# Forecasts and potential futures

FORECASTING IN R

**Rob J. Hyndman**
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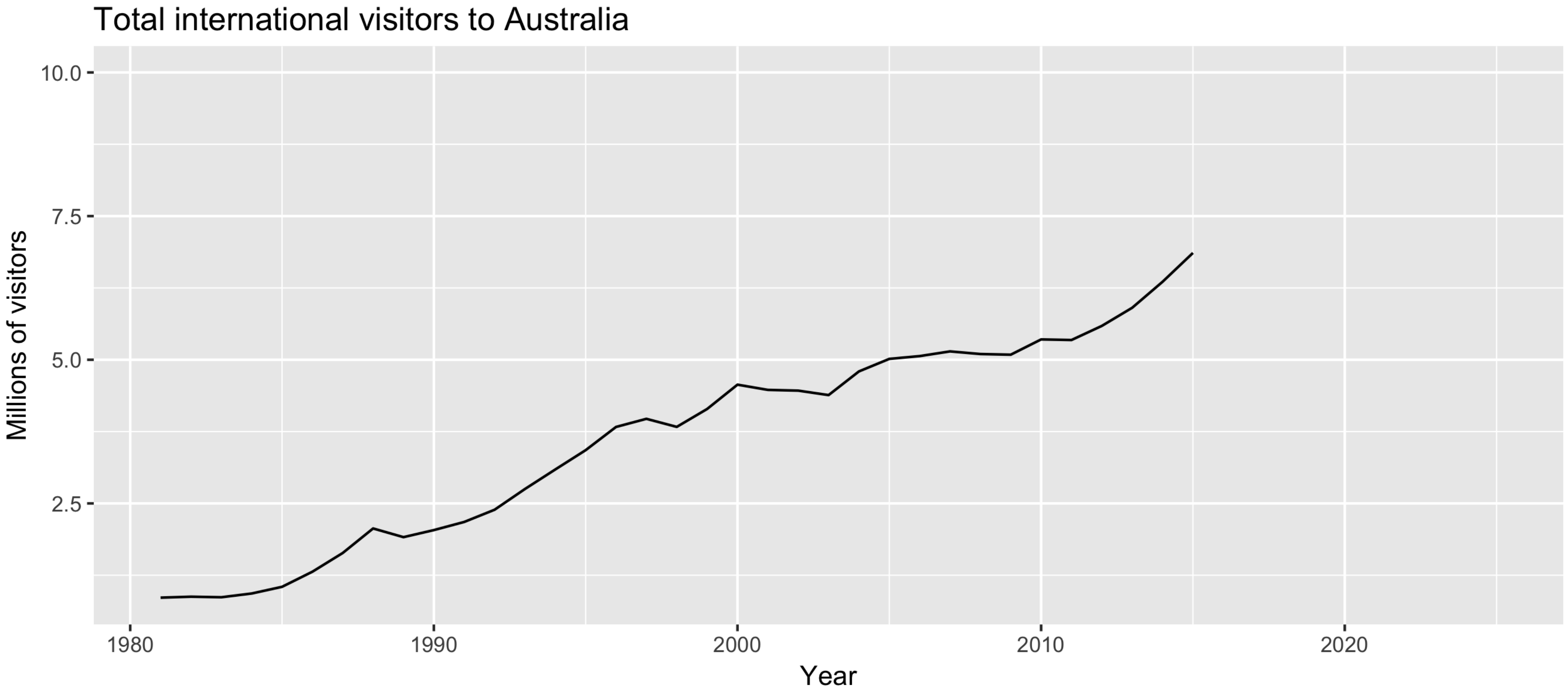
datacamp

