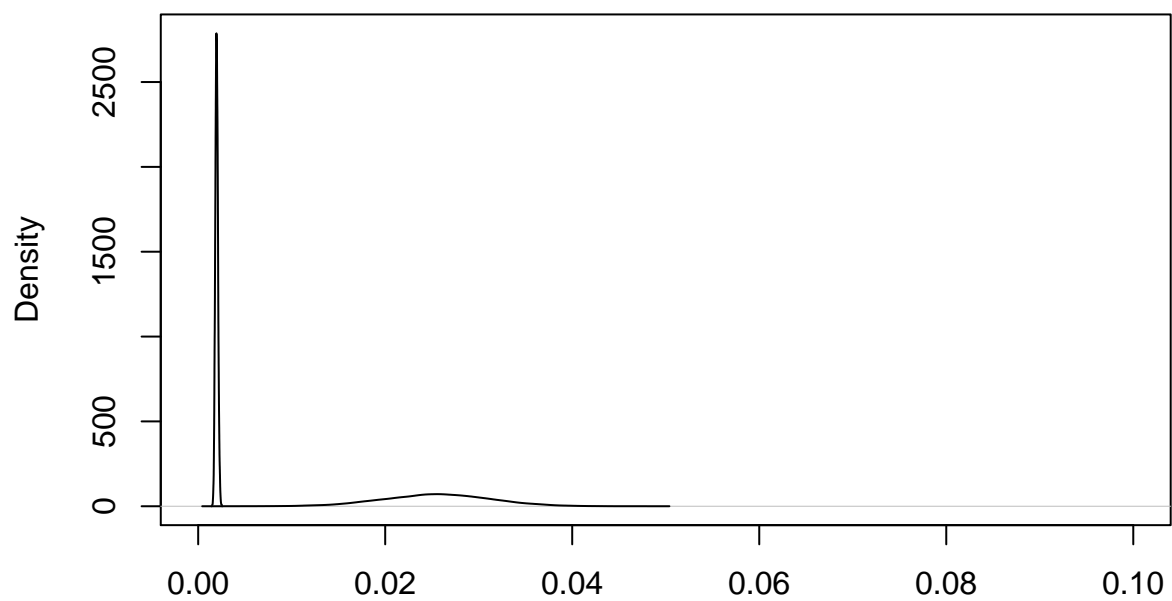
//} // The posterior predictive distribution"

Prep data and run model.

