Forecasts and potential futures

FORECASTING IN R

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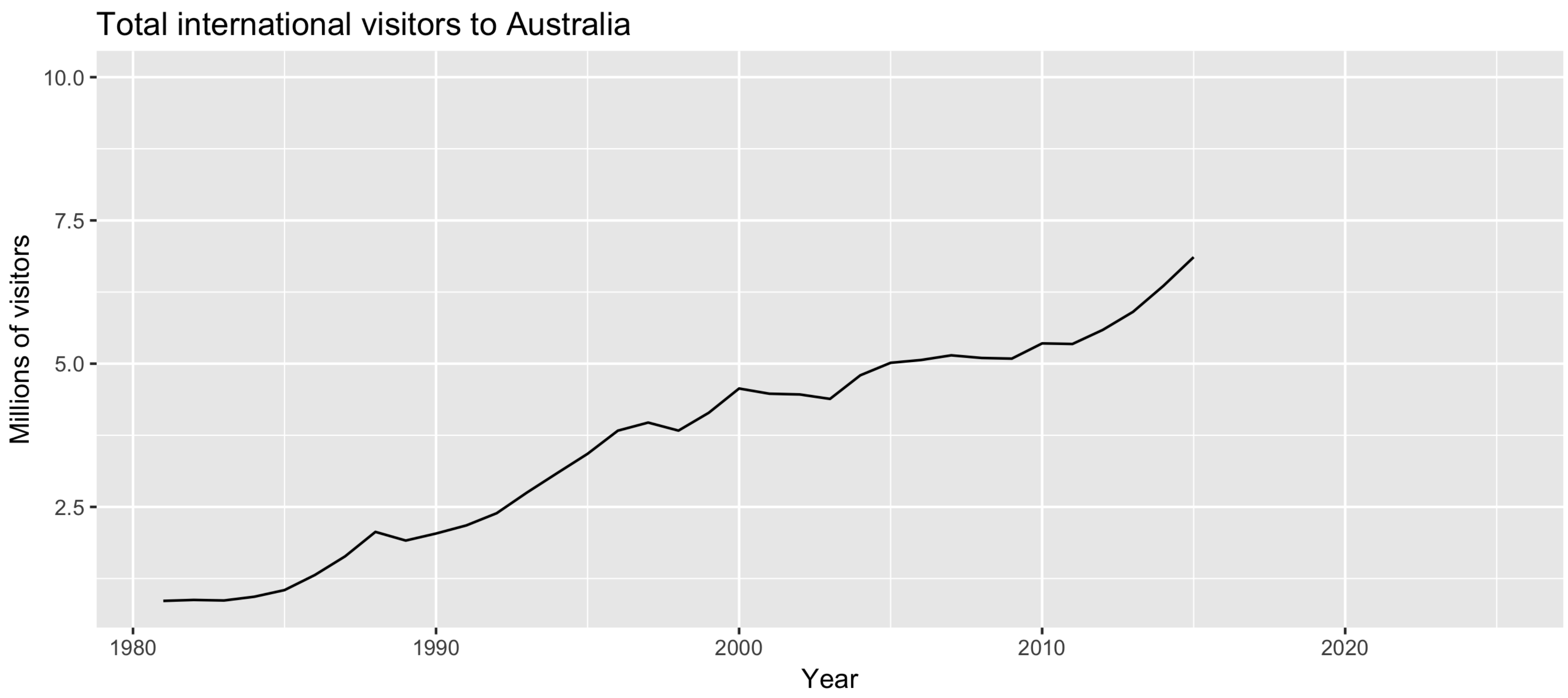
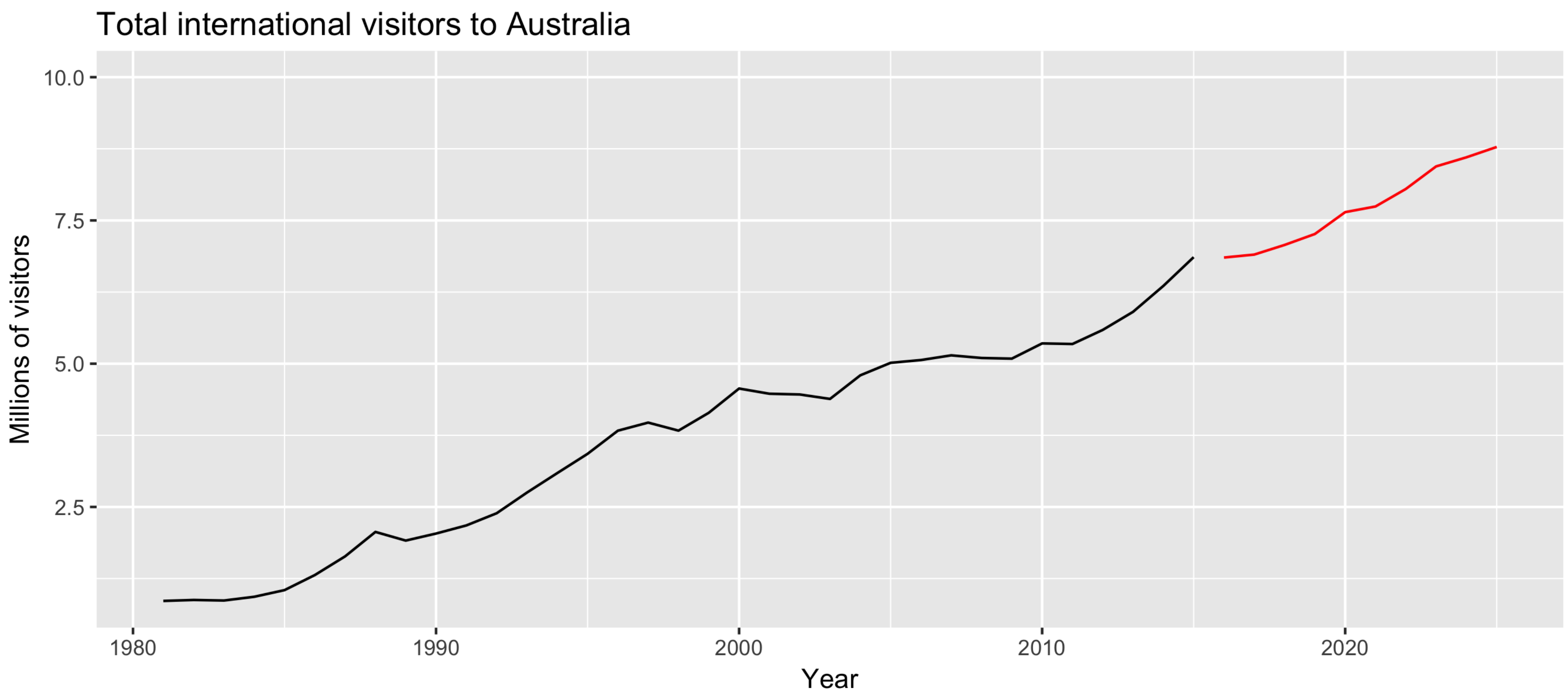
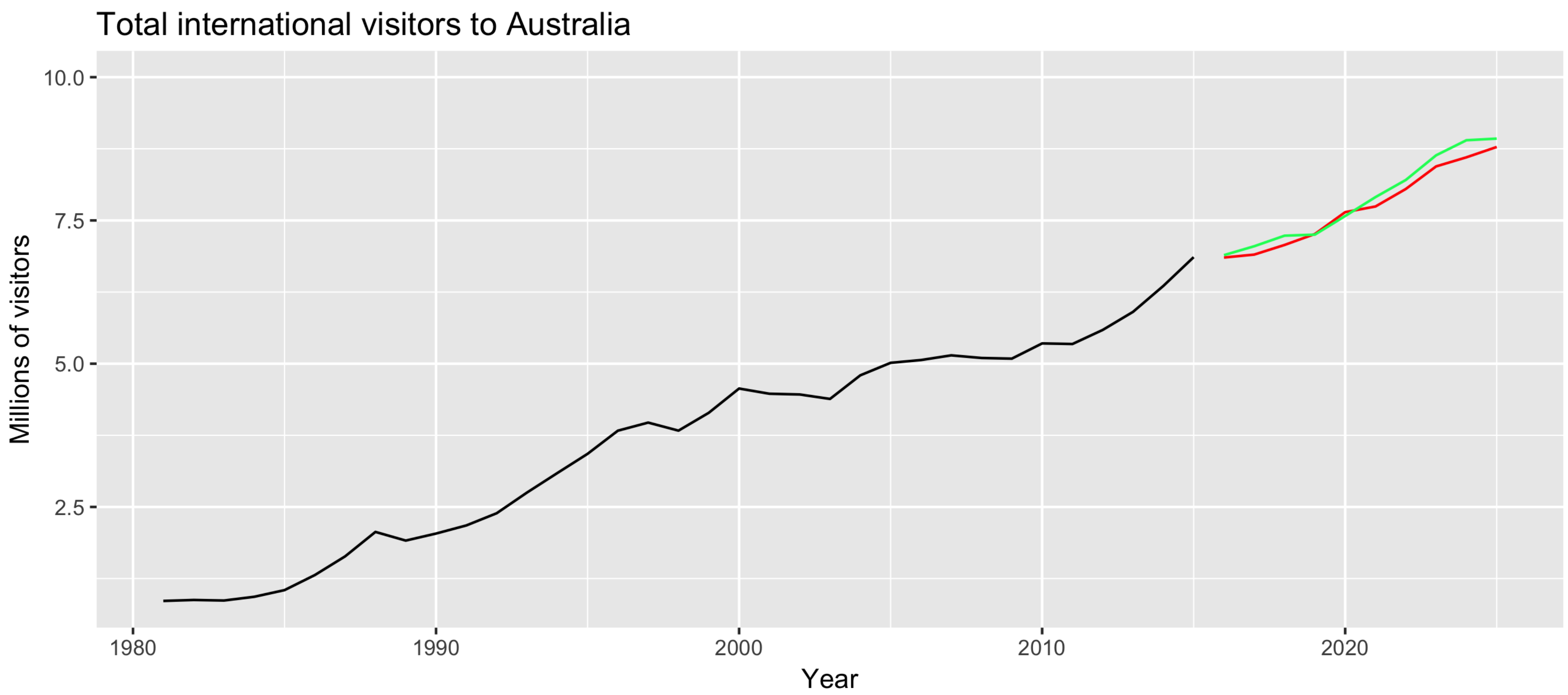
Sample futures