# Sample futures



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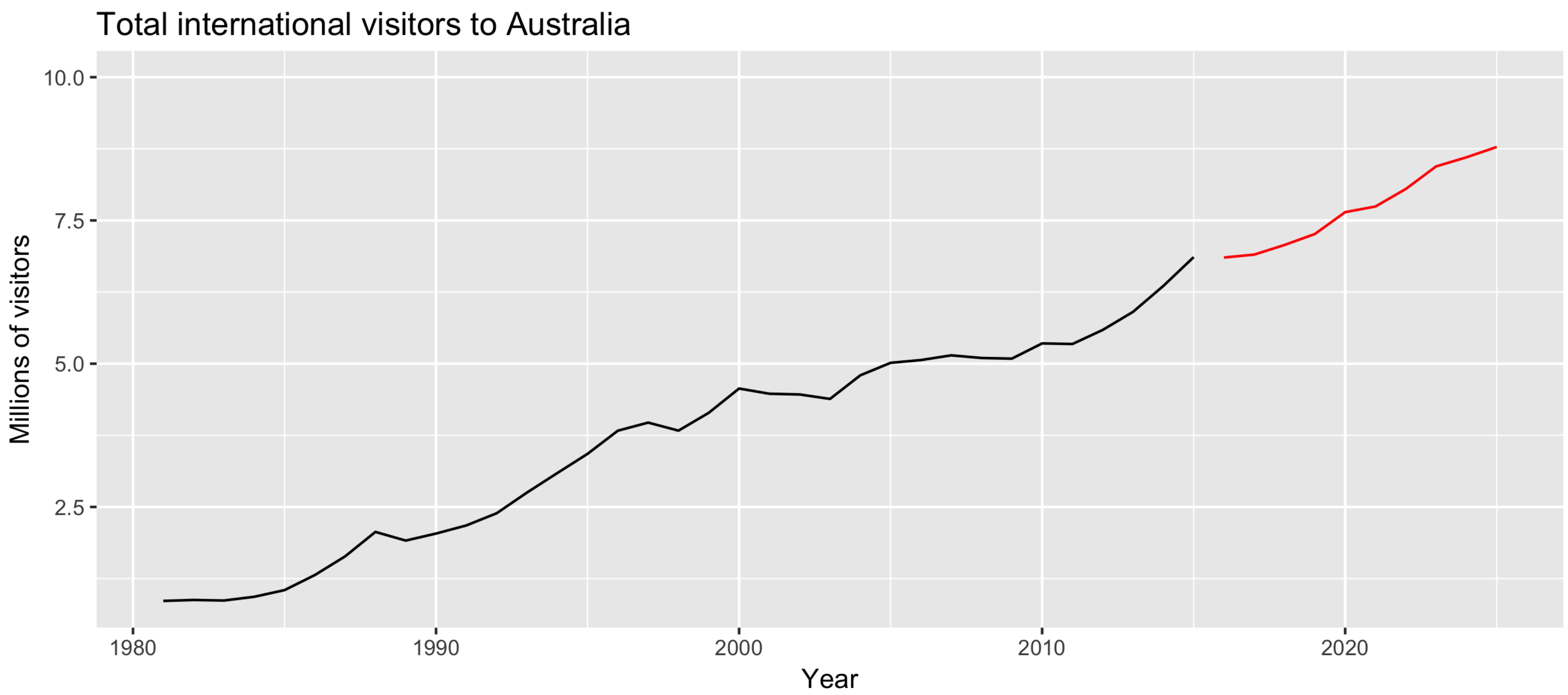

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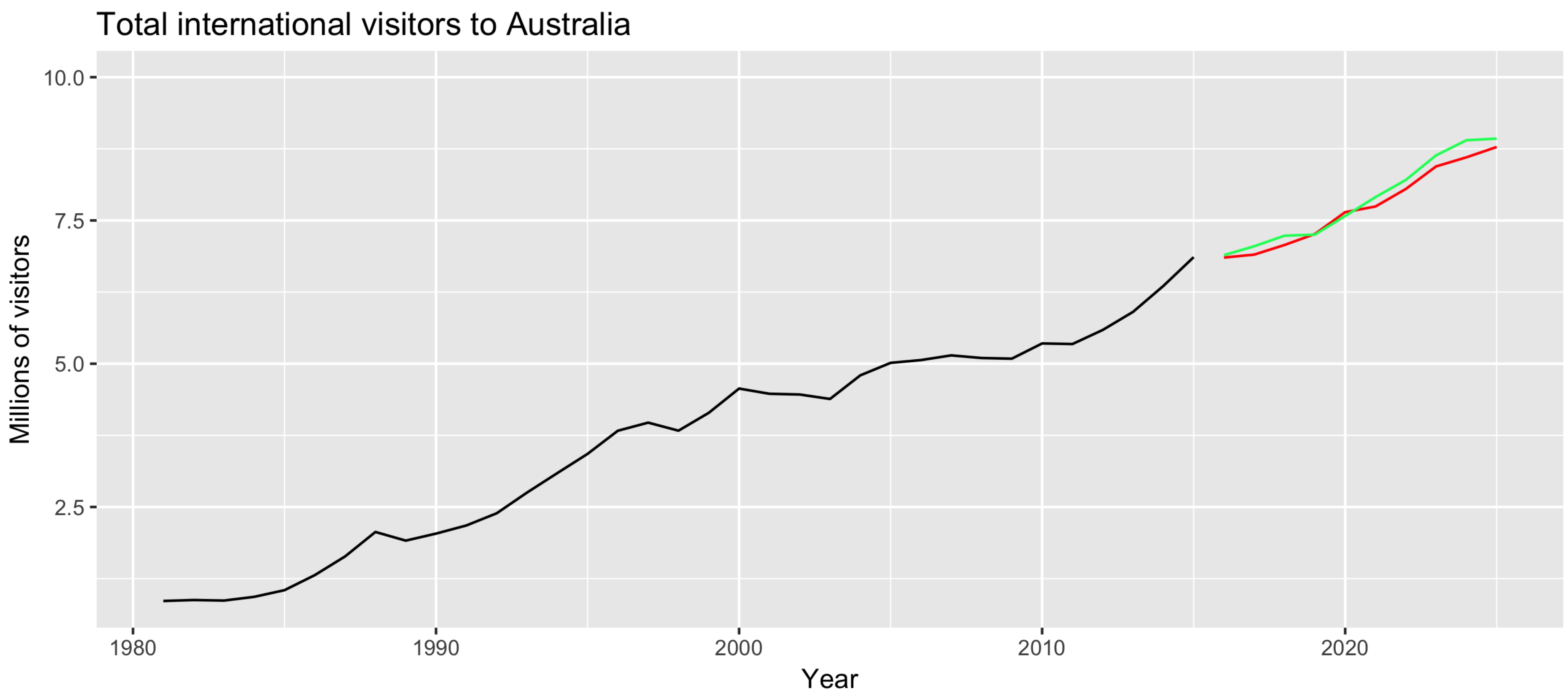

