

Fitting ARIMA Models

Lecture 12

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Assessing Predictive Performance

Test train split

The general approach is to keep the data ordered and split the first `prop%` into the training data and the remainder as testing data.



```
1 co2 = as_tsibble(co2)
2 co2_split = rsample::initial_time_split(co2, prop=0.9)
```

```
1 rsample::training(co2_split)
```

```
# A tsibble: 421 x 2 [1M]
```

```
  index value
```

```
  <mtb> <dbl>
```

```
1 1959 Jan 315.  
2 1959 Feb 316.  
3 1959 Mar 316.  
4 1959 Apr 318.  
5 1959 May 318.  
6 1959 Jun 318  
7 1959 Jul 316.  
8 1959 Aug 315.  
9 1959 Sep 314.  
10 1959 Oct 313.
```

```
# i 411 more rows
```

```
1 rsample::testing(co2_split)
```

```
# A tsibble: 47 x 2 [1M]
```

```
  index value
```

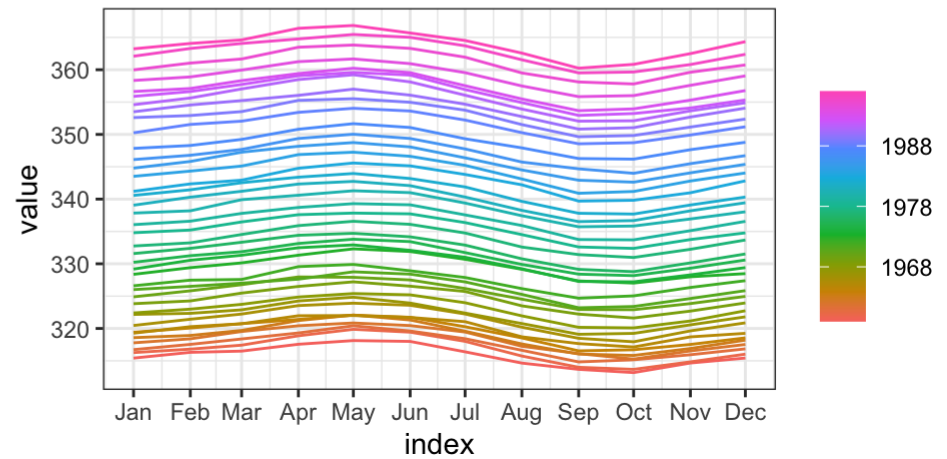
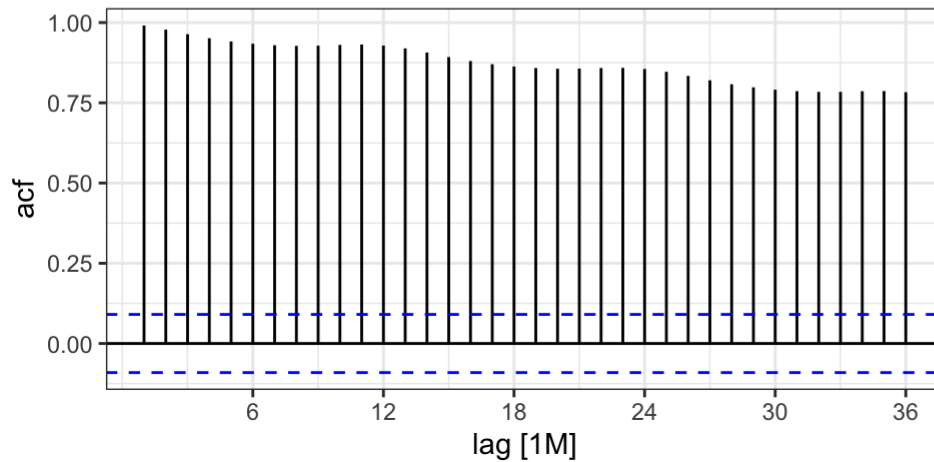
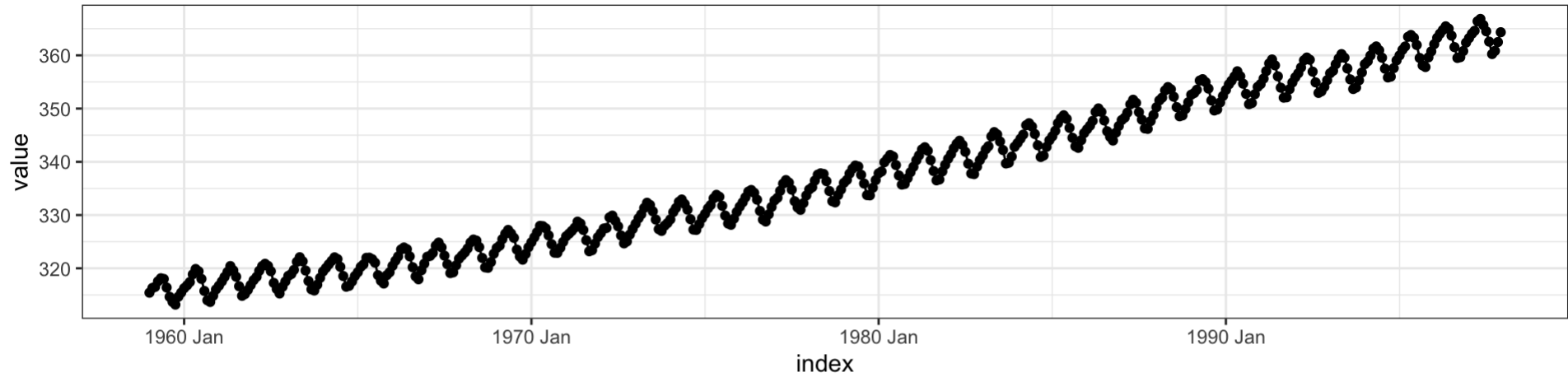
```
  <mtb> <dbl>
```

```
1 1994 Feb 359.  
2 1994 Mar 360.  
3 1994 Apr 361.  
4 1994 May 362.  
5 1994 Jun 361.  
6 1994 Jul 360.  
7 1994 Aug 357.  
8 1994 Sep 356.  
9 1994 Oct 356  
10 1994 Nov 358.
```

```
# i 37 more rows
```

co2 data

```
1 gg_tsdisplay(co2, y = value, lag_max = 36)
```



Model fit (training)

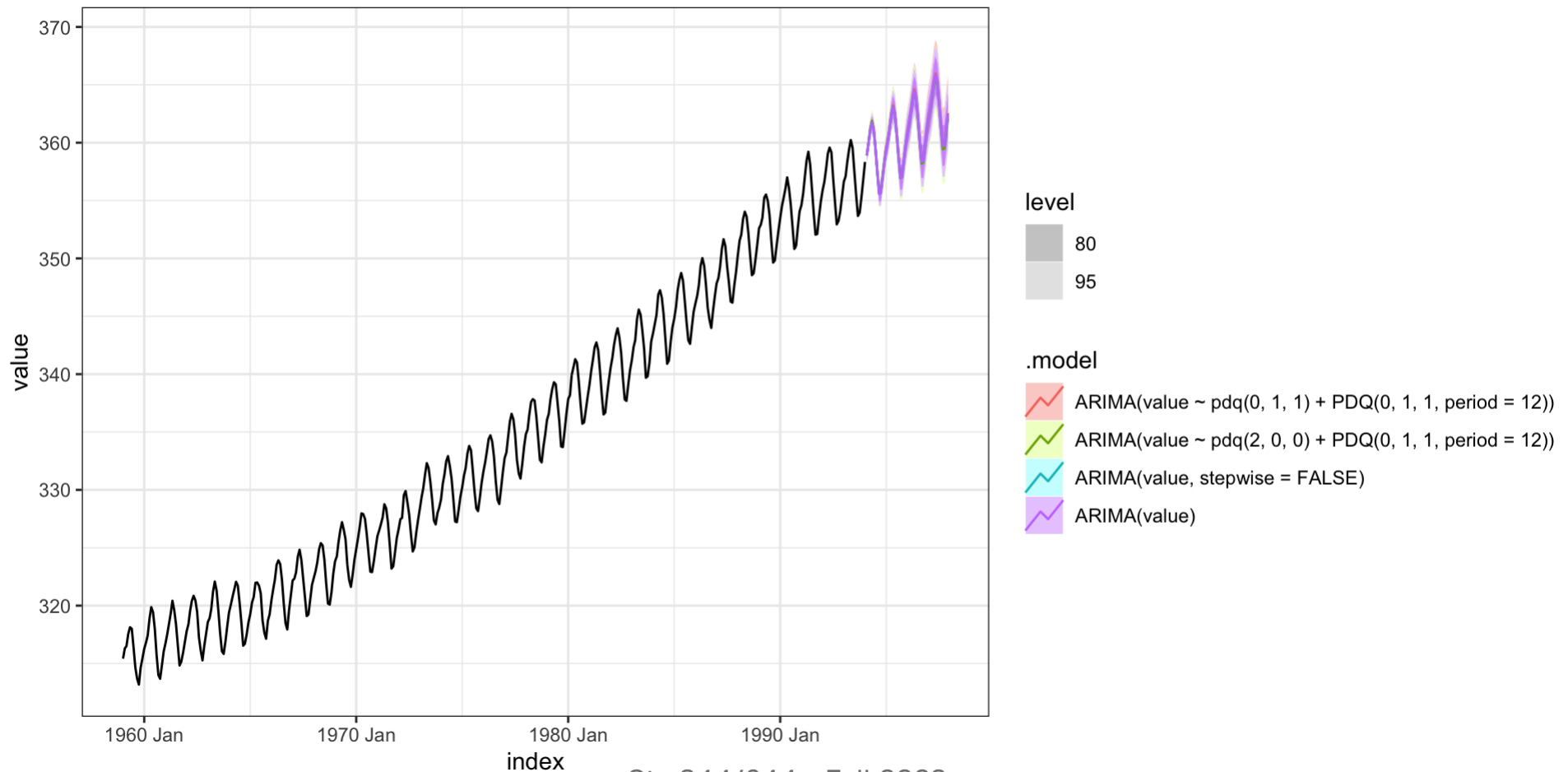
```
1 mm = rsample::training(co2_split) |>
2   model(
3     ARIMA(value~pdq(2,0,0) + PDQ(0,1,1, period=12)),
4     ARIMA(value~pdq(0,1,1) + PDQ(0,1,1, period=12)),
5     ARIMA(value),
6     ARIMA(value, stepwise = FALSE)
7   )
8 glance(mm)
```

