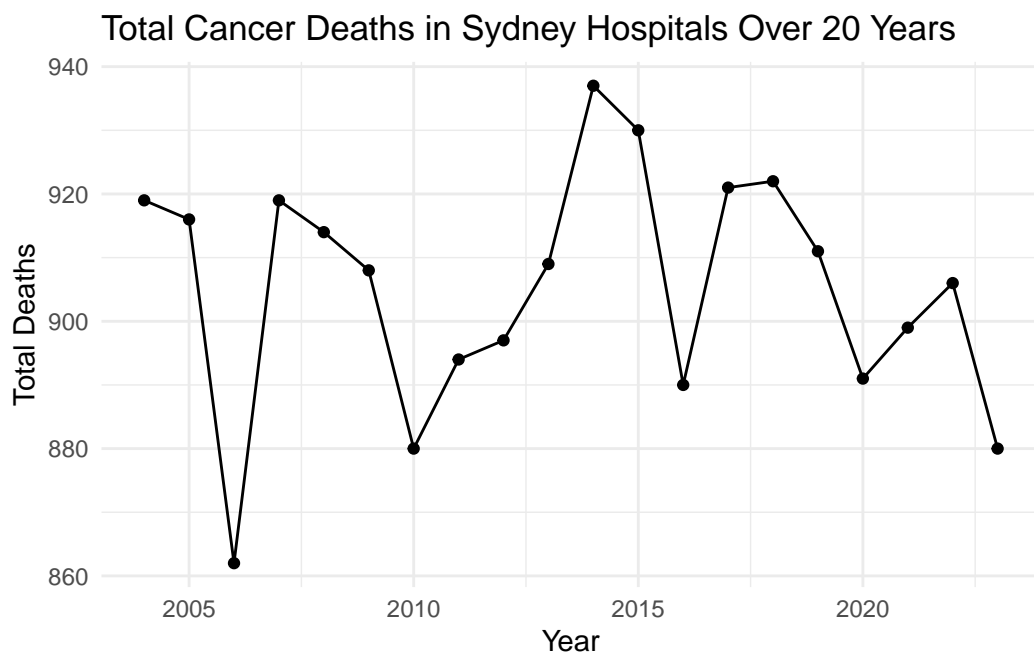


Quiz 12a (Simulate + Explore)

Bernice Bao

Simulate (Question 2)

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
138.0	167.8	181.0	181.1	194.2	225.0

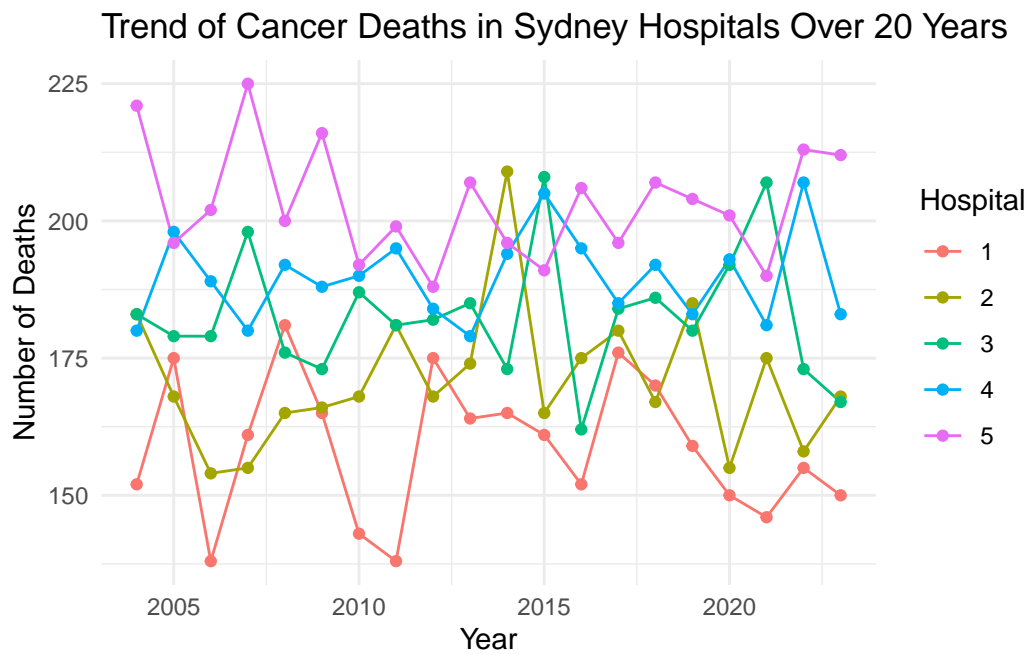


Hospital Deaths	
1	1 158.80
2	2 170.95
3	3 182.75
4	4 189.65
5	5 203.10

Hospital Deaths		
1	1	181
2	2	209
3	3	208
4	4	207
5	5	225

```
[1] 2007
```

```
[1] 5
```