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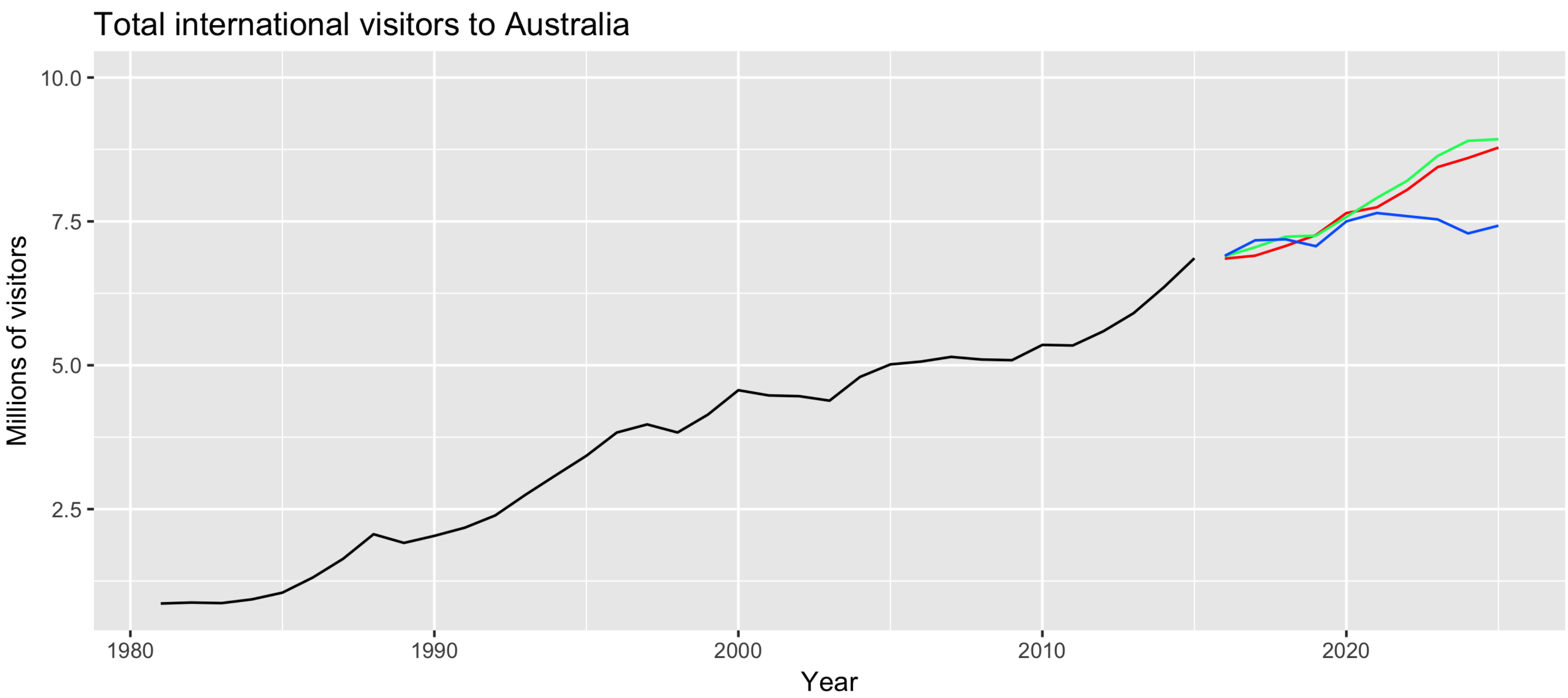

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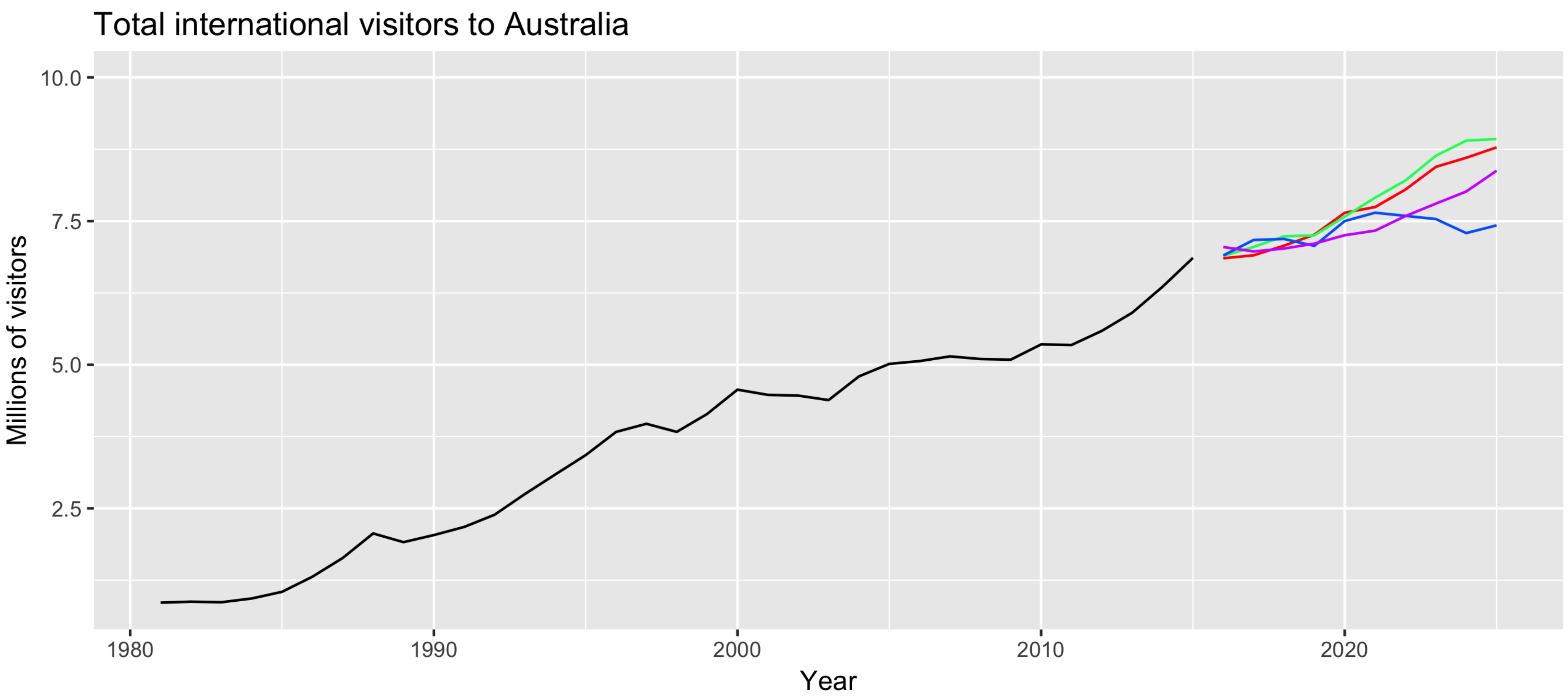