A tibble: 4 × 8

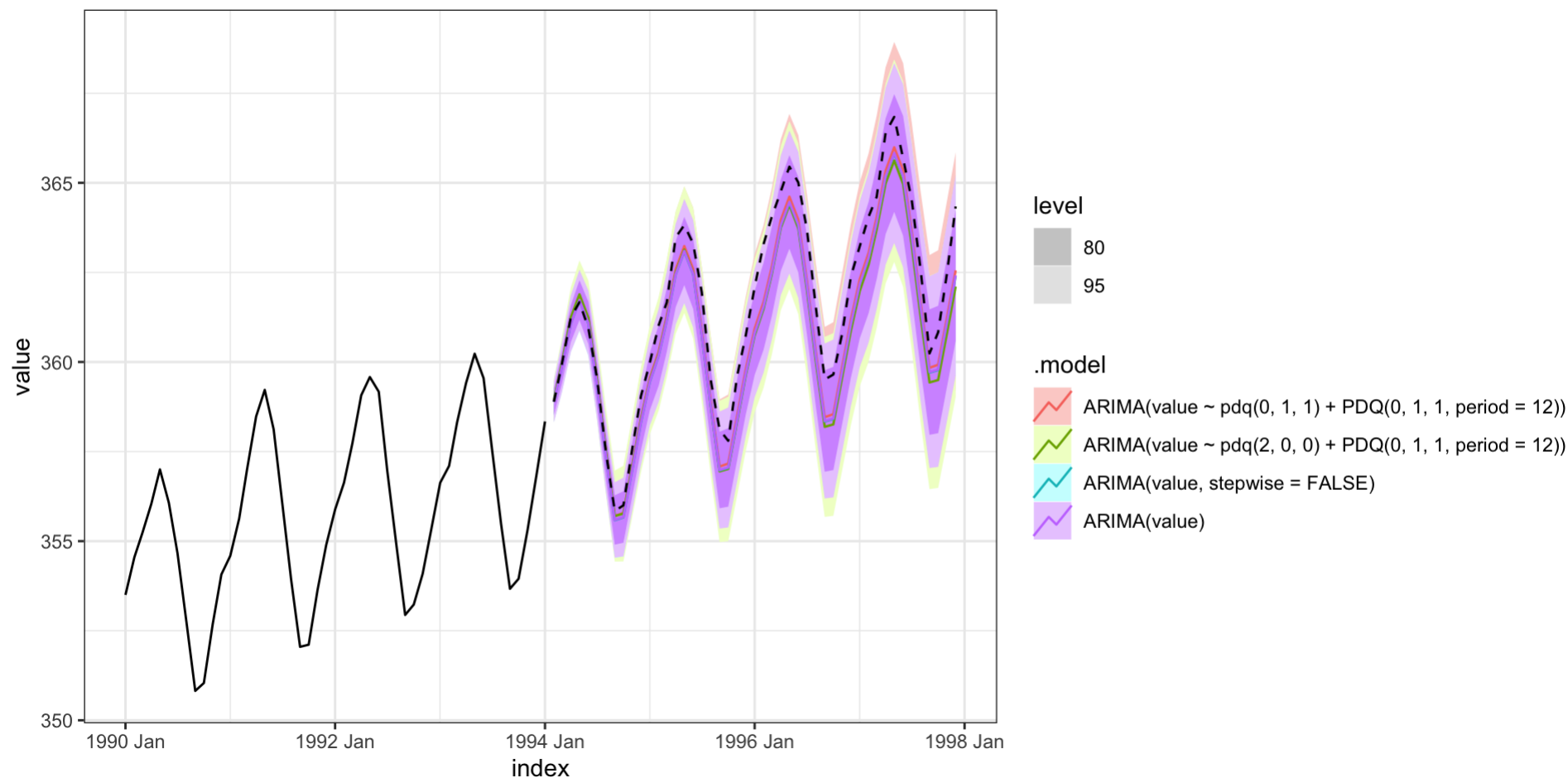
.model	sigma2	log_lik	AIC	AICc	BIC	ar_roots	ma_roots
<chr>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<list>	<list>
1 ARIMA(value ~ pdq(2, 0, 0)...	0.0865	-78.7	167.	167.	187.	<cpl>	<cpl>
2 ARIMA(value ~ pdq(0, 1, 1)...	0.0858	-76.8	160.	160.	172.	<cpl>	<cpl>
3 ARIMA(value)	0.0852	-73.8	160.	160.	184.	<cpl>	<cpl>
4 ARIMA(value, stepwise = FA...	0.0853	-73.7	161.	162.	189.	<cpl>	<cpl>

Forecasting

```
1 mm |>
2   forecast(new_data = rsample::testing(co2_split)) |>
3   autoplot(
4     rsample::training(co2_split)
5   )
```



Forecasting (1990-1996)



Accuracy

Out-of-sample:

```
1 mm |>
2   forecast(new_data = rsample::testing(co2_sp
3   accuracy(rsample::testing(co2_split))
```

A tibble: 4 × 10

	.model	.type	ME	RMSE	MAE	MPE	MAPE
	<chr>	<chr>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
1	ARIMA(val...	Test	0.742	0.881	0.764	0.205	0.211
2	ARIMA(val...	Test	0.929	1.10	0.956	0.256	0.264
3	ARIMA(val...	Test	0.862	0.987	0.871	0.238	0.240
4	ARIMA(val...	Test	0.875	1.00	0.883	0.241	0.244

i 3 more variables: MASE <dbl>, RMSSE <dbl>,
ACF1 <dbl>

Within-sample:

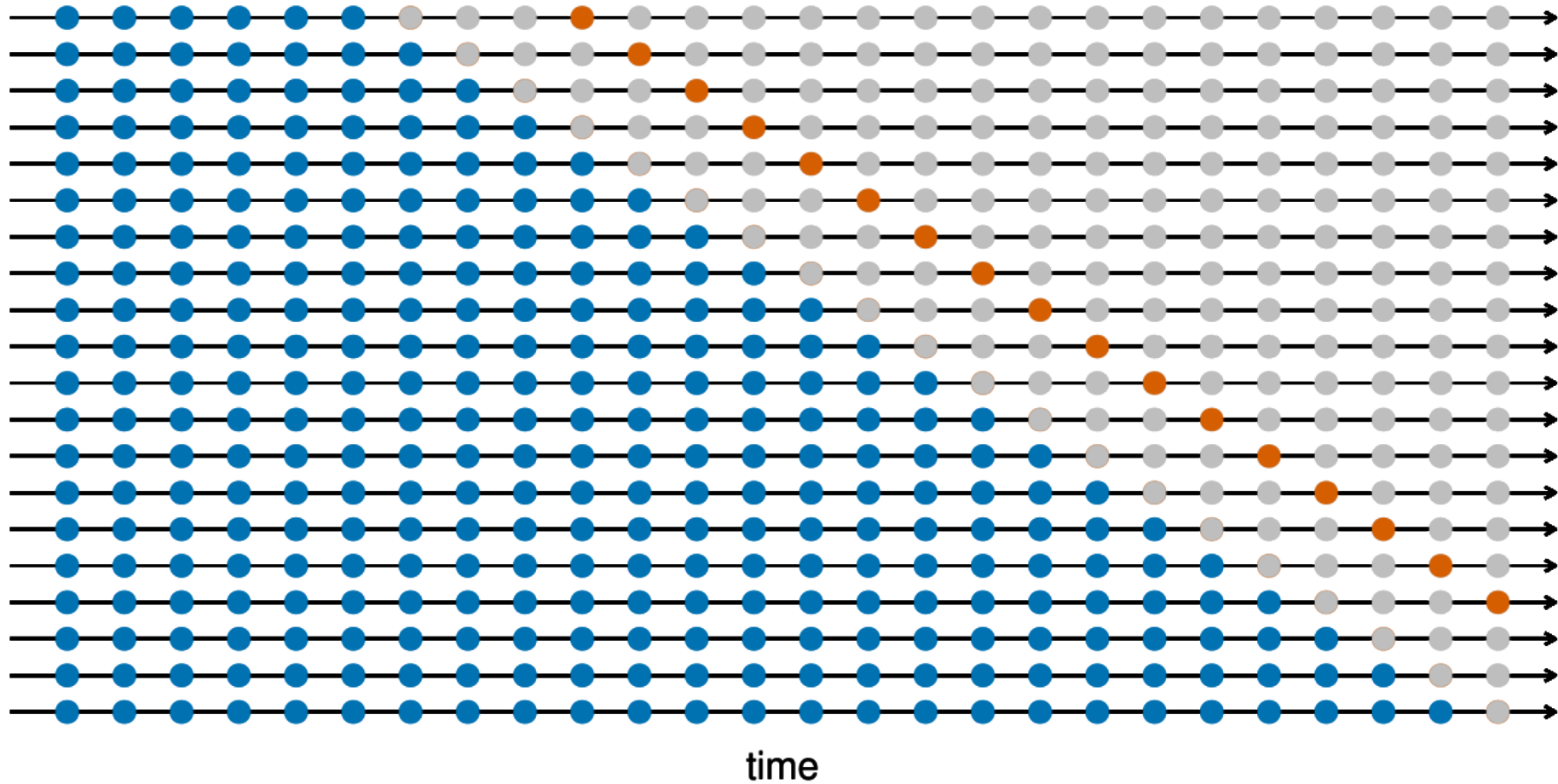
```
1 mm |>
2   accuracy()
```

A tibble: 4 × 10

	.model	.type	ME	RMSE	MAE	MPE	MAPE
	<chr>	<chr>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
1	ARIMA...	Trai...	0.0118	0.288	0.234	0.00340	0.0701
2	ARIMA...	Trai...	0.0118	0.288	0.229	0.00349	0.0685
3	ARIMA...	Trai...	0.0144	0.286	0.227	0.00426	0.0680
4	ARIMA...	Trai...	0.0149	0.285	0.227	0.00440	0.0680

i 3 more variables: MASE <dbl>, RMSSE <dbl>,
ACF1 <dbl>

Rolling forecasting origin



One-step forecasts on test data

```
1 mm |>
2   refit(rsample::testing(co2_split)) |>
3   accuracy()
```

```
# A tibble: 4 × 10
```

	.model	.type	ME	RMSE	MAE	MPE	MAPE	MASE	RMSSE	ACF1
	<chr>	<chr>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
1	ARIMA(value ~ pdq...	Trai...	0.135	0.322	0.294	0.0376	0.0815	0.179	0.186	0.0796
2	ARIMA(value ~ pdq...	Trai...	-0.0401	0.318	0.220	-0.0111	0.0608	0.134	0.184	0.0383
3	ARIMA(value)	Trai...	-0.0479	0.319	0.219	-0.0133	0.0606	0.133	0.185	0.0250
4	ARIMA(value, step...	Trai...	-0.0487	0.320	0.219	-0.0135	0.0606	0.133	0.185	0.0252

Model Fitting

Fitting ARIMA

For an ARIMA(p, d, q) model,

- Assumes that the data is stationary after differencing
- Handling d is straight forward, just difference the original data d times (leaving n - d observations)

$$y'_t = \Delta^d y_t$$

- After differencing, fit an ARMA(p, q) model to y'_t .
- To keep things simple we'll assume $w_t \stackrel{\text{iid}}{\sim} N(0, \sigma_w^2)$

MLE - Stationarity & iid normal errors

If both of these assumptions are met, then the time series y_t will also be normal.