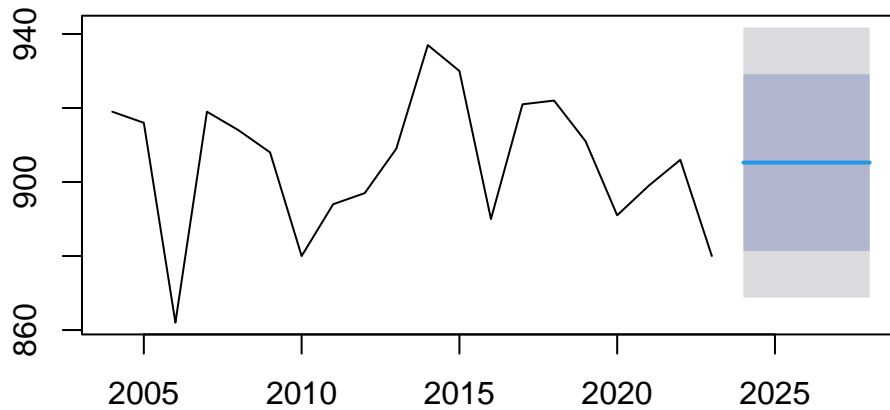
	[,1]	[,2]	[,3]	[,4]	[,5]
[1,]	1.000000000	0.09771522	-0.07541234	0.007501716	-0.08631512
[2,]	0.097715224	1.00000000	-0.21644782	-0.146893103	-0.20572856
[3,]	-0.075412343	-0.21644782	1.00000000	-0.108566836	-0.27000566
[4,]	0.007501716	-0.14689310	-0.10856684	1.00000000	-0.25289689
[5,]	-0.086315124	-0.20572856	-0.27000566	-0.252896893	1.00000000

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
factor(Hospital)	4	23202	5801	45.52	<2e-16 ***
Residuals	95	12106	127		

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```
Registered S3 method overwritten by 'quantmod':  
  method      from  
as.zoo.data.frame zoo
```

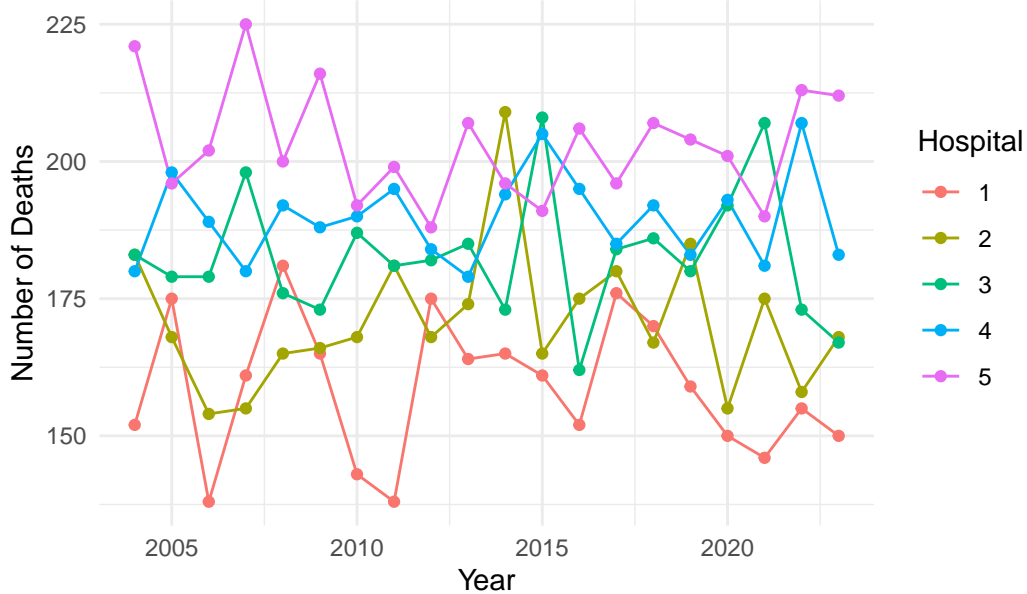
Forecast of Total Cancer Deaths in Sydney Hospitals



Explore (Question 4)