Sample futures



Sample futures



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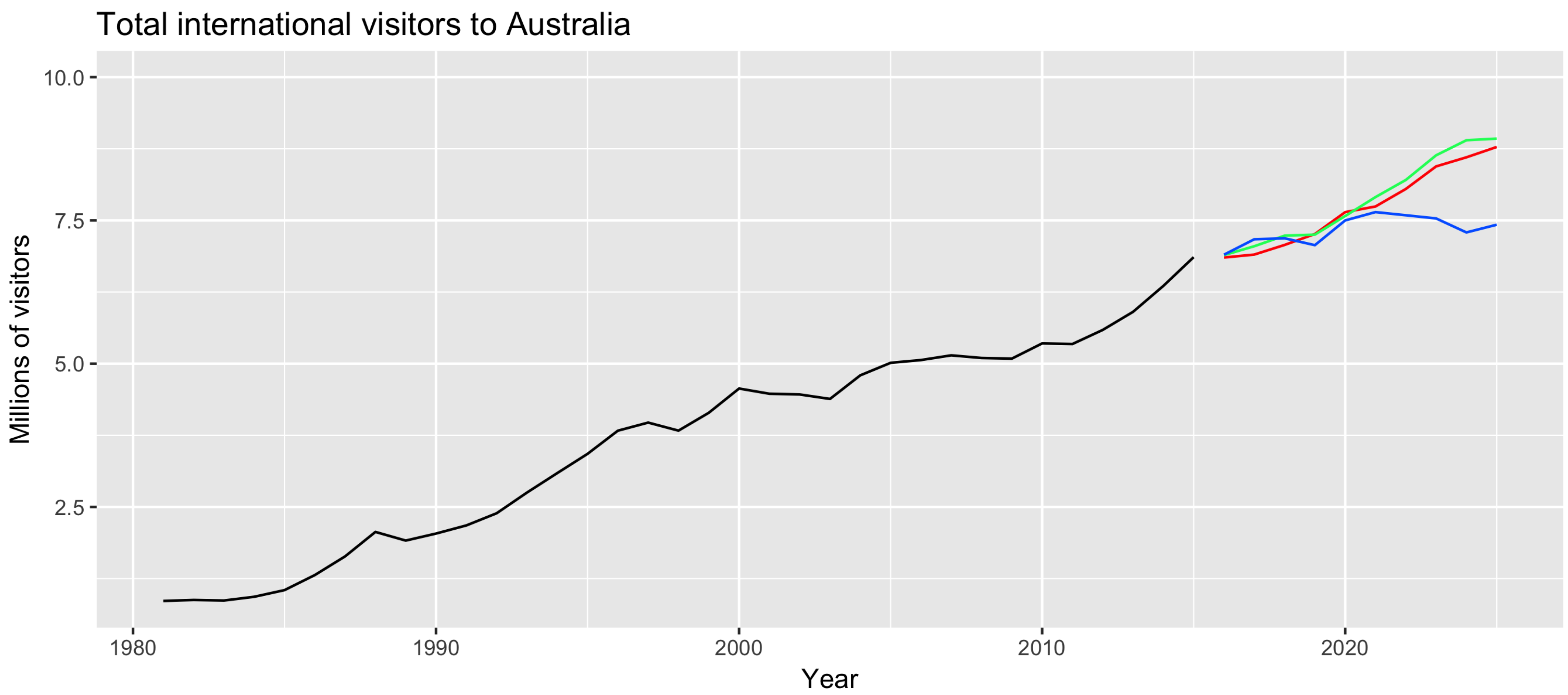
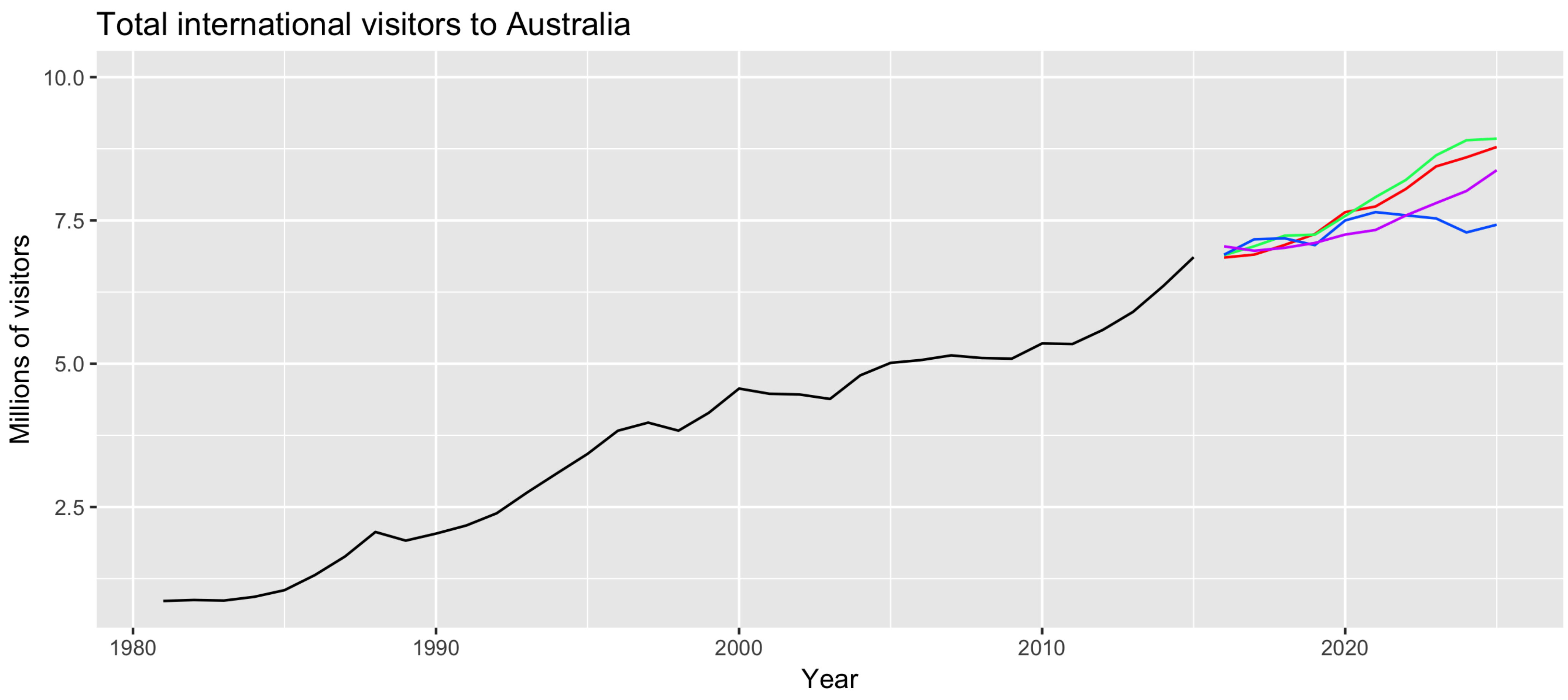