In general, the vector $\mathbf{y} = (y_1, y_2, \dots, y_t)'$ will have a multivariate normal distribution with mean $\{\boldsymbol{\mu}\}_i = E(y_i) = E(y_t)$ and covariance $\boldsymbol{\Sigma}$ where $\{\boldsymbol{\Sigma}\}_{ij} = \gamma(i - j)$.

and therefore the joint density of $\mathbf{y}$ is given by

$$f_{\mathbf{y}}(\mathbf{y}) = (2\pi)^{-t/2} \det(\boldsymbol{\Sigma})^{-1/2} \times \exp\left(-\frac{1}{2}(\mathbf{y} - \boldsymbol{\mu})' \boldsymbol{\Sigma}^{-1} (\mathbf{y} - \boldsymbol{\mu})\right)$$

AR

Fitting AR(1)

$$y_t = \delta + \phi y_{t-1} + w_t$$

We need to estimate three parameters: δ , ϕ , and σ_w^2 , we know

$$E(y_t) = \frac{\delta}{1 - \phi} \quad \text{Var}(y_t) = \frac{\sigma_w^2}{1 - \phi^2}$$

$$\gamma(h) = \frac{\sigma_w^2}{1 - \phi^2} \phi^{|h|}$$

Using these properties it is possible to write the distribution of y as a MVN but that does not make it easy to write down a (simplified) closed form for the MLE estimate for δ , θ , and σ_w^2 .

Conditional Density

We can also rewrite the density as follows,

$$\begin{aligned} f(\mathbf{y}) &= f(y_t, y_{t-1}, \dots, y_2, y_1) \\ &= f(y_t | y_{t-1}, \dots, y_2, y_1) f(y_{t-1} | y_{t-2}, \dots, y_2, y_1) \cdots f(y_2 | y_1) f(y_1) \\ &= f(y_t | y_{t-1}) f(y_{t-1} | y_{t-2}) \cdots f(y_2 | y_1) f(y_1) \end{aligned}$$

where,

$$\begin{aligned} y_1 &\sim N \left(\delta, \frac{\sigma_w^2}{1 - \phi^2} \right) \\ y_t | y_{t-1} &\sim N \left(\delta + \phi y_{t-1}, \sigma_w^2 \right) \\ f(y_t | y_{t-1}) &= \frac{1}{\sqrt{2\pi\sigma_w^2}} \exp \left(-\frac{1}{2} \frac{(y_t - \delta + \phi y_{t-1})^2}{\sigma_w^2} \right) \end{aligned}$$

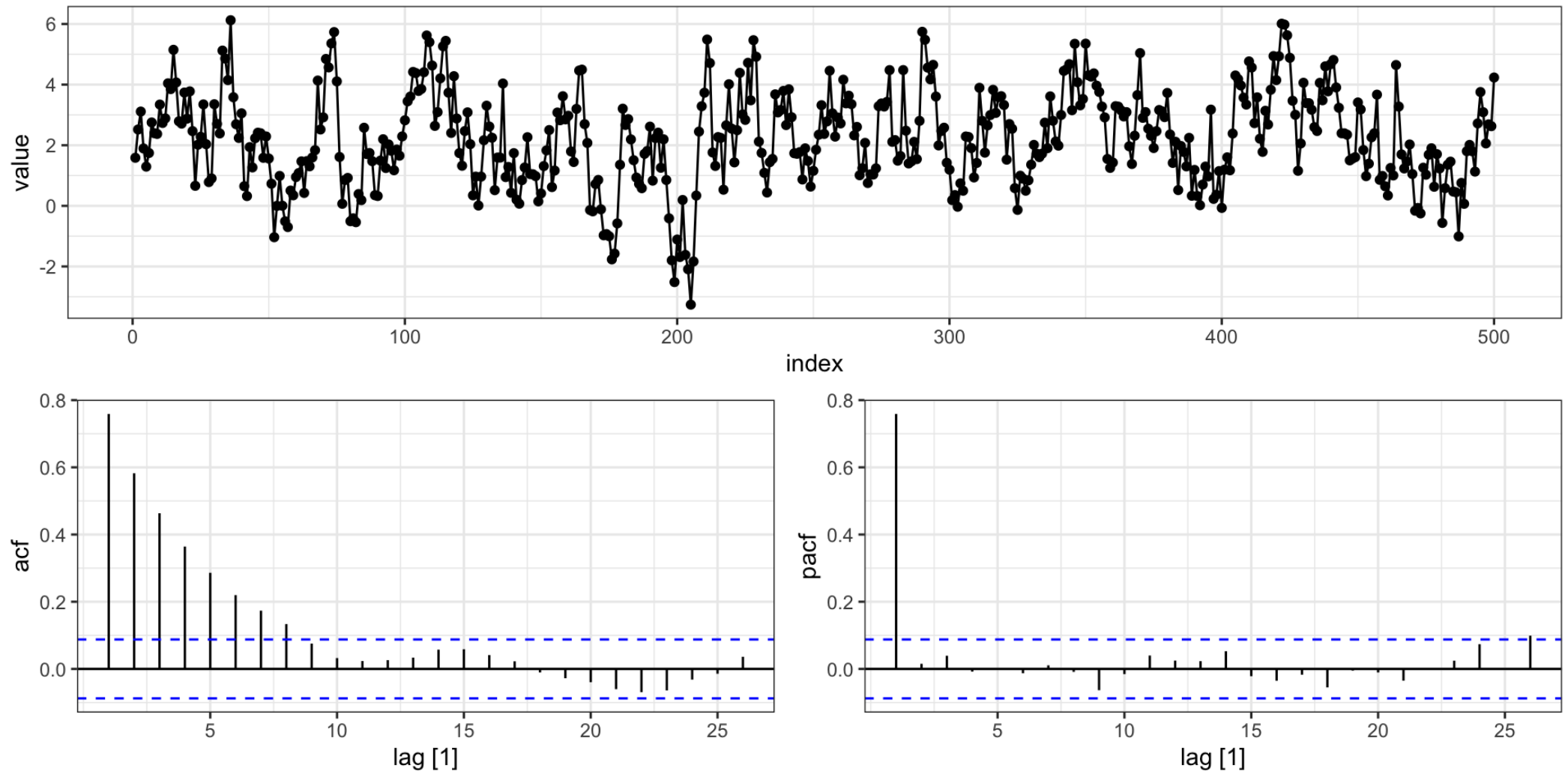
Log likelihood of AR(1)

$$\log f(y_t | y_{t-1}) = -\frac{1}{2} \left(\log 2\pi + \log \sigma_w^2 + \frac{1}{\sigma_w^2} (y_t - \delta + \phi y_{t-1})^2 \right)$$

$$\begin{aligned} \ell(\delta, \phi, \sigma_w^2) &= \log f(\mathbf{y}) = \log f(y_1) + \sum_{i=2}^t \log f(y_i | y_{i-1}) \\ &= -\frac{1}{2} \left(\log 2\pi + \log \sigma_w^2 - \log(1 - \phi^2) + \frac{(1 - \phi^2)}{\sigma_w^2} (y_1 - \delta)^2 \right) \\ &\quad - \frac{1}{2} \left((n-1) \log 2\pi + (n-1) \log \sigma_w^2 + \frac{1}{\sigma_w^2} \sum_{i=2}^n (y_i - \delta + \phi y_{i-1})^2 \right) \\ &= -\frac{1}{2} \left(n \log 2\pi + n \log \sigma_w^2 - \log(1 - \phi^2) \right. \\ &\quad \left. + \frac{1}{\sigma_w^2} \left((1 - \phi^2)(y_1 - \delta)^2 + \sum_{i=2}^n (y_i - \delta + \phi y_{i-1})^2 \right) \right) \end{aligned}$$

AR(1) Example

with $\phi = 0.75$, $\delta = 0.5$, and $\sigma_w^2 = 1$,



ARIMA

```
1 ar1_arima = model(ar1, ARIMA(value~pdq(1,0,0)))  
2 report(ar1_arima)
```

Series: value

Model: ARIMA(1,0,0) w/ mean

Coefficients:

	ar1	constant
	0.7601	0.5320
s.e.	0.0290	0.0453

sigma² estimated as 1.045: log likelihood=-719.84

AIC=1445.67 AICc=1445.72 BIC=1458.32

lm

```
1 ar1_lm = lm(value ~ lag(value), data=ar1)
2 summary(ar1_lm)
```

Call:

```
lm(formula = value ~ lag(value), data = ar1)
```

Residuals:

Min	1Q	Median	3Q	Max
-2.7194	-0.6991	-0.0139	0.6323	3.3518

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	0.53138	0.07898	6.728	4.74e-11 ***
lag(value)	0.76141	0.02918	26.090	< 2e-16 ***

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

Residual standard error: 1.023 on 497 degrees of freedom

(1 observation deleted due to missingness)

Multiple R-squared: 0.578, Adjusted R-squared: 0.5771

F-statistic: 680.7 on 1 and 497 DF, p-value: < 2.2e-16

Bayesian AR(1) Model

```
1 library(brms) # must be loaded for arma to work
2 ( ar1_brms = brm(value ~ arma(p = 1, q = 0), data=ar1, refresh=0, backend="cmdstanr") )
```

Family: gaussian

Links: mu = identity; sigma = identity

Formula: value ~ arma(p = 1, q = 0)

Data: ar1 (Number of observations: 500)

Draws: 4 chains, each with iter = 2000; warmup = 1000; thin = 1;
total post-warmup draws = 4000

Correlation Structures:

	Estimate	Est.Error	l-95% CI	u-95% CI	Rhat	Bulk_ESS	Tail_ESS
ar[1]	0.76	0.03	0.70	0.82	1.00	3562	3138

Population-Level Effects:

	Estimate	Est.Error	l-95% CI	u-95% CI	Rhat	Bulk_ESS	Tail_ESS
Intercept	2.20	0.20	1.81	2.59	1.00	3359	2829

Family Specific Parameters:

	Estimate	Est.Error	l-95% CI	u-95% CI	Rhat	Bulk_ESS	Tail_ESS
sigma	1.02	0.03	0.96	1.09	1.00	3888	2909

Draws were sampled using sample(hmc). For each parameter, Bulk_ESS and Tail_ESS are effective sample size measures, and Rhat is the potential

brms Intercept vs δ ?