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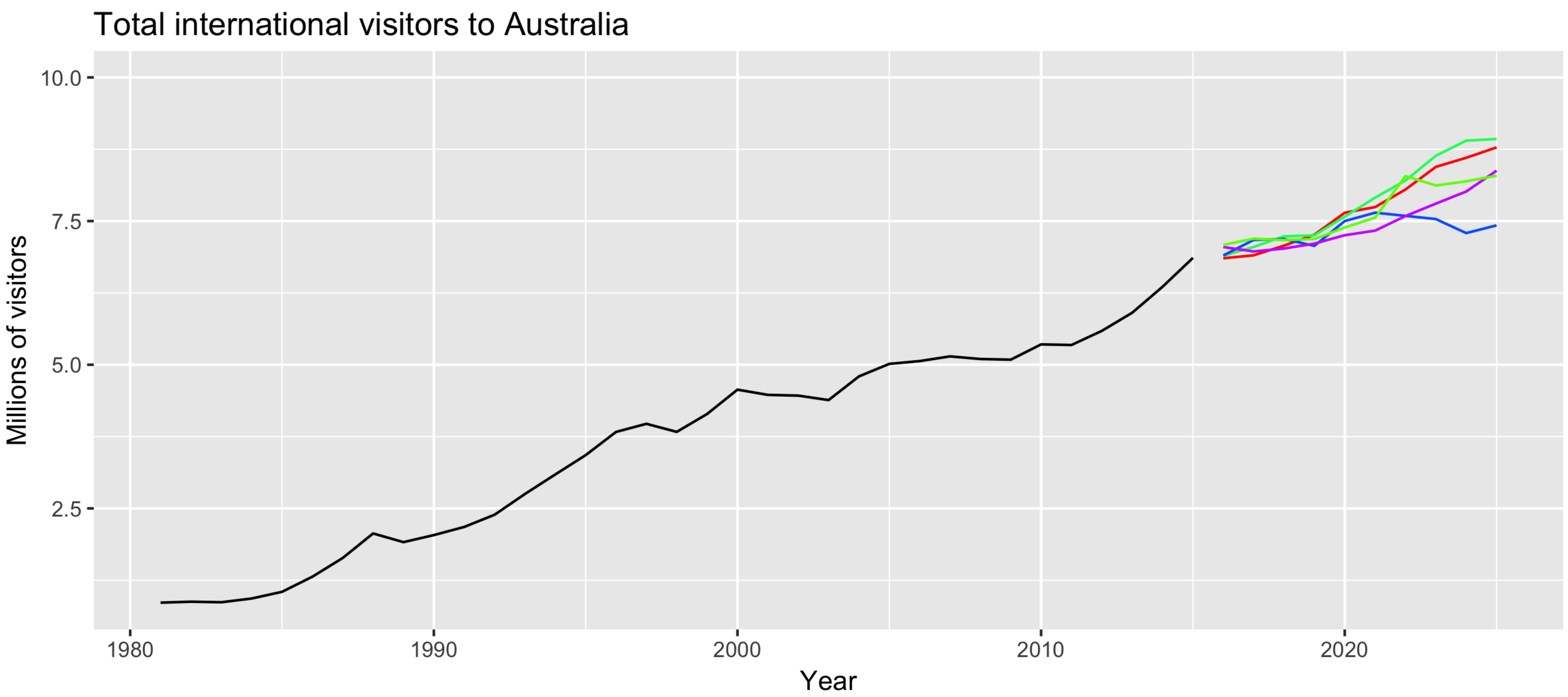