Sample futures



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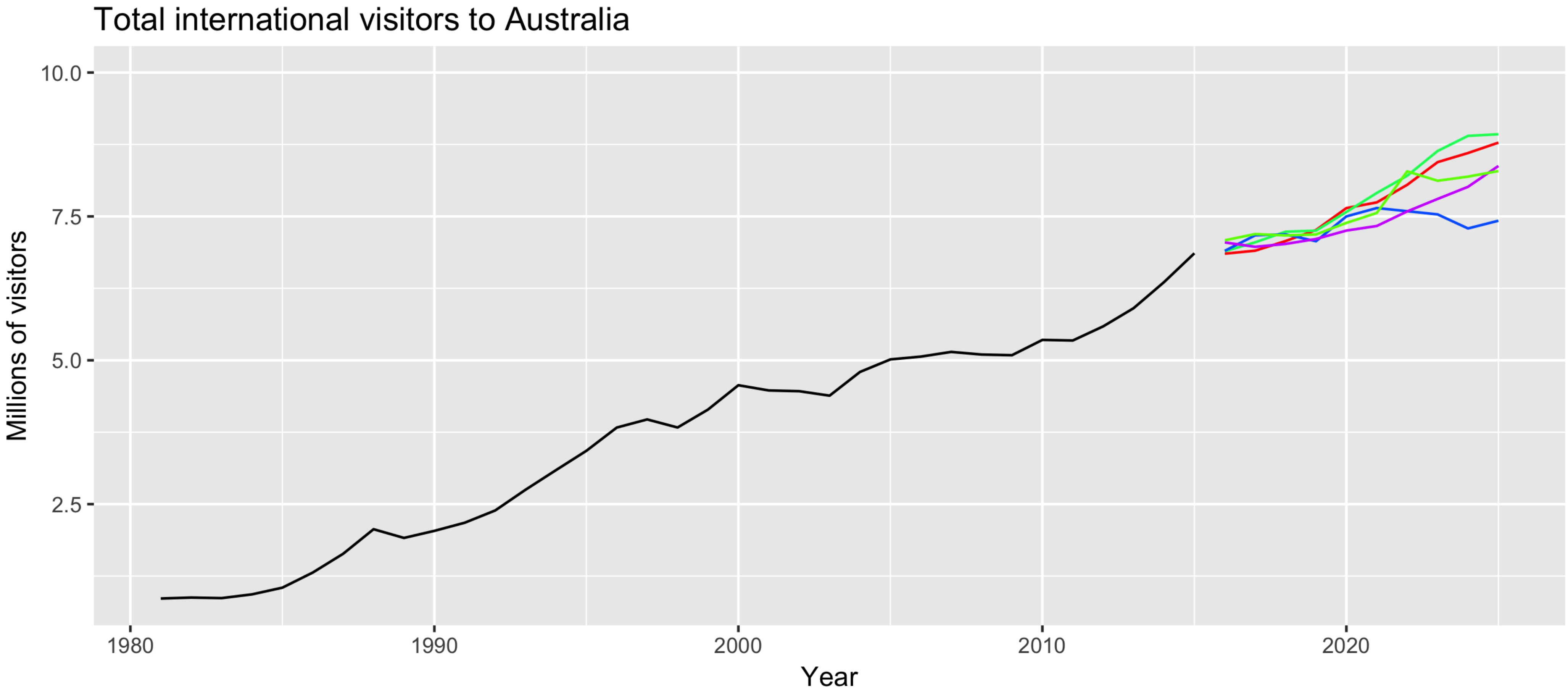