The reported Intercept from the brms model is $E(y_t)$ and not δ - for an ARIMA(1,0,0)

$$E(y_t) = \frac{\delta}{1 - \phi} \Rightarrow \delta = E(y_t) * (1 - \phi)$$

True $E(y_t)$:

```
1  0.5 / (1-0.75)
```

```
[1] 2
```

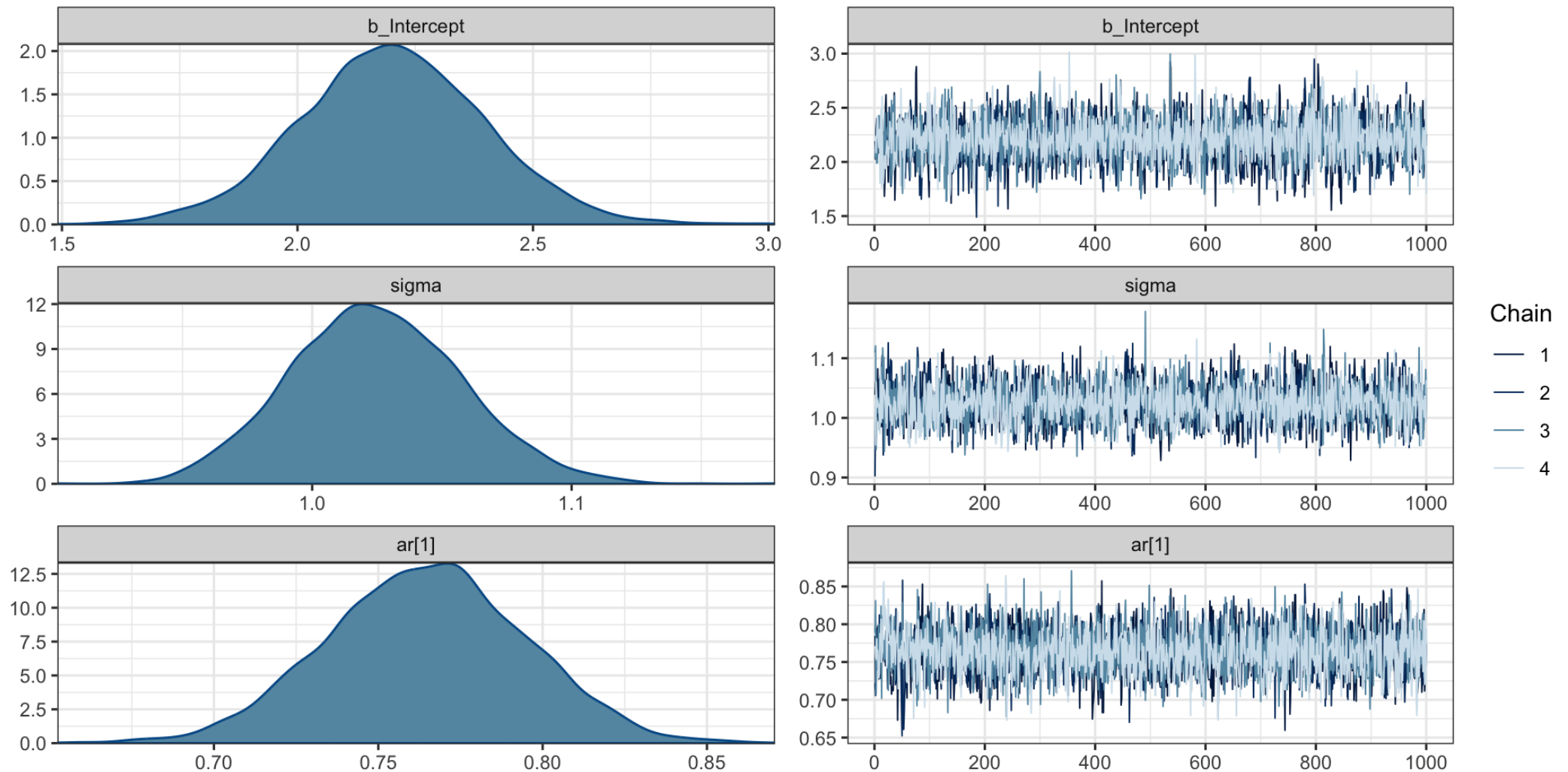
Posterior mean δ :

```
1  summary(ar1_brms)$fixed$Estimate *  
2  (1 - summary(ar1_brms)$cor_pars$Estimate)
```

```
[1] 0.5184077
```