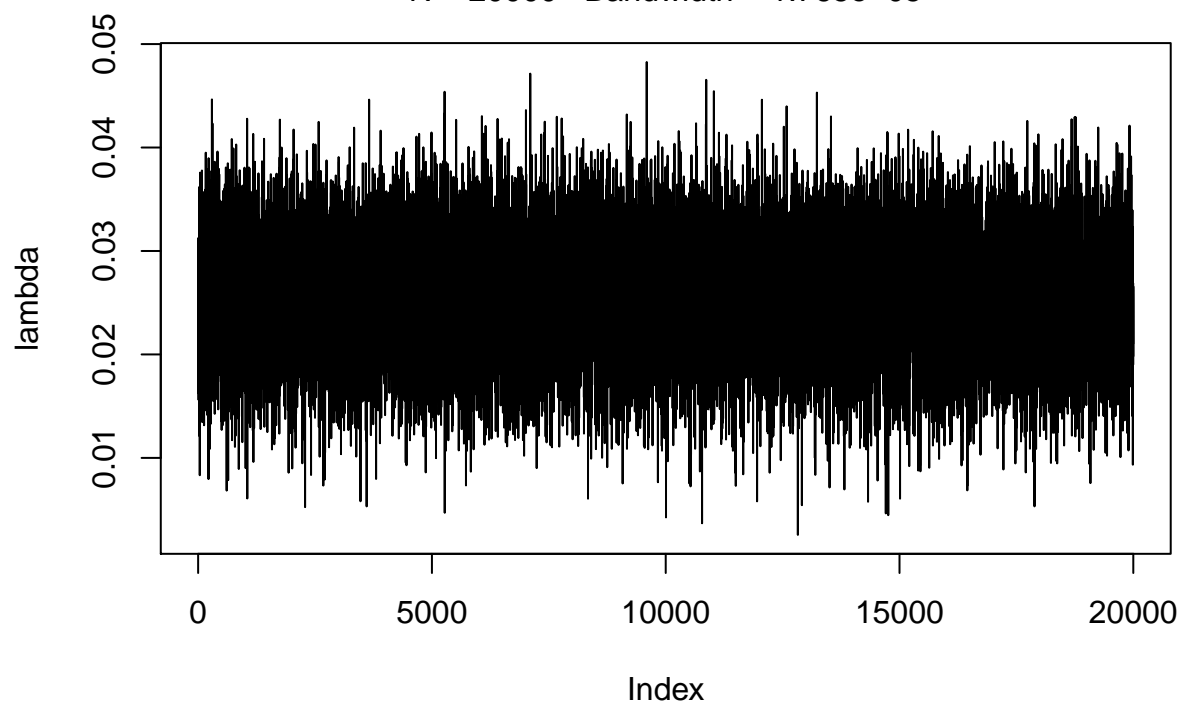
Summarize

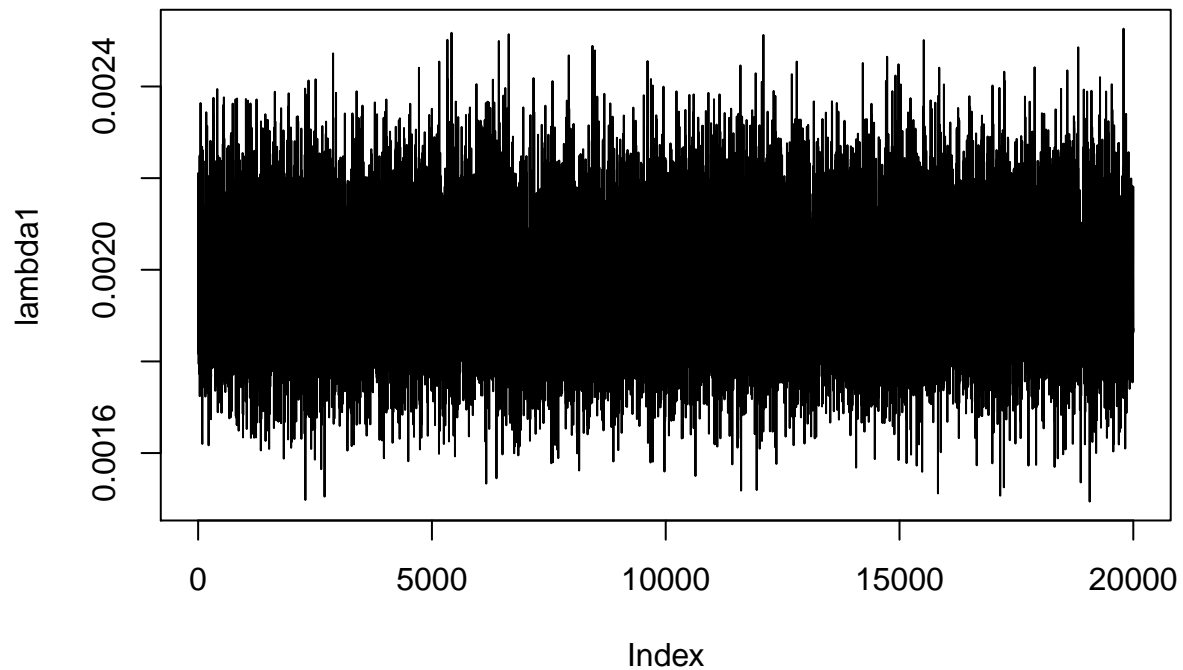
```

**density.default(x = lambda1)**



N = 20000 Bandwidth = 1.765e-05





Results

```
#move this into stan model later
rho <- matrix(nrow = length(lambda1))
for(i in 1:length(lambda1)){
  rho[i] <- integrate(function(x) {lambda1[i]*exp(-lambda[i]*x)}, lower = 0, upper = Inf)$value
}
```

```
median(rho)
```

```
## [1] 0.07715701
```

```
quantile(rho, probs = c(.025, .975))
```

```
##      2.5%      97.5%
```

```
## 0.05242317 0.14023800
```