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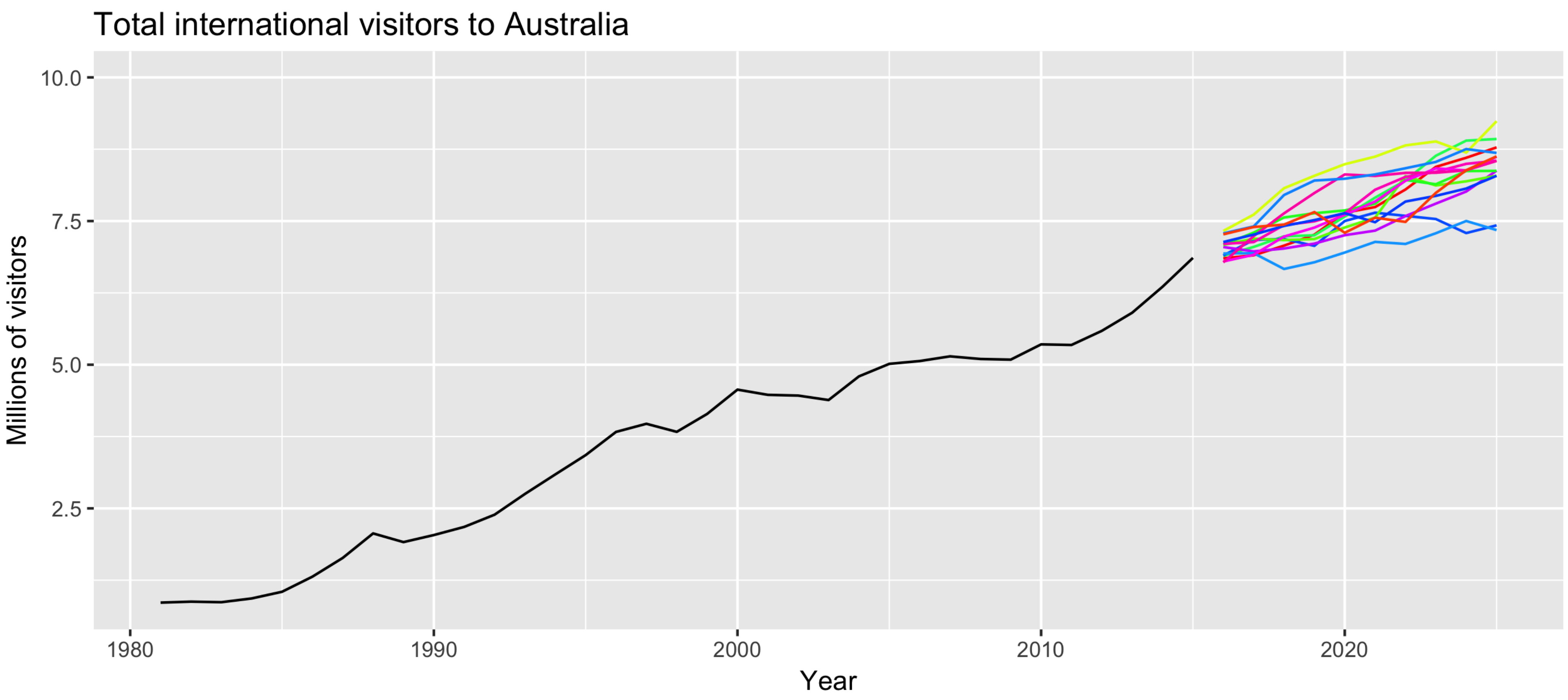
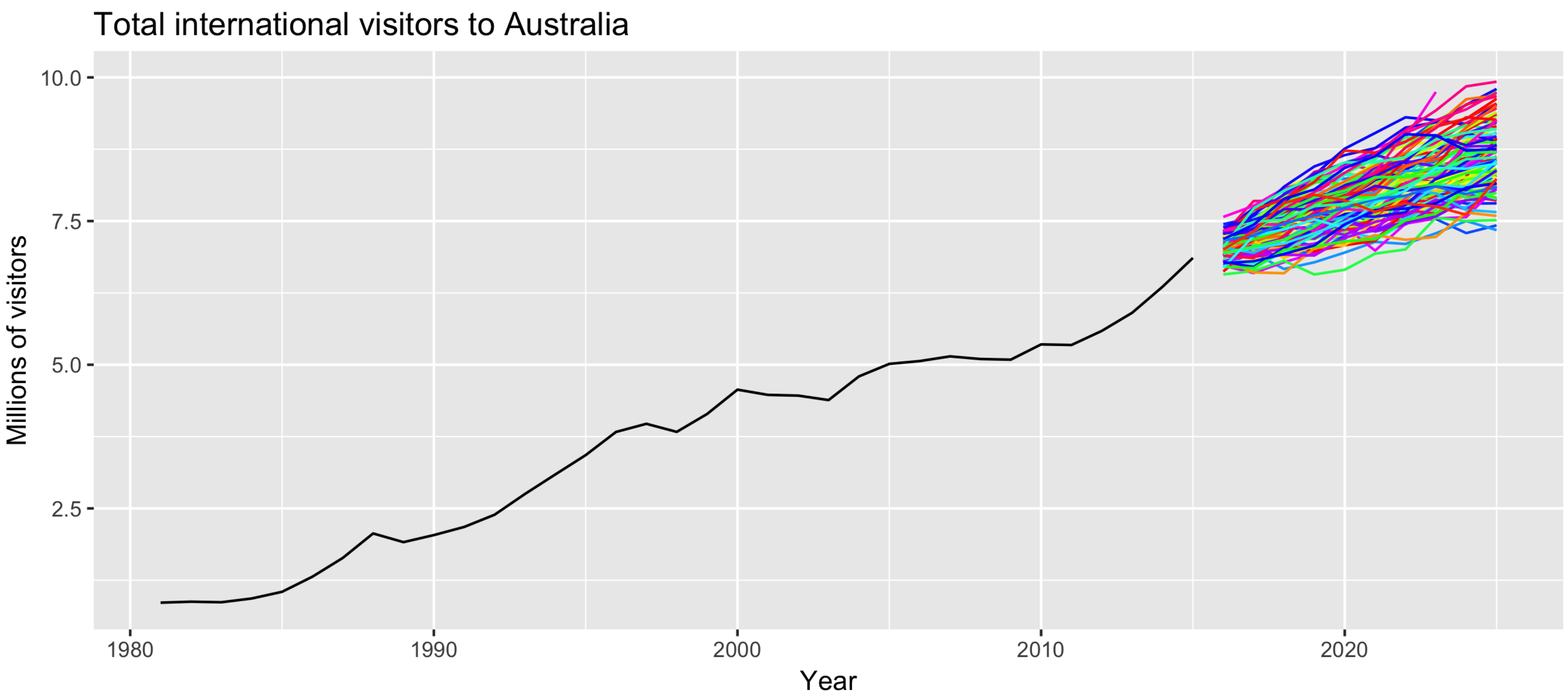
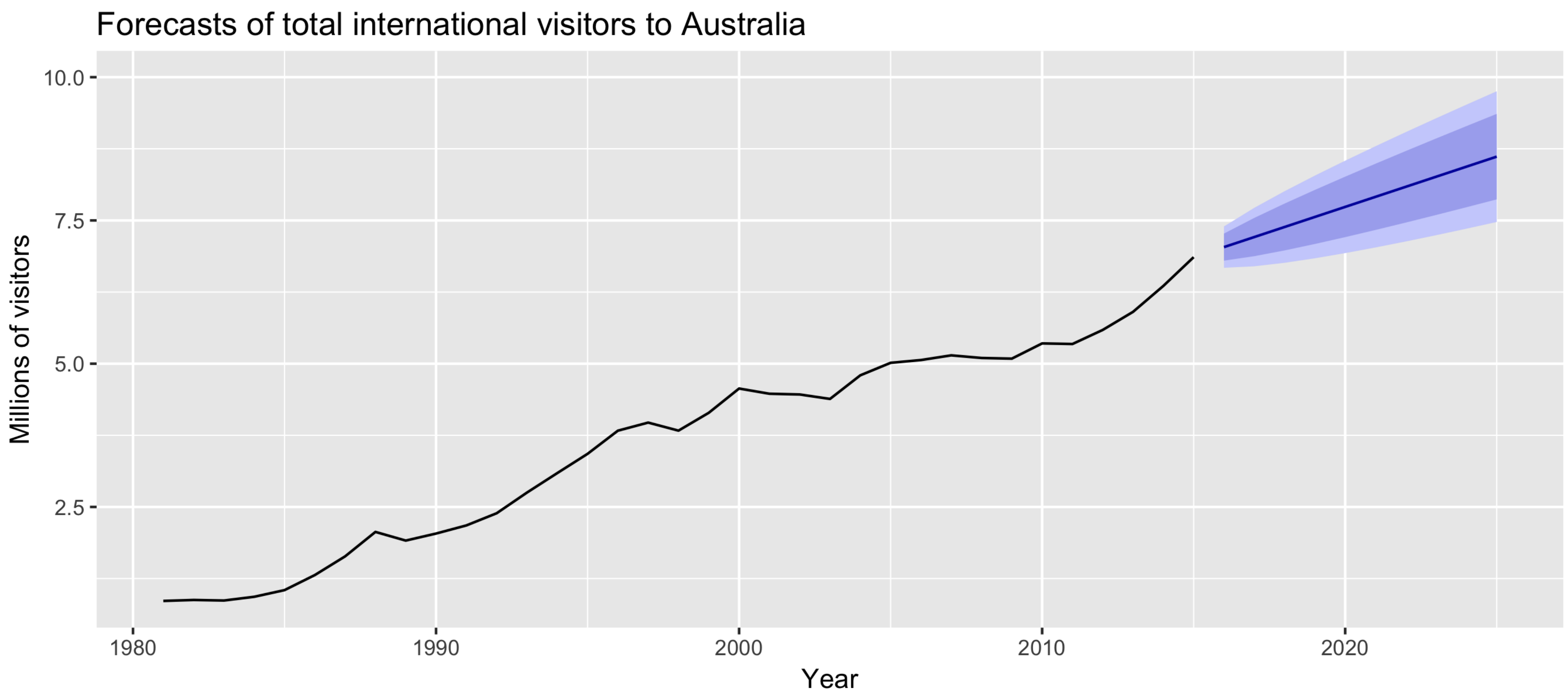