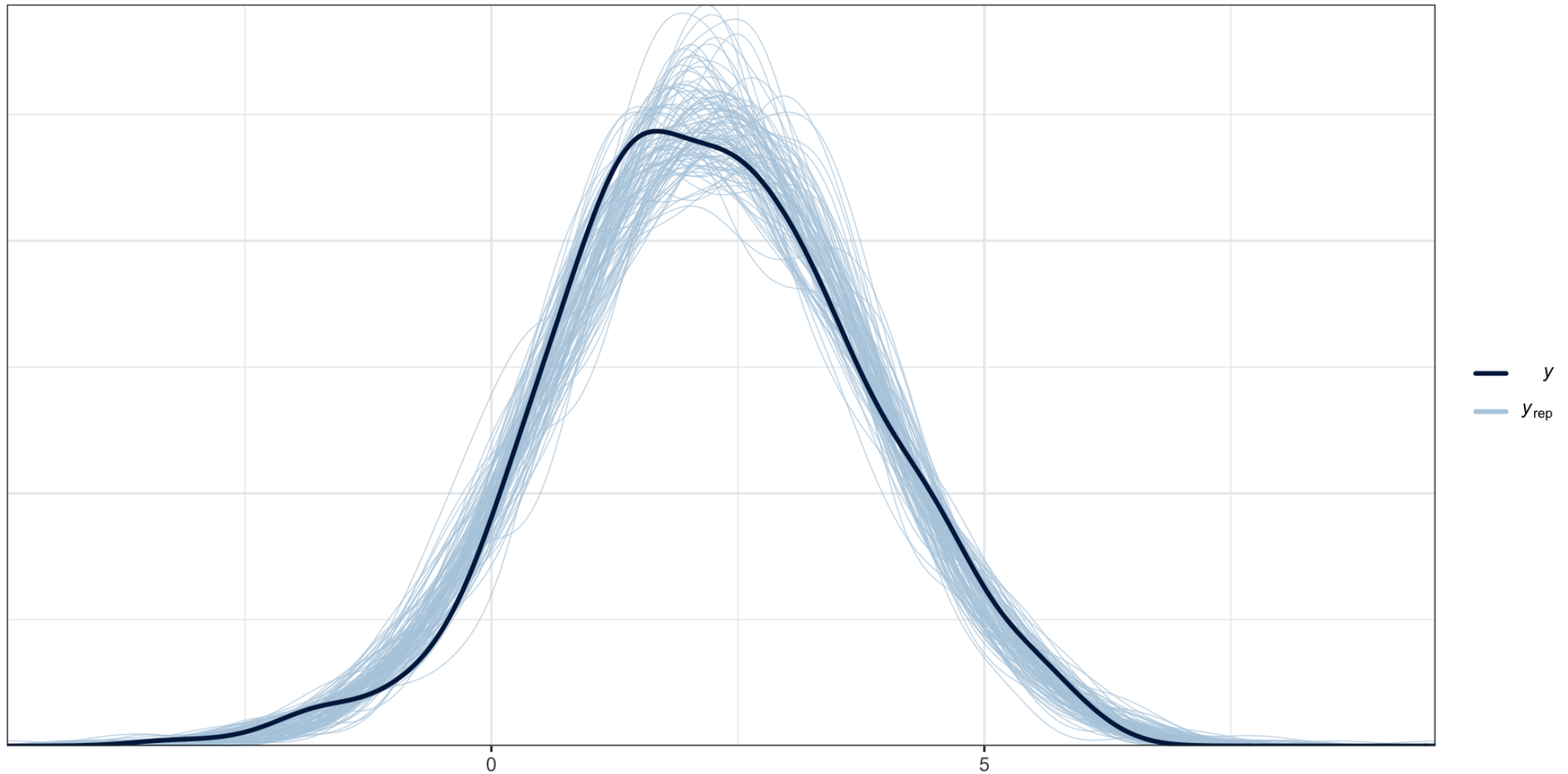
Chains

```
1 plot(ar1_brms)
```

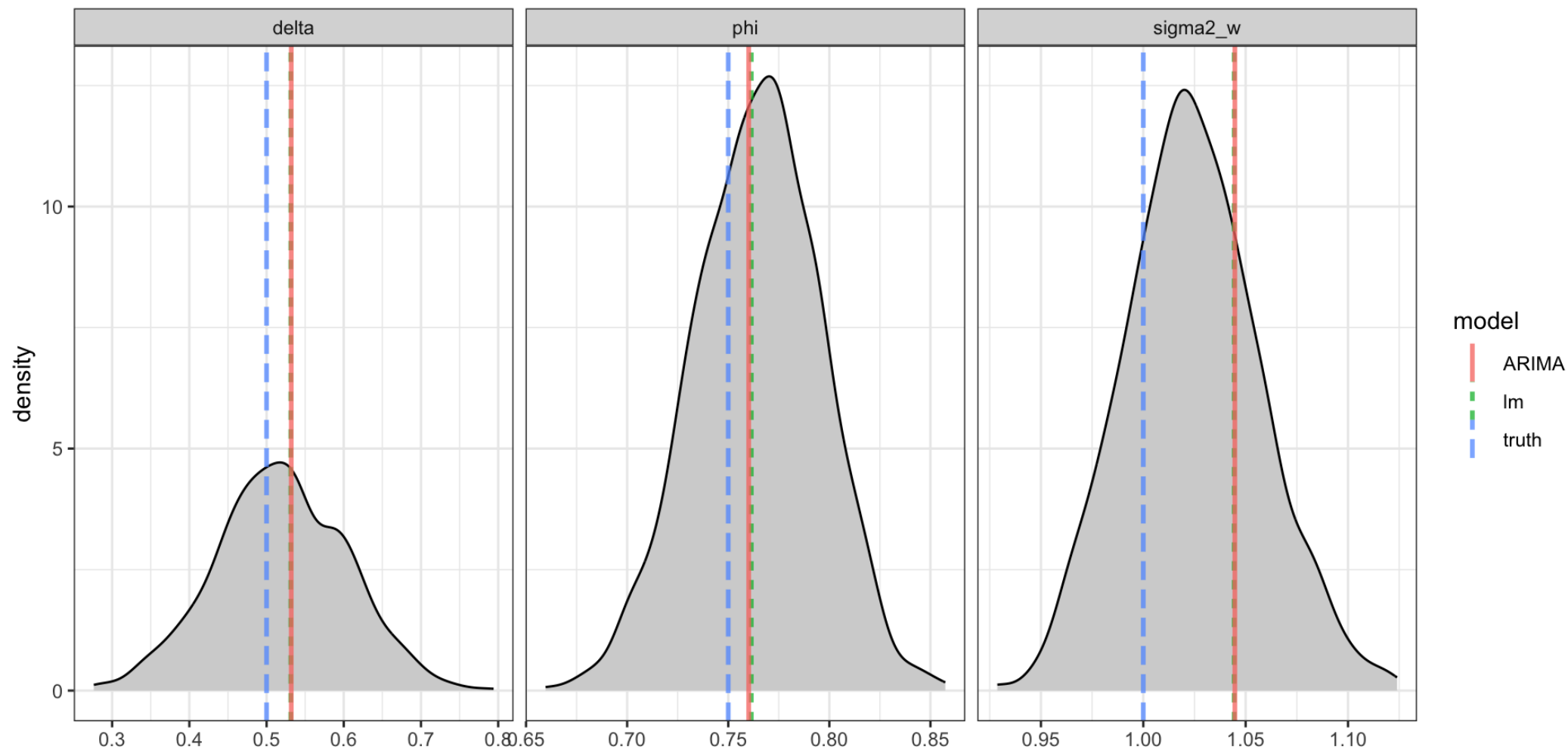


PP Checks

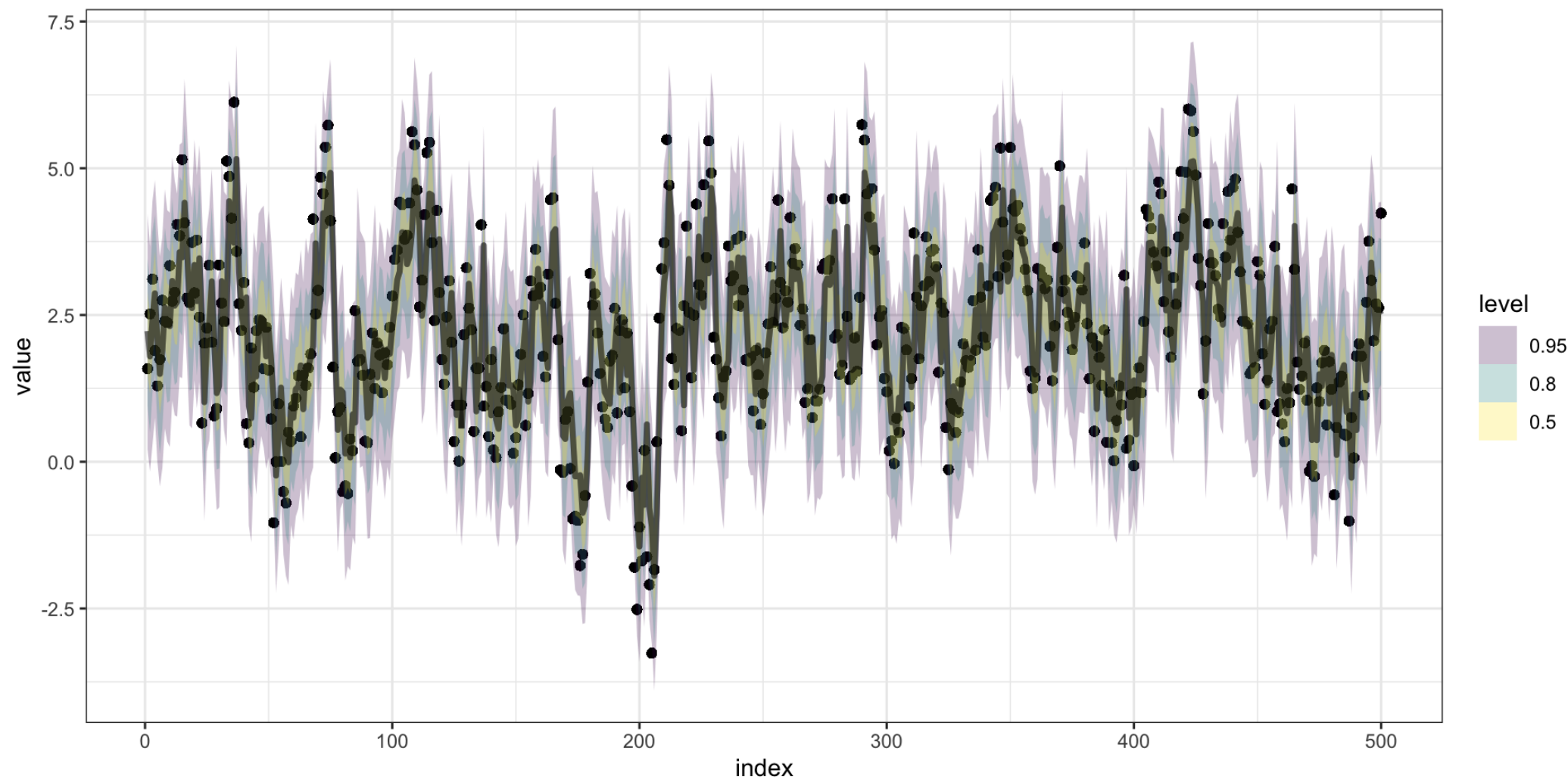
```
1 pp_check(ar1_brms, ndraws=100)
```



Posteriors



Predictions

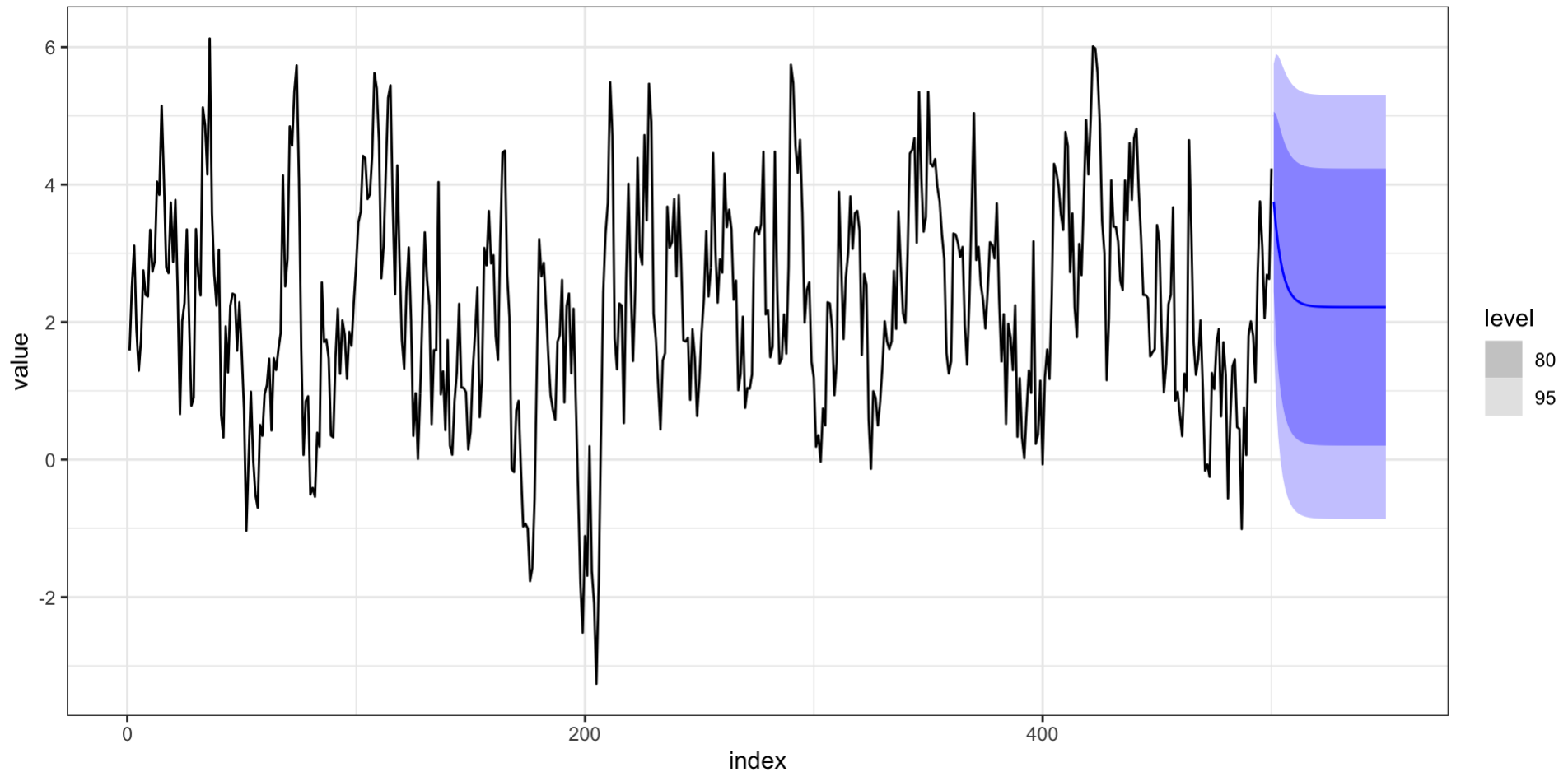


Forecasting

```
1 arl_brms_fc = arl_brms |>
2   predicted_draws_fix(
3     newdata = tibble(index=501:550, value=NA)
4   ) |>
5   filter(.chain == 1)
```

Forecasting (ARIMA)

```
1 arl_arma |>  
2   forecast(h=50) |>  
3   autoplot(arl)
```



Fitting AR(p)

Lagged Regression

As with the AR(1), we can rewrite the density using conditioning,

$$\begin{aligned} f(\mathbf{y}) &= f(y_t, y_{t-1}, \dots, y_2, y_1) \\ &= f(y_n | y_{n-1}, \dots, y_{n-p}) \cdots f(y_{p+1} | y_p, \dots, y_1) f(y_p, \dots, y_1) \end{aligned}$$

Regressing y_t on $y_{t-1}, \dots, y_{t-p}$ gets us an approximate solution, but it ignores the $f(y_1, y_2, \dots, y_p)$ part of the likelihood.

How much does this matter (vs. using the full likelihood)?

- If p is near to n then probably a lot
- If $p \ll n$ then probably not much

Method of Moments

Recall for an AR(p) process,

$$\gamma(0) = \sigma_w^2 + \phi_1 \gamma(1) + \phi_2 \gamma(2) + \dots + \phi_p \gamma(p)$$

$$\gamma(h) = \phi_1 \gamma(h-1) + \phi_2 \gamma(h-2) + \dots + \phi_p \gamma(h-p)$$

We can rewrite the first equation in terms of σ_w^2 ,

$$\sigma_w^2 = \gamma(0) - \phi_1 \gamma(1) - \phi_2 \gamma(2) - \dots - \phi_p \gamma(p)$$

these are called the Yule-Walker equations.

Yule-Walker

These equations can be rewritten into matrix notation as follows

$$\begin{array}{ccc} \mathbf{\Gamma}_p & \boldsymbol{\phi} & = \boldsymbol{\gamma}_p \\ p \times p & p \times 1 & p \times 1 \end{array} \qquad \begin{array}{ccc} \sigma_w^2 & = & \gamma(0) - \boldsymbol{\phi}' \boldsymbol{\gamma}_p \\ 1 \times 1 & & 1 \times 1 \quad 1 \times p \quad p \times 1 \end{array}$$

where

$$\begin{array}{c} \mathbf{\Gamma}_p \\ p \times p \end{array} = \gamma(j - k)_{j,k}$$

$$\begin{array}{c} \boldsymbol{\phi} \\ p \times 1 \end{array} = (\phi_1, \phi_2, \dots, \phi_p)'$$

$$\begin{array}{c} \boldsymbol{\gamma}_p \\ p \times 1 \end{array} = (\gamma(1), \gamma(2), \dots, \gamma(p))'$$

If we estimate the covariance structure from the data we obtain $\hat{\boldsymbol{\gamma}}_p$ and $\hat{\mathbf{\Gamma}}_p$ which we can plug in and solve for $\boldsymbol{\phi}$ and σ_w^2 ,

$$\begin{array}{ccc} \hat{\boldsymbol{\phi}} & = & \hat{\mathbf{\Gamma}}_p^{-1} \hat{\boldsymbol{\gamma}}_p \\ \sigma_w^2 & = & \gamma(0) - \hat{\boldsymbol{\gamma}}_p' \hat{\mathbf{\Gamma}}_p^{-1} \hat{\boldsymbol{\gamma}}_p \end{array}$$

ARMA

Fitting ARMA(2,2)

$$y_t = \delta + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \theta_1 w_{t-1} + \theta_2 w_{t-2} + w_t$$

We now need to estimate six parameters: δ , ϕ_1 , ϕ_2 , θ_1 , θ_2 and σ_w^2 .