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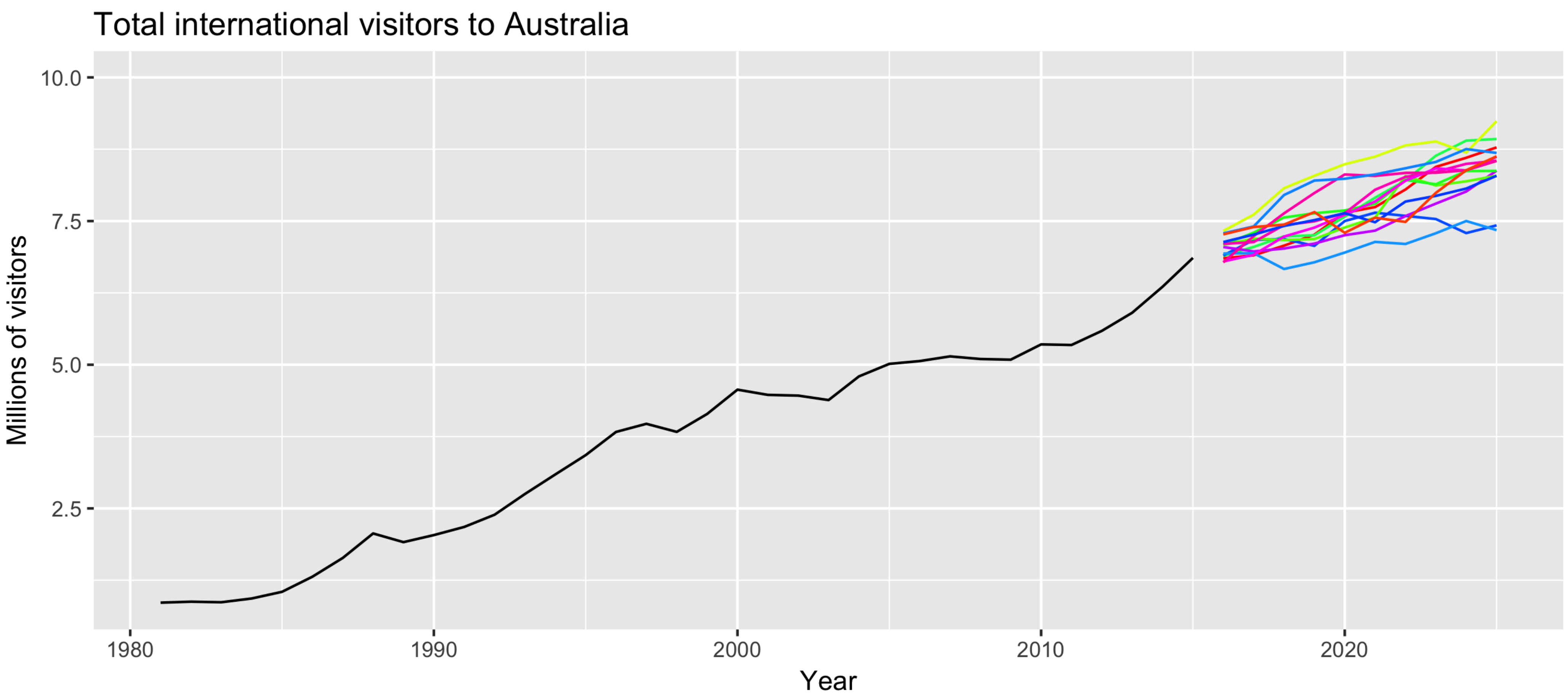