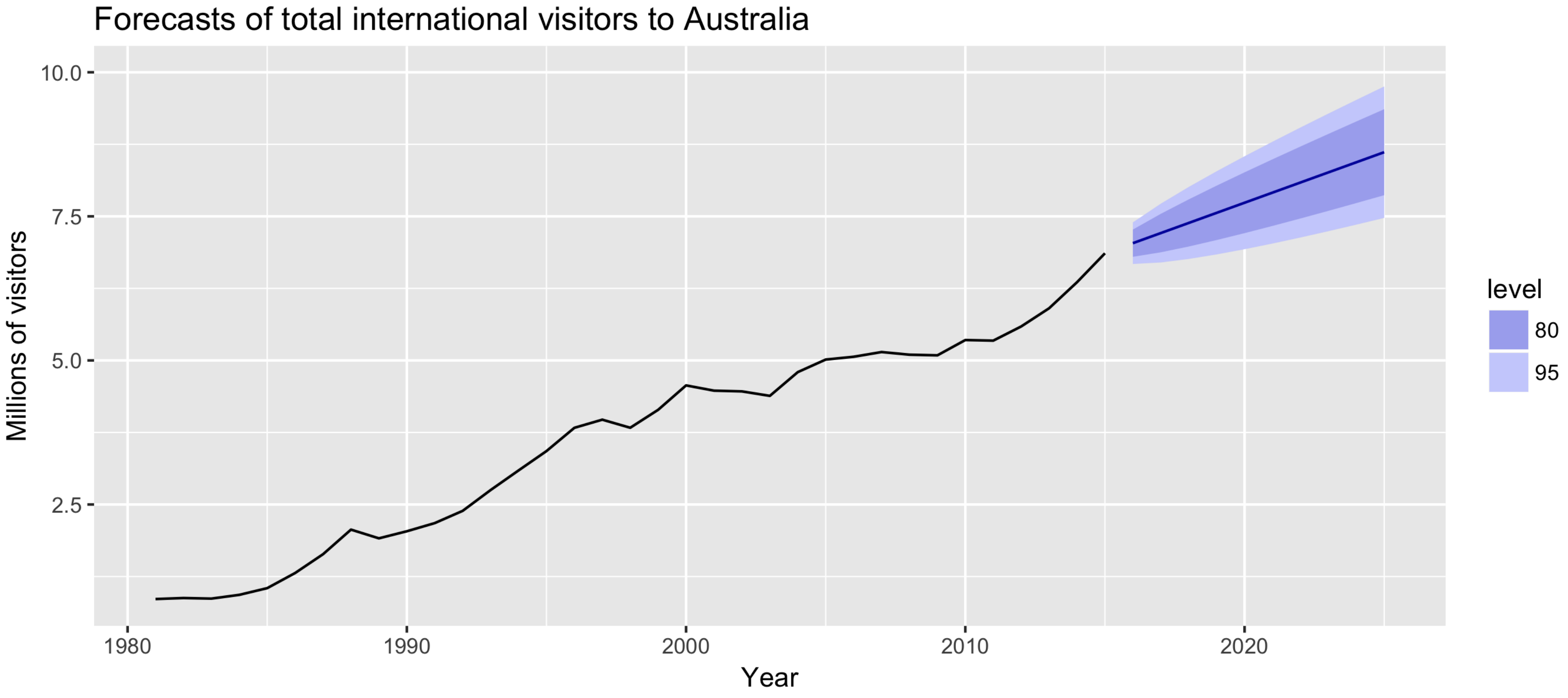
Sample futures



Forecast intervals



Forecast intervals



80% forecast intervals should contain 80% of future observations

95% forecast intervals should contain 95% of future observations

Let's practice!

FORECASTING IN R

Fitted values and residuals

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Fitted values and residuals

A *fitted* value is the forecast of an observation using all previous observations

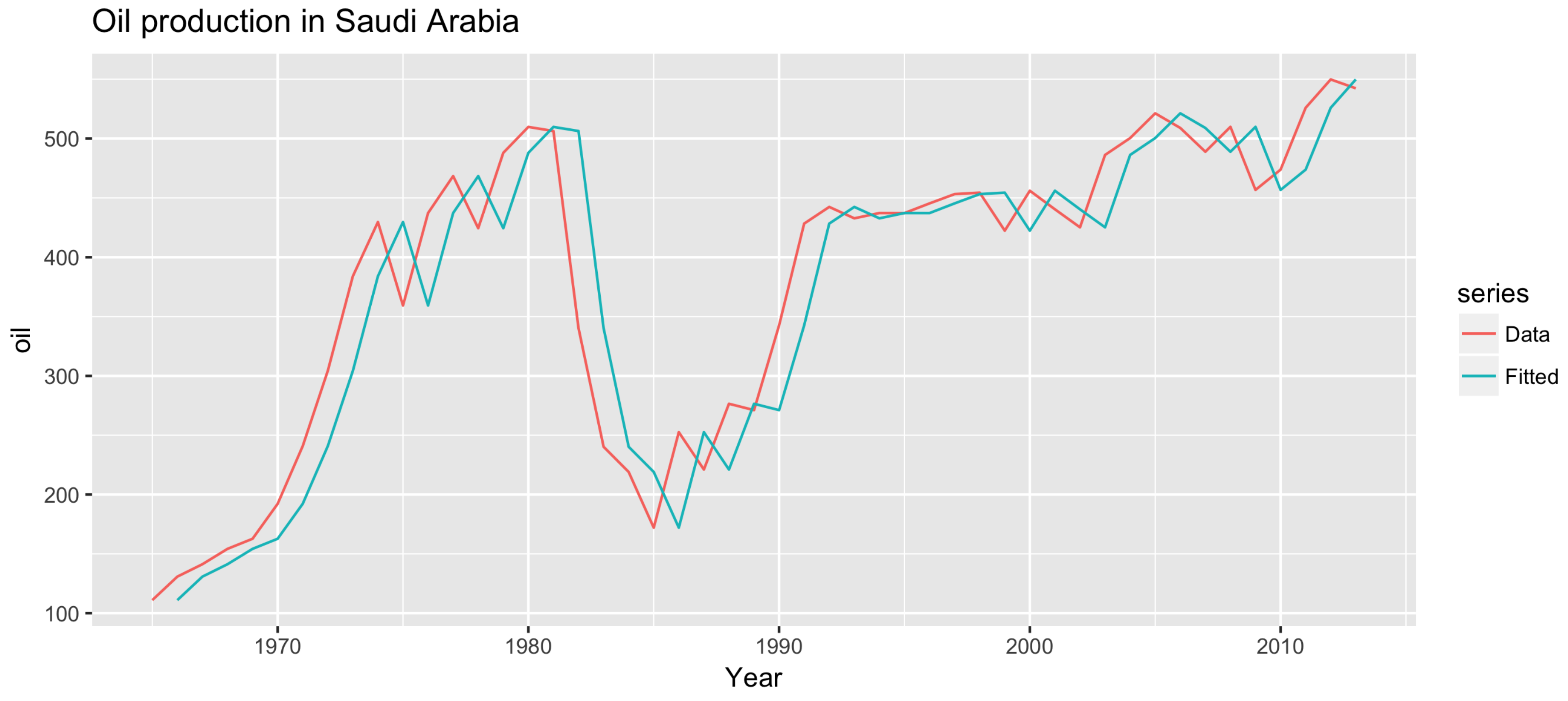
- That is, they are one-step forecasts
- Often not true forecasts since parameters are estimated on all data