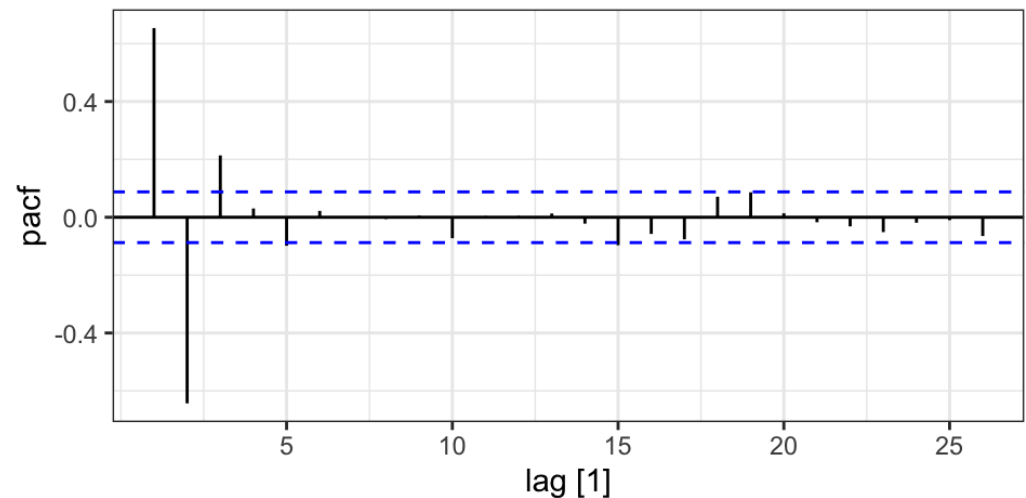
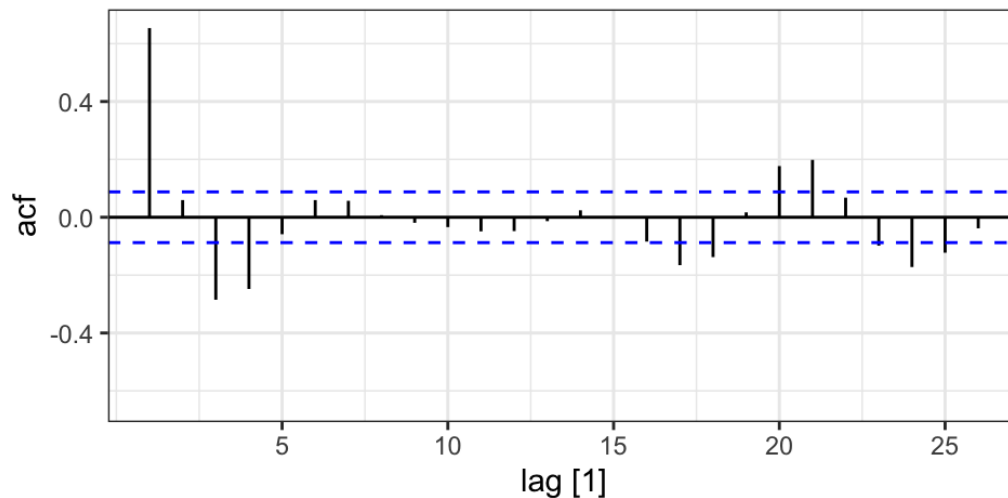
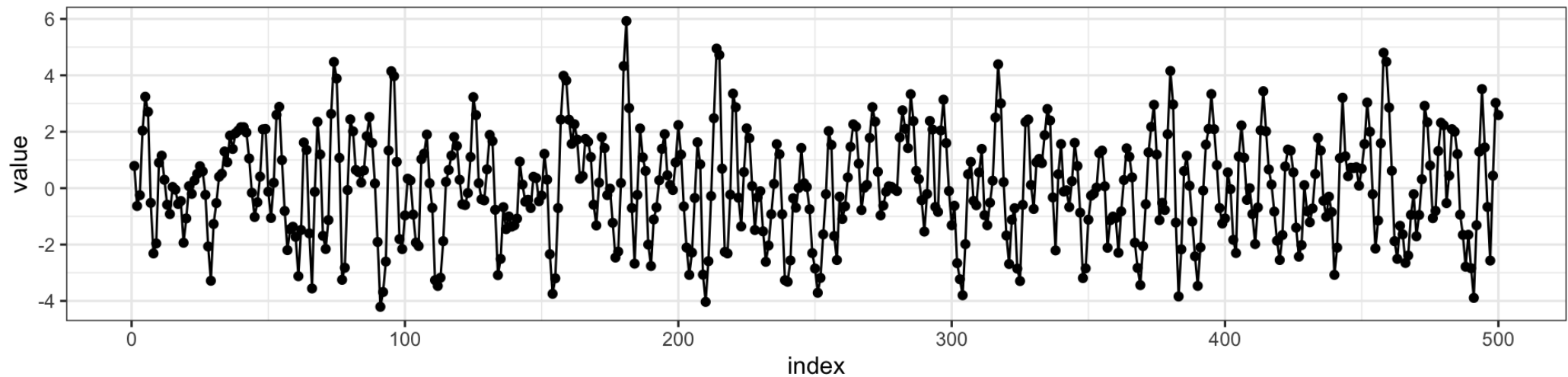
We could figure out $E(y_t)$, $\text{Var}(y_t)$, and $\text{Cov}(y_t, y_{t+h})$, but the last two are going to be pretty nasty and the full MVN likelihood is similarly going to be unpleasant to work with.

Like the AR(1) and AR(p) processes we want to use conditioning to simplify things.

$$y_t | \delta, y_{t-1}, y_{t-2}, w_{t-1}, w_{t-2} \\ \sim N(\delta + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \theta_1 w_{t-1} + \theta_2 w_{t-2}, \sigma_w^2)$$

ARMA(2,2) Example

with $\phi = (0.75, -0.5)$, $\theta = (0.5, 0.2)$, $\delta = 0$, and $\sigma_w^2 = 1$ using the same models



ARIMA

```
1 model(d, ARIMA(value ~ 1+pdq(2,0,2))) |> report()
```

Series: value

Model: ARIMA(2,0,2) w/ mean

Coefficients:

	ar1	ar2	ma1	ma2	constant
	0.7294	-0.4972	0.4888	0.2538	0.0400
s.e.	0.0868	0.0586	0.0941	0.0727	0.0807

sigma² estimated as 1.084: log likelihood=-728.01

AIC=1468.01 AICc=1468.18 BIC=1493.3

AR only lm

```
1 lm(value ~ lag(value,1) + lag(value,2), data=d) |> summary()
```

Call:

```
lm(formula = value ~ lag(value, 1) + lag(value, 2), data = d)
```

Residuals:

	Min	1Q	Median	3Q	Max
	-2.95562	-0.69955	0.00587	0.77063	3.13283

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	0.02892	0.04802	0.602	0.547
lag(value, 1)	1.07883	0.03430	31.455	<2e-16 ***
lag(value, 2)	-0.64708	0.03438	-18.820	<2e-16 ***

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

Residual standard error: 1.071 on 495 degrees of freedom

(2 observations deleted due to missingness)

Multiple R-squared: 0.6677, Adjusted R-squared: 0.6664

F-statistic: 497.4 on 2 and 495 DF, p-value: < 2.2e-16

Hannan-Rissanen Algorithm

1. Estimate a high order AR (remember $AR \Leftrightarrow MA$ when stationary + invertible)
2. Use AR to estimate values for unobserved w_t via `lm()` with `lag()`s
3. Regress y_t onto $y_{t-1}, \dots, y_{t-p}, \hat{w}_{t-1}, \dots, \hat{w}_{t-q}$
4. Update $\hat{w}_{t-1}, \dots, \hat{w}_{t-q}$ based on current model,
5. Goto step 3, repeat until convergence

Hannan-Rissanen - Step 1 & 2

```
1 (ar.mle(d$value, order.max = 10))
```

Call:

```
ar.mle(x = d$value, order.max = 10)
```

Coefficients:

1	2	3	4	5
1.2135	-0.8334	0.0921	0.1544	-0.0989

Order selected 5 σ^2 estimated as 1.072

```
1 ar = model(d, ARIMA(value ~ 0 + pdq(10,0,0)))
2 report(ar)
```

Series: value

Model: ARIMA(10,0,0)

Coefficients:

	ar1	ar2	ar3	ar4	ar5
	1.2167	-0.8380	0.0929	0.1696	-0.1273
s.e.	0.0446	0.0702	0.0796	0.0800	0.0807
	ar6	ar7	ar8	ar9	ar10
	0.0199	0.0275	-0.0839	0.1000	-0.0732
s.e.	0.0809	0.0809	0.0808	0.0713	0.0453