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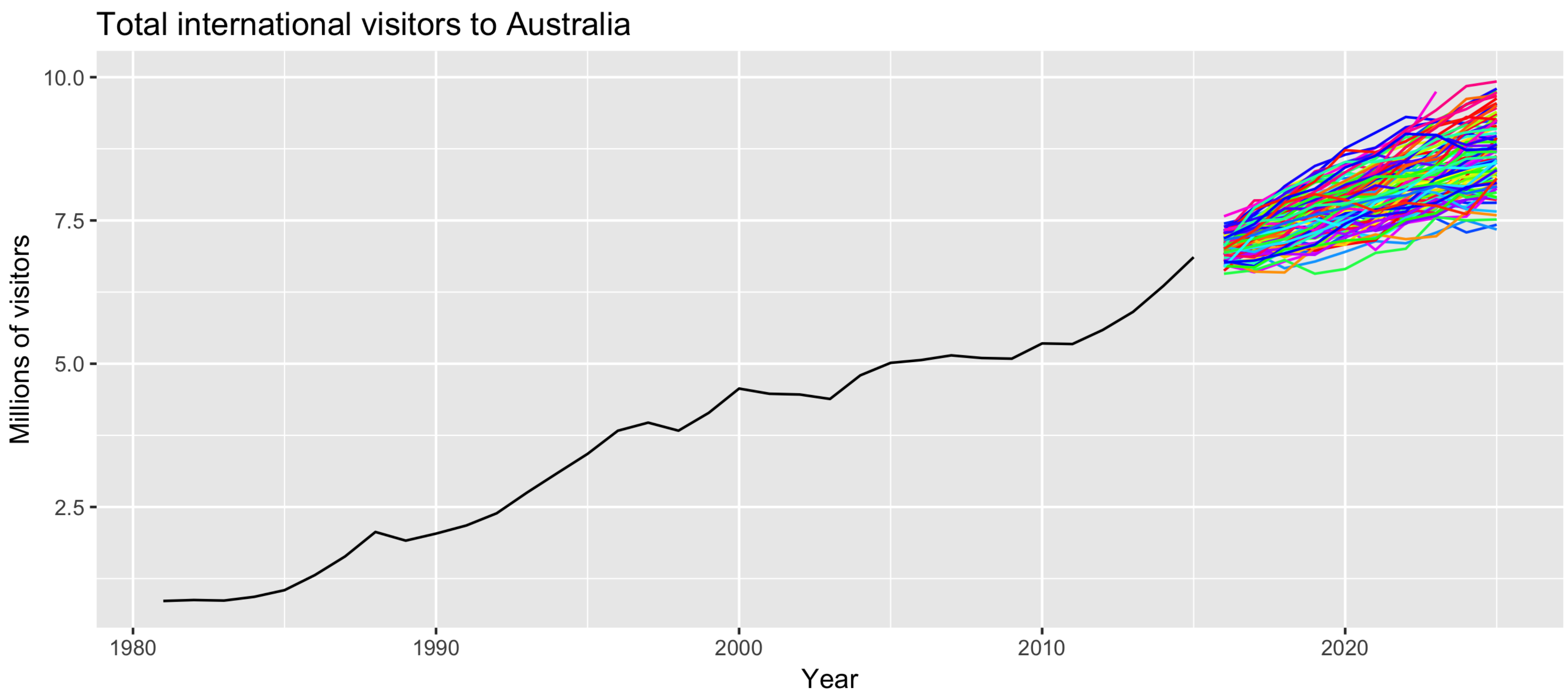
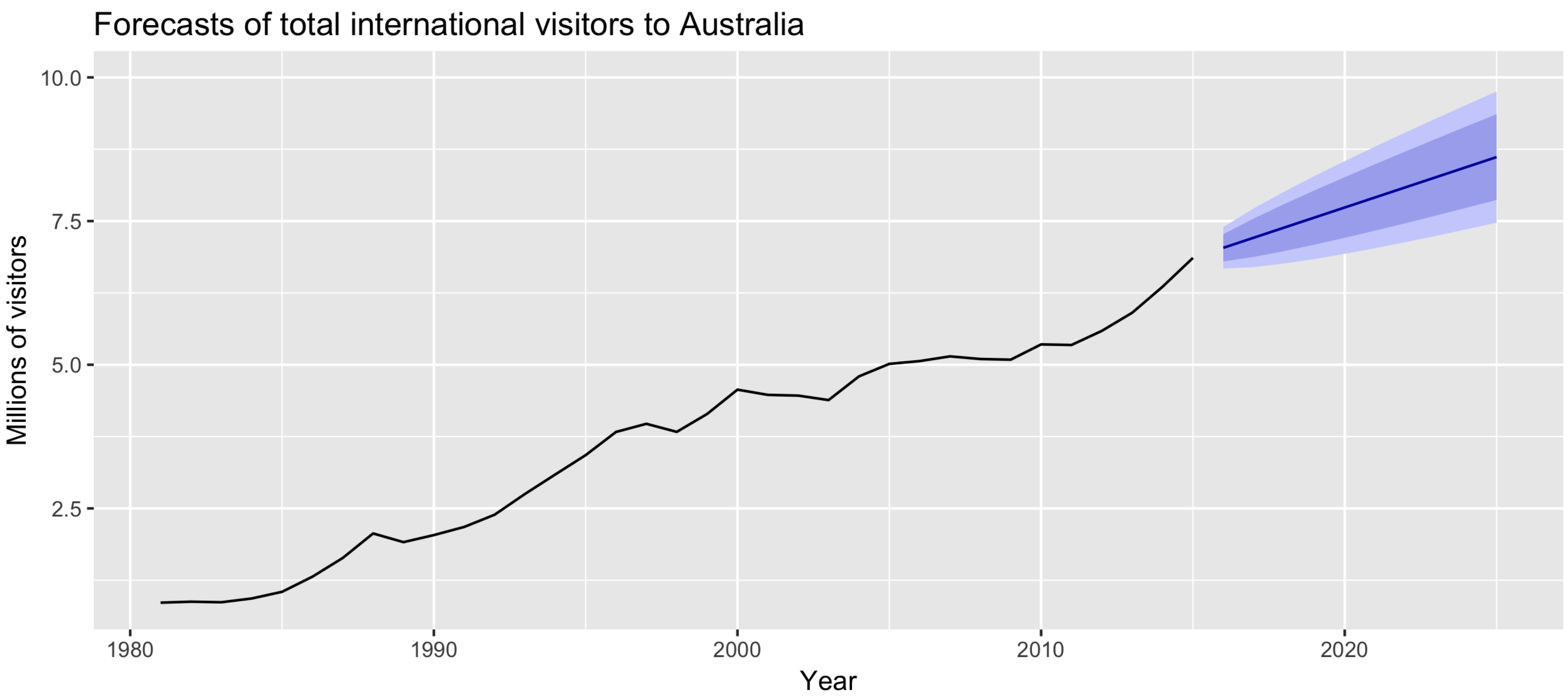