A *residual* is the difference between an observation and its fitted value

- That is, they are one-step forecast errors

Example: oil production

```
fc <- naive(oil)
autoplot(oil, series = "Data") + xlab("Year") +
  autolayer(fitted(fc), series = "Fitted") +
  ggtitle("Oil production in Saudi Arabia")
```



Example: oil production

```
autoplot(residuals(fc))
```

Residuals should look like white noise

Essential assumptions

- They should be uncorrelated
- They should have mean zero

Useful properties (for computing prediction intervals)

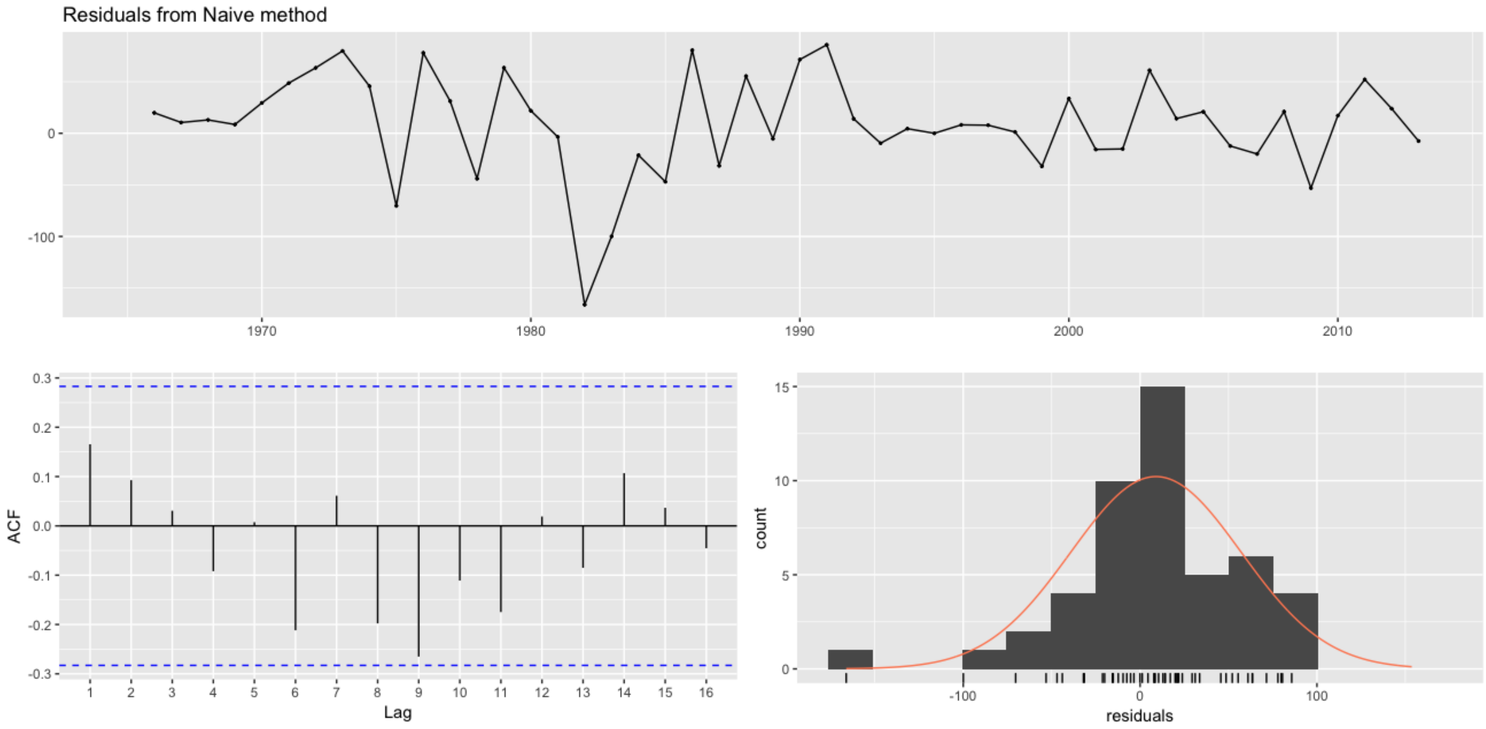
- They should have constant variance
- They should be normally distributed

We can test these assumptions using the `checkresiduals()` function.

checkresiduals()

```
checkresiduals(fc)
```

```
    Ljung-Box test
data:  residuals
Q* = 12.59, df = 10, p-value = 0.2475
Model df: 0.   Total lags used: 10
```



Let's practice!

FORECASTING IN R

Training and test sets

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Training and test sets

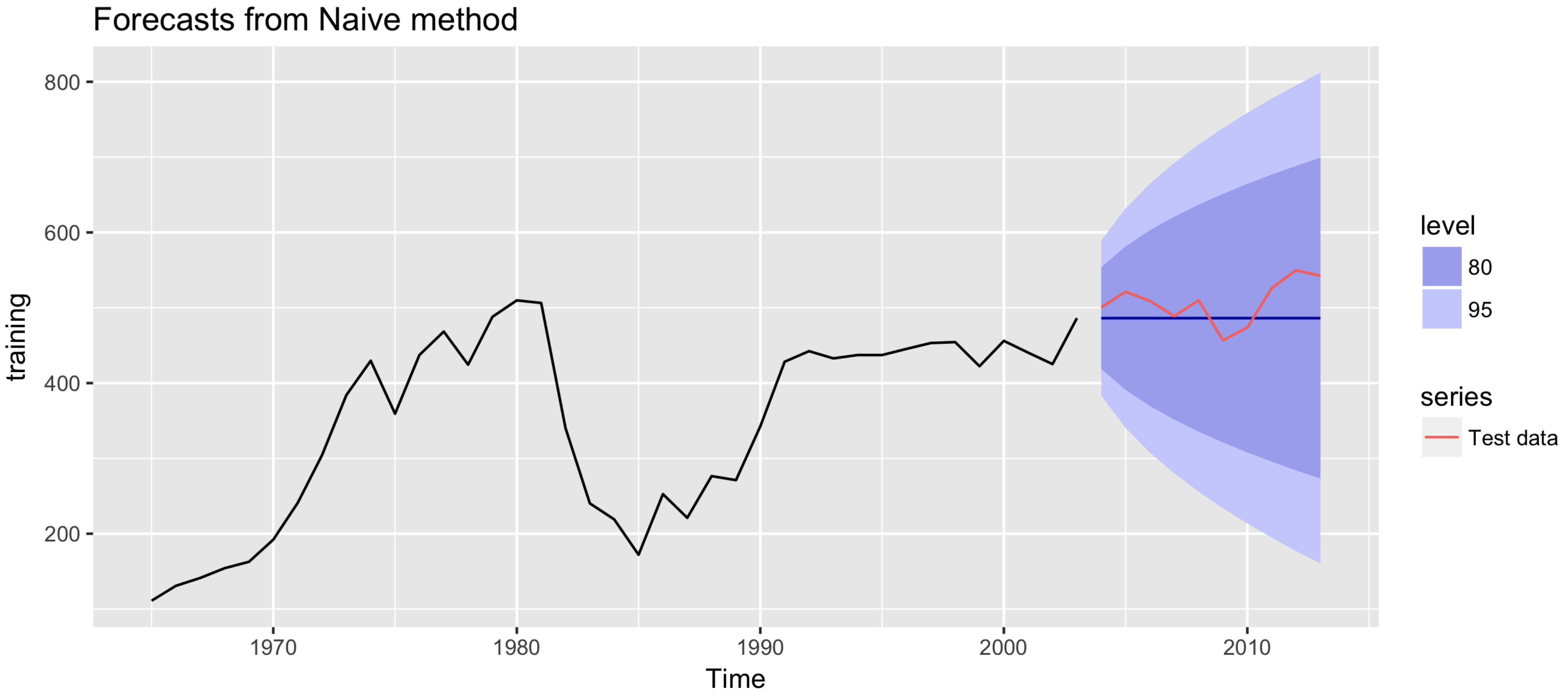
Training and test sets

Training and test sets

- The **test set** must **not** be used for any aspect of calculating forecasts
- Build forecasts using **training set**
- A model which fits the training data well will **not necessarily forecast well**

Example: Saudi Arabian oil production

```
training <- window(oil, end = 2003)
test <- window(oil, start = 2004)
fc <- naive(training, h = 10)
autoplot(fc) + autolayer(test, series = "Test data")
```



Forecast errors

Forecast "error" = the difference between observed value and its forecast in the test set.