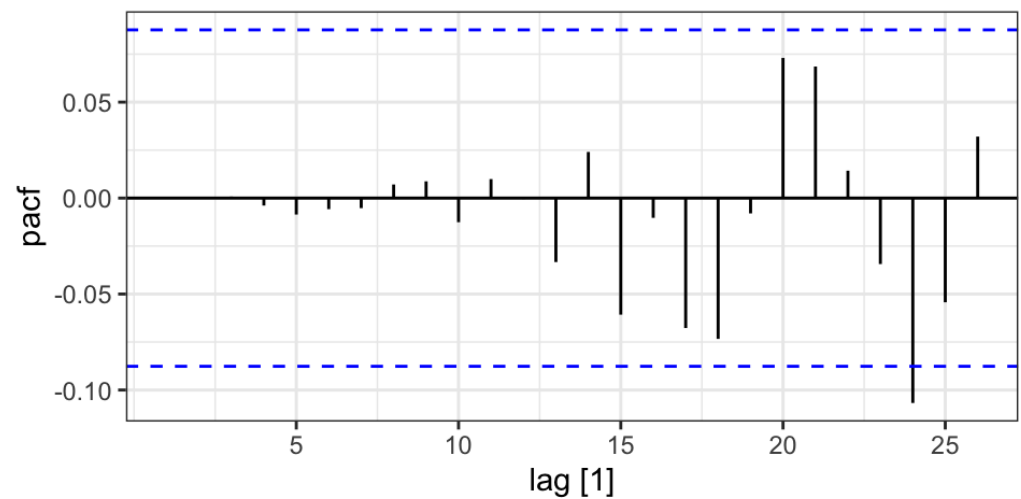
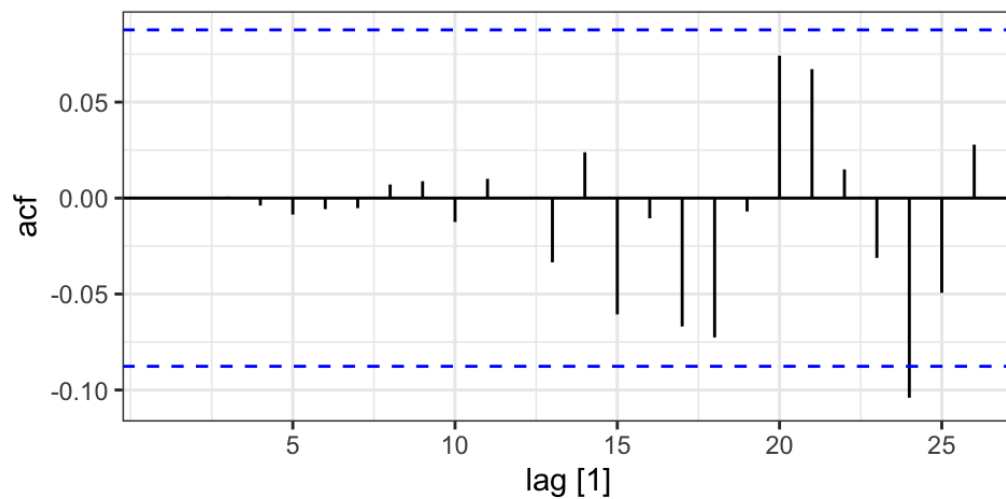
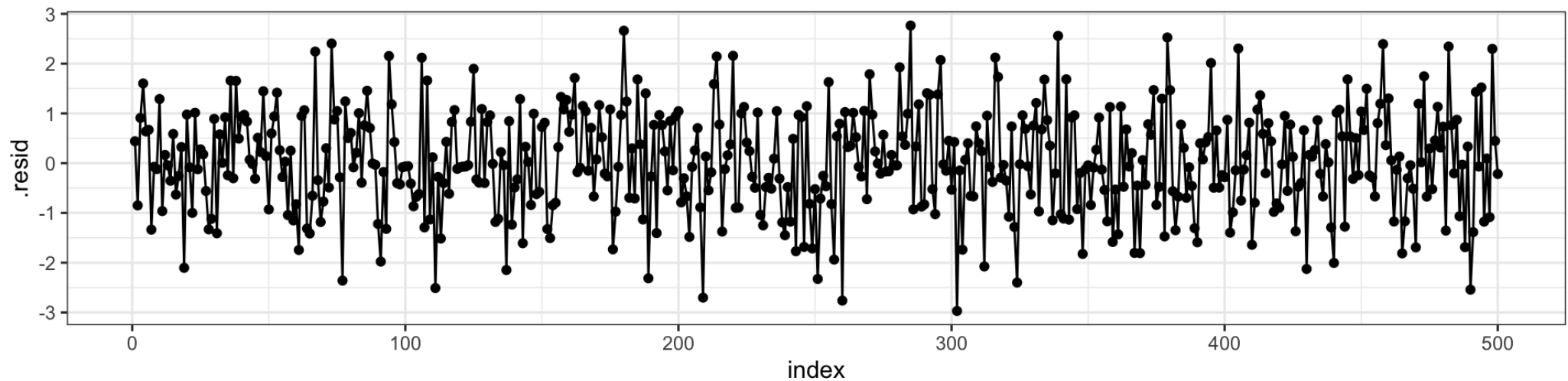
σ^2 estimated as 1.089: log

likelihood=-726.61

AIC=1475.22 AICc=1475.76 BIC=1521.58

Residuals

```
1 residuals(ar) |>  
2 gg_tsdisplay(y=.resid, plot_type="partial")
```



Hannan-Rissanen - Step 3

```
1 d = mutate(d, w_hat = residuals(ar)$resid)
2 (lm2 = lm(value ~ lag(value,1) + lag(value,2) + lag(w_hat,1) + lag(w_hat,2), data=d)) |>
3   summary()
```

Call:

```
lm(formula = value ~ lag(value, 1) + lag(value, 2) + lag(w_hat,
  1) + lag(w_hat, 2), data = d)
```

Residuals:

	Min	1Q	Median	3Q	Max
	-2.95027	-0.67742	-0.06244	0.71858	2.75976

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	0.02114	0.04679	0.452	0.65165
lag(value, 1)	0.75166	0.07469	10.064	< 2e-16 ***
lag(value, 2)	-0.50657	0.04264	-11.881	< 2e-16 ***
lag(w_hat, 1)	0.46618	0.08744	5.332	1.49e-07 ***
lag(w_hat, 2)	0.23440	0.08200	2.859	0.00443 **

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

Residual standard error: 1.043 on 493 degrees of freedom

(2 observations deleted due to missingness)

Multiple R-squared: 0.6861 Adjusted R-squared: 0.6836

Hannan-Rissanen - Step 4

```
1 d = mutate(d, w_hat = augment(lm2, newdata = d)$resid)
2 (lm3 = lm(value ~ lag(value,1) + lag(value,2) + lag(w_hat,1) + lag(w_hat,2), data=d)) |>
3   summary()
```

Call:

```
lm(formula = value ~ lag(value, 1) + lag(value, 2) + lag(w_hat,
  1) + lag(w_hat, 2), data = d)
```

Residuals:

	Min	1Q	Median	3Q	Max
	-2.94447	-0.66913	-0.05082	0.74799	2.82135

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	0.03373	0.04685	0.720	0.47181
lag(value, 1)	0.75139	0.07502	10.016	< 2e-16 ***
lag(value, 2)	-0.50684	0.04272	-11.866	< 2e-16 ***
lag(w_hat, 1)	0.46361	0.08739	5.305	1.71e-07 ***
lag(w_hat, 2)	0.23576	0.08184	2.881	0.00414 **

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

Residual standard error: 1.042 on 491 degrees of freedom

(4 observations deleted due to missingness)

Multiple R-squared: 0.6877 Adjusted R-squared: 0.6851

Hannan-Rissanen - Step 3.2 + 4.2

```
1 d = mutate(d, w_hat = augment(lm3, newdata = d)$resid)
2 (lm4 = lm(value ~ lag(value,1) + lag(value,2) + lag(w_hat,1) + lag(w_hat,2), data=d)) |>
3   summary()
```

Call:

```
lm(formula = value ~ lag(value, 1) + lag(value, 2) + lag(w_hat,
  1) + lag(w_hat, 2), data = d)
```

Residuals:

	Min	1Q	Median	3Q	Max
	-2.97496	-0.67003	-0.04571	0.76249	2.78324

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	0.02735	0.04700	0.582	0.56093
lag(value, 1)	0.75600	0.07540	10.026	< 2e-16 ***
lag(value, 2)	-0.50689	0.04287	-11.825	< 2e-16 ***
lag(w_hat, 1)	0.45663	0.08792	5.194	3.03e-07 ***
lag(w_hat, 2)	0.22510	0.08229	2.736	0.00645 **

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

Residual standard error: 1.044 on 489 degrees of freedom

(6 observations deleted due to missingness)

Multiple R-squared: 0.6045 Adjusted R-squared: 0.6010

Hannan-Rissanen - Step 3.3 + 4.3

```
1 d = mutate(d, w_hat = augment(lm4, newdata = d)$resid)
2 (lm5 = lm(value ~ lag(value,1) + lag(value,2) + lag(w_hat,1) + lag(w_hat,2), data=d)) |>
3   summary()
```

Call:

```
lm(formula = value ~ lag(value, 1) + lag(value, 2) + lag(w_hat,
  1) + lag(w_hat, 2), data = d)
```

Residuals:

	Min	1Q	Median	3Q	Max
	-2.95849	-0.66820	-0.03764	0.74071	2.77925

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	0.02909	0.04699	0.619	0.53617
lag(value, 1)	0.73934	0.07568	9.770	< 2e-16 ***
lag(value, 2)	-0.50027	0.04291	-11.657	< 2e-16 ***
lag(w_hat, 1)	0.47620	0.08792	5.416	9.57e-08 ***
lag(w_hat, 2)	0.24336	0.08249	2.950	0.00333 **

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

Residual standard error: 1.042 on 487 degrees of freedom

(8 observations deleted due to missingness)

Multiple R-squared: 0.6850 Adjusted R-squared: 0.6822

Hannan-Rissanen - Step 3.4 + 4.4

```
1 d = mutate(d, w_hat = augment(lm5, newdata = d)$resid)
2 (lm6 = lm(value ~ lag(value,1) + lag(value,2) + lag(w_hat,1) + lag(w_hat,2), data=d)) |>
3   summary()
```

Call:

```
lm(formula = value ~ lag(value, 1) + lag(value, 2) + lag(w_hat,
  1) + lag(w_hat, 2), data = d)
```

Residuals:

	Min	1Q	Median	3Q	Max
	-2.96225	-0.68420	-0.04689	0.75628	2.77699

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	0.02844	0.04721	0.602	0.54718
lag(value, 1)	0.75148	0.07681	9.784	< 2e-16 ***
lag(value, 2)	-0.50068	0.04335	-11.550	< 2e-16 ***
lag(w_hat, 1)	0.46357	0.08938	5.186	3.16e-07 ***
lag(w_hat, 2)	0.22960	0.08355	2.748	0.00622 **

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

Residual standard error: 1.044 on 485 degrees of freedom

(10 observations deleted due to missingness)

Multiple R-squared: 0.685 Adjusted R-squared: 0.684

BRMS

```
1 ( arma22_brms = brm(  
2   value~arma(p=2,q=2)-1, data=d,  
3   chains=2, refresh=0, iter = 5000, cores = 4  
4 ) )
```

Family: gaussian

Links: mu = identity; sigma = identity

Formula: value ~ arma(p = 2, q = 2) - 1

Data: d (Number of observations: 500)

Draws: 2 chains, each with iter = 5000; warmup = 2500; thin = 1;
total post-warmup draws = 5000

Correlation Structures:

	Estimate	Est.Error	l-95% CI	u-95% CI	Rhat	Bulk_ESS	Tail_ESS
ar[1]	0.73	0.09	0.55	0.89	1.00	1864	2605
ar[2]	-0.49	0.06	-0.60	-0.37	1.00	2205	3109
ma[1]	0.49	0.09	0.31	0.67	1.00	1884	2629
ma[2]	0.25	0.07	0.10	0.38	1.00	2150	2858