# Forecast intervals



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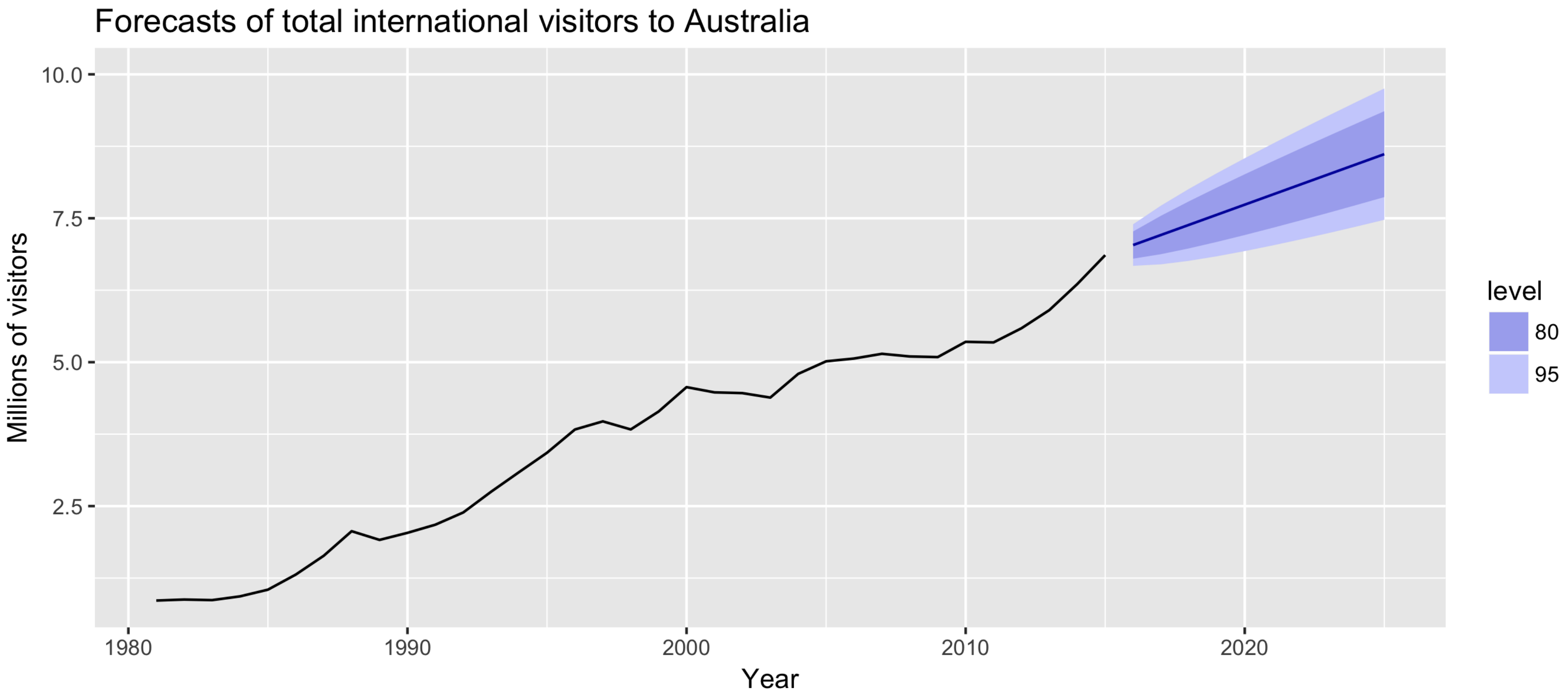


80% forecast intervals should contain 80% of future observations

95% forecast intervals should contain 95% of future observations

# Let's practice!

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# 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

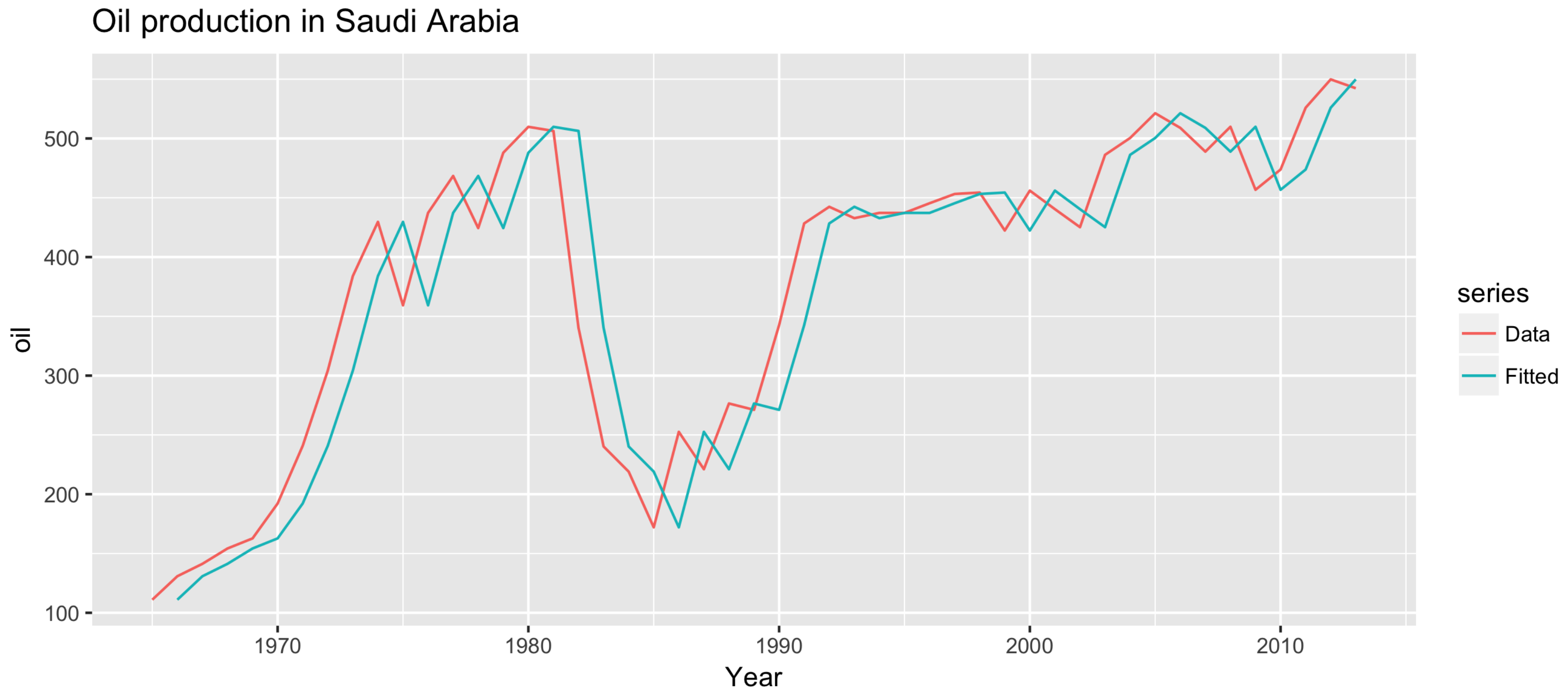
- That is, they are one-step forecasts
- Often not true forecasts since parameters are estimated on all data