$\neq$ **residuals**

- which are errors on the **training set** (vs. **test set**)
- which are based on **one-step** forecasts (vs. **multi-step**)

Compute accuracy using forecast errors on test data

Measures of forecast accuracy

- Observation: y_t
- Forecast: $\hat{y}_t$
- Forecast error: $e_t = y_t - \hat{y}_t$

Accuracy measure	Calculation
Mean absolute error	$\text{MAE} = avg(\mid e_t \mid)$
Mean squared error	$\text{MSE} = avg(e_t^2)$
Mean absolute percentage error	$\text{MAPE} = 100 \times avg(\mid \frac{e_t}{y_t} \mid)$
Mean absolute scaled error	$\text{MASE} = \frac{\text{MAE}}{Q}$ where Q is a scaling constant

The accuracy() command

```
accuracy(fc, test)
```

```
                 ME   RMSE    MAE    MPE   MAPE   MASE   ACF1 Theil's U
Training set  9.874  52.56  39.43  2.507 12.571 1.0000 0.1802        NA
Test set     21.602  35.10  29.98  3.964  5.778 0.7603 0.4030     1.185
```

Let's practice!

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Time series cross-validation

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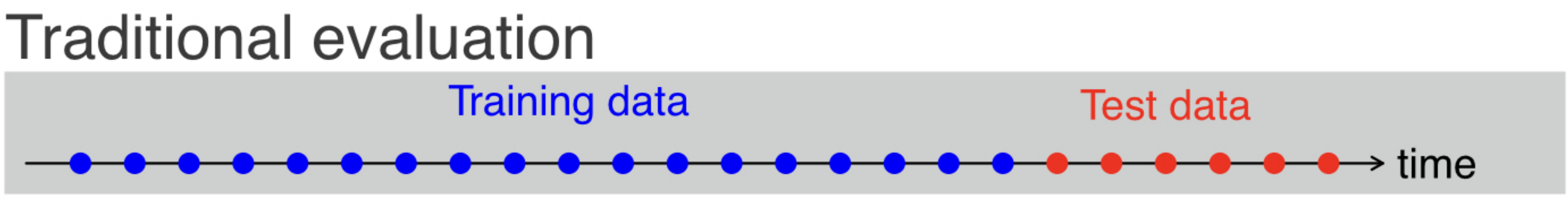
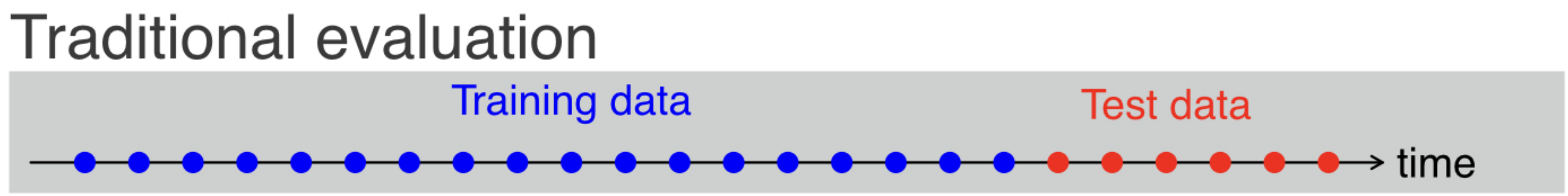
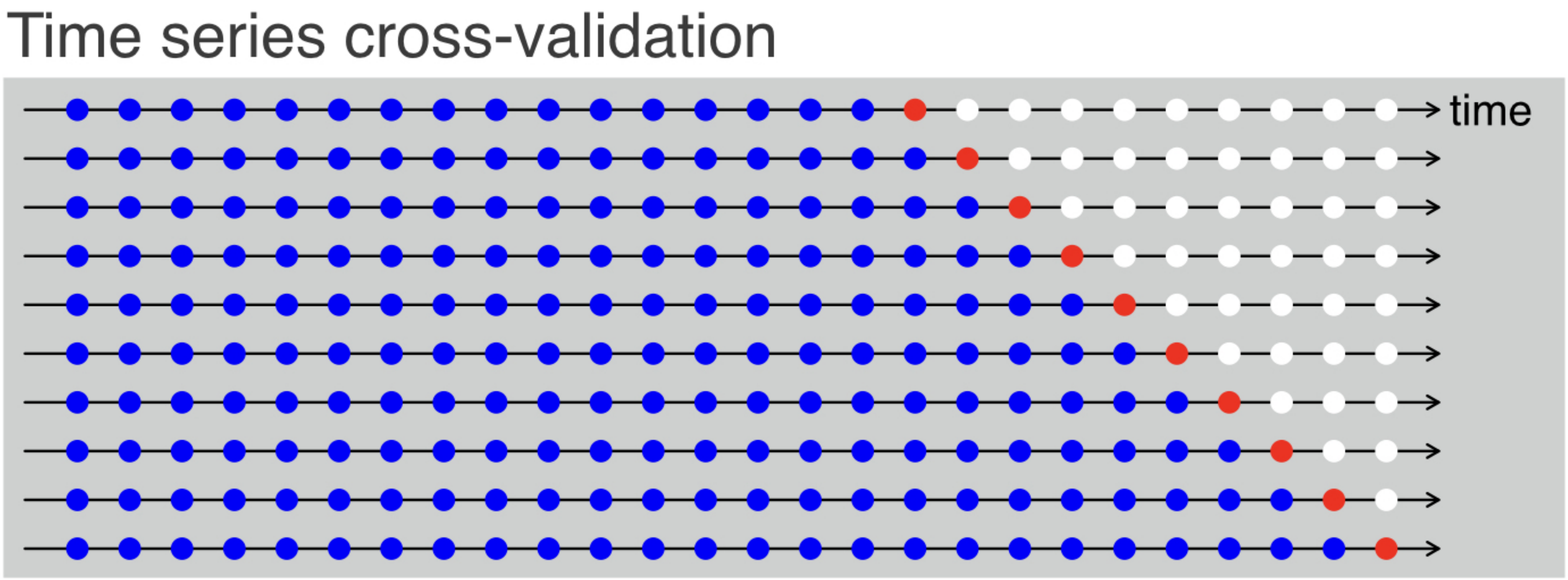
Time series cross-validation