```
# Plot the simulated data  
ggplot(df, aes(x = Year, y = Deaths, color = factor(Hospital))) +  
  geom_line() +  
  geom_point() +  
  labs(title = "Number of Cancer Deaths in Sydney Hospitals Over 20 Years",  
        x = "Year",  
        y = "Number of Deaths",  
        color = "Hospital") +  
  theme_minimal()
```

Number of Cancer Deaths in Sydney Hospitals Over 20 Years



```
# Load necessary libraries
library(rstanarm)
```

Loading required package: Rcpp

This is rstanarm version 2.32.1

- See <https://mc-stan.org/rstanarm/articles/priors> for changes to default priors!
- Default priors may change, so it's safest to specify priors, even if equivalent to the default
- For execution on a local, multicore CPU with excess RAM we recommend calling

```
options(mc.cores = parallel::detectCores())
```

```
# Fit a simple linear regression model
model <- stan_glm(Deaths ~ Year + factor(Hospital), data = df, family = "poisson")
```

SAMPLING FOR MODEL 'count' NOW (CHAIN 1).

Chain 1:

Chain 1: Gradient evaluation took 4.4e-05 seconds

Chain 1: 1000 transitions using 10 leapfrog steps per transition would take 0.44 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: 0.065 seconds (Warm-up)

Chain 1: 0.064 seconds (Sampling)

Chain 1: 0.129 seconds (Total)

Chain 1:

SAMPLING FOR MODEL 'count' NOW (CHAIN 2).

Chain 2:

Chain 2: Gradient evaluation took 1.1e-05 seconds

Chain 2: 1000 transitions using 10 leapfrog steps per transition would take 0.11 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: 0.067 seconds (Warm-up)
Chain 2: 0.062 seconds (Sampling)
Chain 2: 0.129 seconds (Total)
Chain 2:

SAMPLING FOR MODEL 'count' NOW (CHAIN 3).

Chain 3:
Chain 3: Gradient evaluation took 1e-05 seconds
Chain 3: 1000 transitions using 10 leapfrog steps per transition would take 0.1 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: 0.064 seconds (Warm-up)
Chain 3: 0.067 seconds (Sampling)
Chain 3: 0.131 seconds (Total)
Chain 3:

SAMPLING FOR MODEL 'count' NOW (CHAIN 4).

Chain 4:
Chain 4: Gradient evaluation took 1e-05 seconds
Chain 4: 1000 transitions using 10 leapfrog steps per transition would take 0.1 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: 0.063 seconds (Warm-up)
Chain 4: 0.064 seconds (Sampling)
Chain 4: 0.127 seconds (Total)
Chain 4:

```

```

# Print the summary of the model
summary(model)

```

Model Info:

```

function: stan_glm
family: poisson [log]
formula: Deaths ~ Year + factor(Hospital)
algorithm: sampling
sample: 4000 (posterior sample size)
priors: see help('prior_summary')
observations: 100
predictors: 6

```

Estimates:

	mean	sd	10%	50%	90%
(Intercept)	5.4	2.5	2.2	5.4	8.7
Year	0.0	0.0	0.0	0.0	0.0
factor(Hospital)2	0.1	0.0	0.0	0.1	0.1
factor(Hospital)3	0.1	0.0	0.1	0.1	0.2
factor(Hospital)4	0.2	0.0	0.1	0.2	0.2
factor(Hospital)5	0.2	0.0	0.2	0.2	0.3

Fit Diagnostics:

	mean	sd	10%	50%	90%
mean_PPD	181.0	1.9	178.6	181.0	183.5

The mean_ppd is the sample average posterior predictive distribution of the outcome variable

MCMC diagnostics

	mcse	Rhat	n_eff
(Intercept)	0.0	1.0	4836
Year	0.0	1.0	4841
factor(Hospital)2	0.0	1.0	1683
factor(Hospital)3	0.0	1.0	1810
factor(Hospital)4	0.0	1.0	1984
factor(Hospital)5	0.0	1.0	1839
mean_PPD	0.0	1.0	3078
log-posterior	0.0	1.0	1841

For each parameter, mcse is Monte Carlo standard error, n_eff is a crude measure of effective