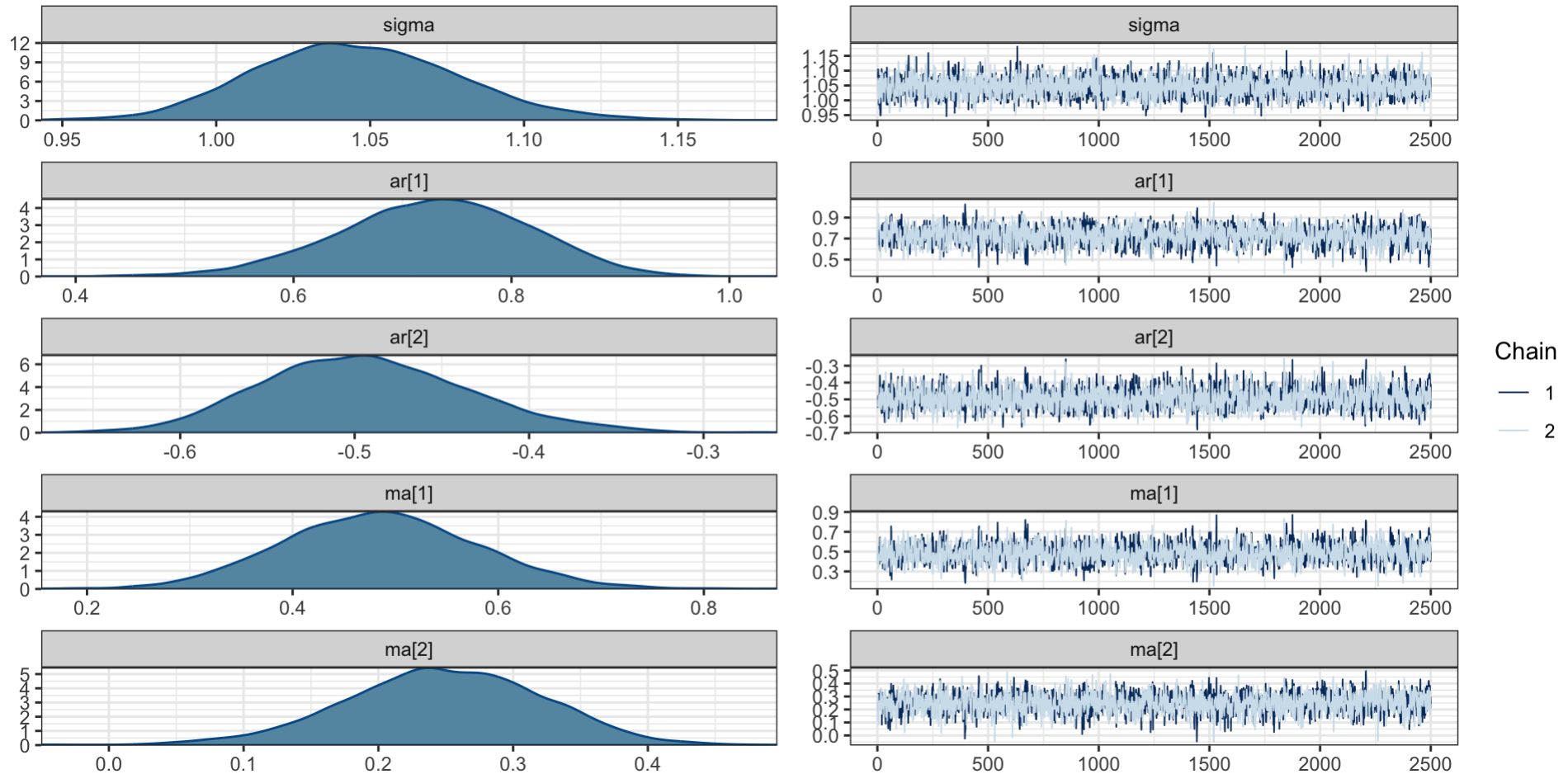
Family Specific Parameters:

	Estimate	Est.Error	l-95% CI	u-95% CI	Rhat	Bulk_ESS	Tail_ESS
sigma	1.05	0.03	0.98	1.11	1.00	2811	2968

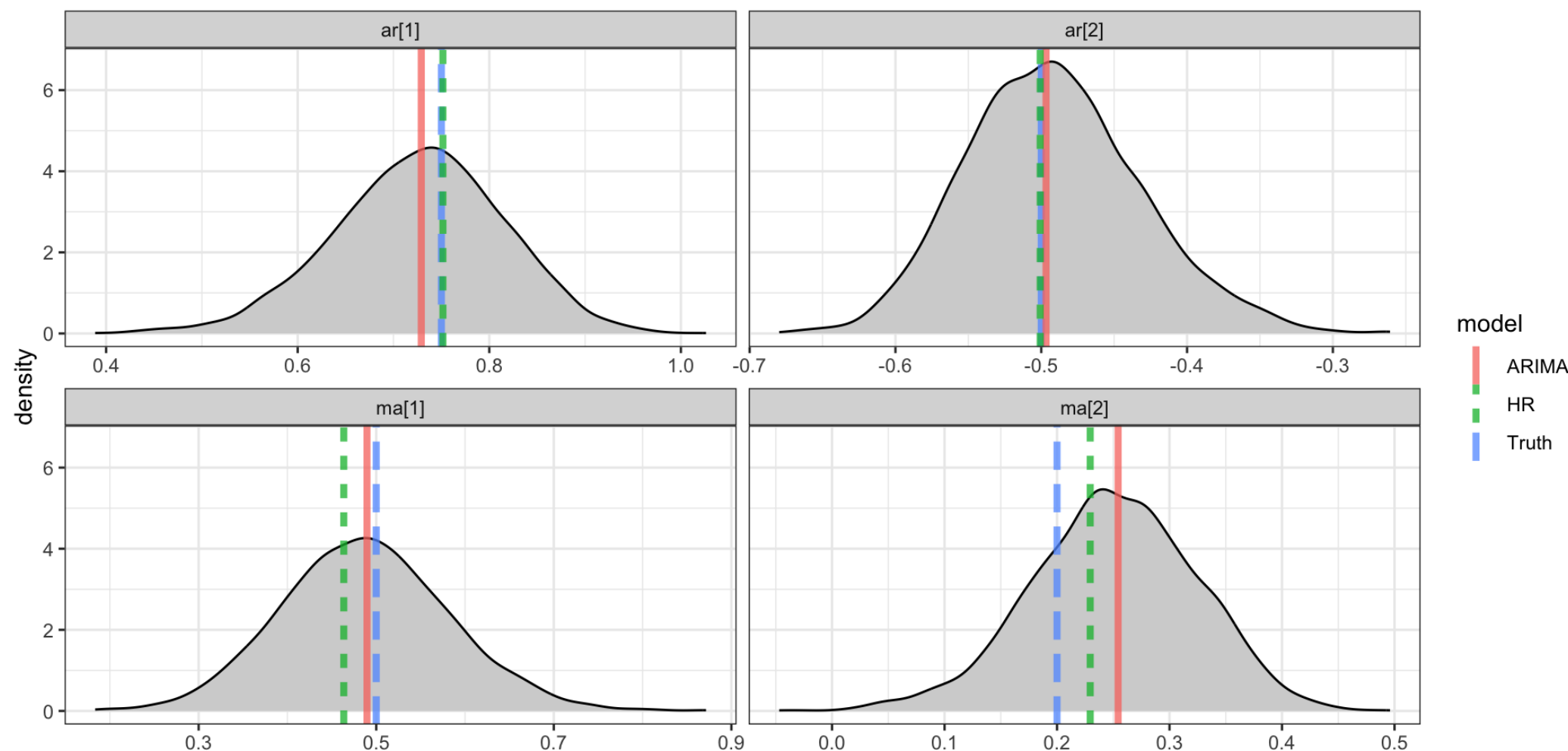
Draws were sampled using sampling(NUTS). For each parameter, Bulk_ESS
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Chains

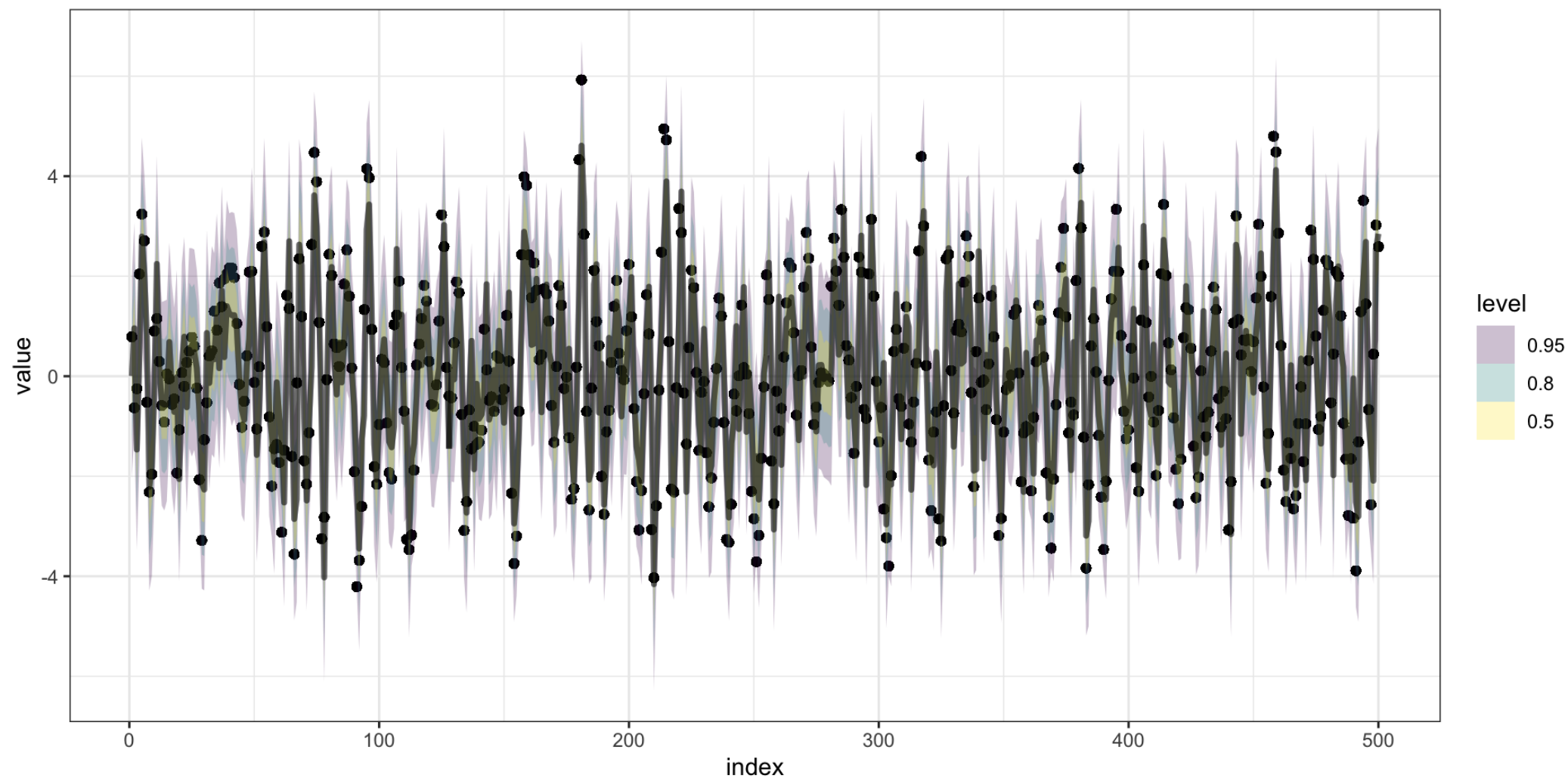
```
1 plot(arma22_brms)
```



Comparison



Predictions



Forecasting

```
1 arma22_brms_fc = arma22_brms |>
2   predicted_draws_fix(
3     newdata = tibble(index=501:550)
4   ) |>
5   filter(.chain == 1)
```