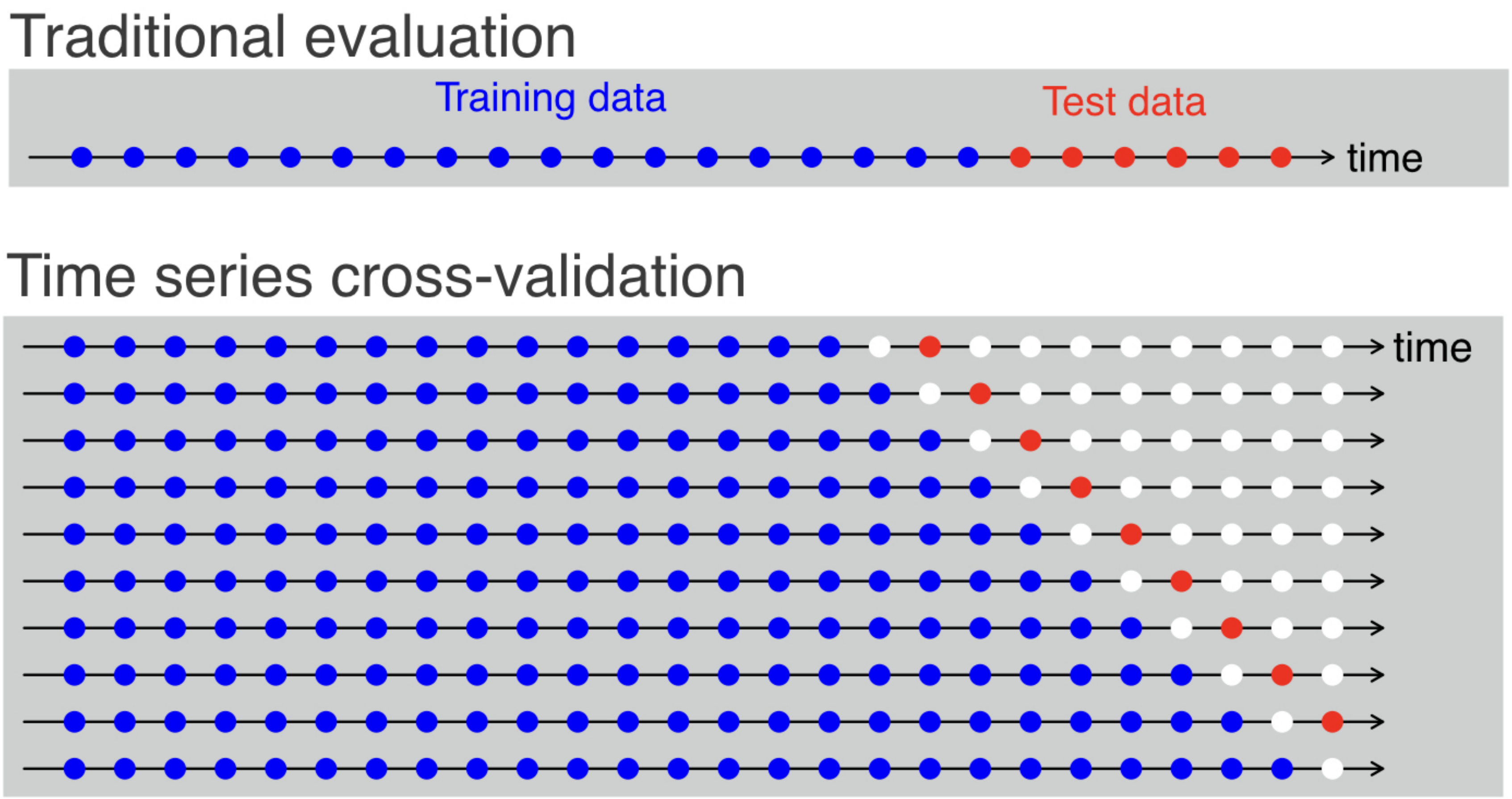


Time series cross-validation

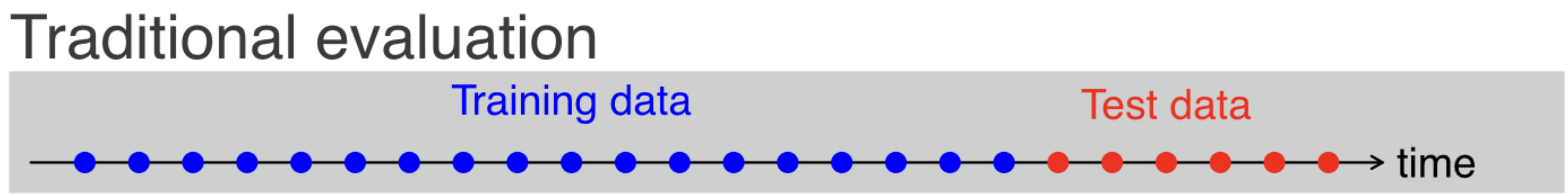


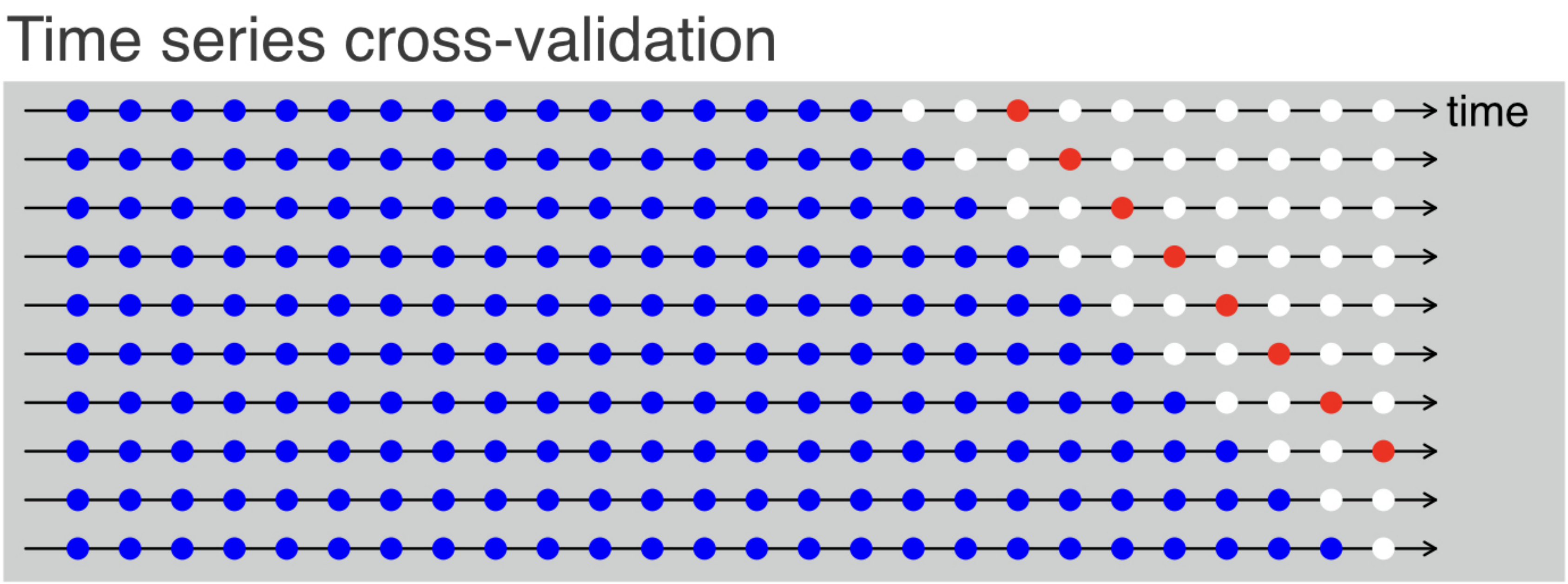


Time series cross-validation



Time series cross-validation





tsCV function

MSE using time series cross-validation

```
e <- tsCV (oil, forecastfunction = naive, h = 1)
mean(e^2 , na.rm = TRUE)
```

```
2355.753
```

When there are no parameters to be estimated, tsCV with h=1 will give the same values as residuals

tsCV function

```
sq <- function(u){u^2}
tsCV(oil, forecastfunction = naive, h = 10) %>%
  sq() %>% colMeans(na.rm=TRUE)
```

```
      h=1        h=2        h=3        h=4        h=5        h=6
 2355.753   5734.838   9842.239  14299.997  18560.887  23264.410
      h=7        h=8        h=9       h=10
26932.799  30766.136  32892.200  32986.214
```

The MSE increases with the forecast horizon

tsCV function

- Choose the model with the smallest MSE computed using time series cross-validation
- Compute it at the forecast horizon of most interest to you

Let's practice!

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