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)

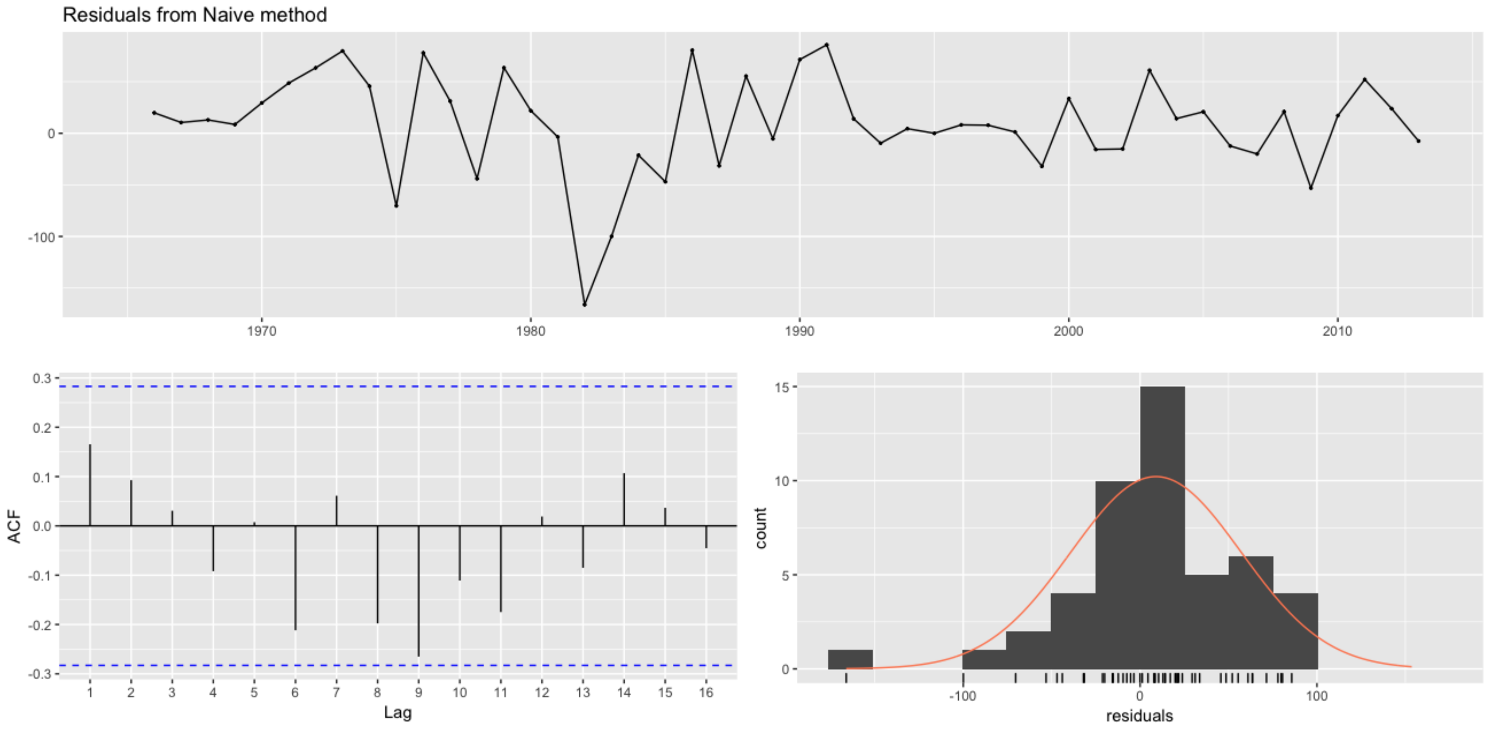
- They should have constant variance
- They should be normally distributed

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
```



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# Training and test sets

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# Training and test sets

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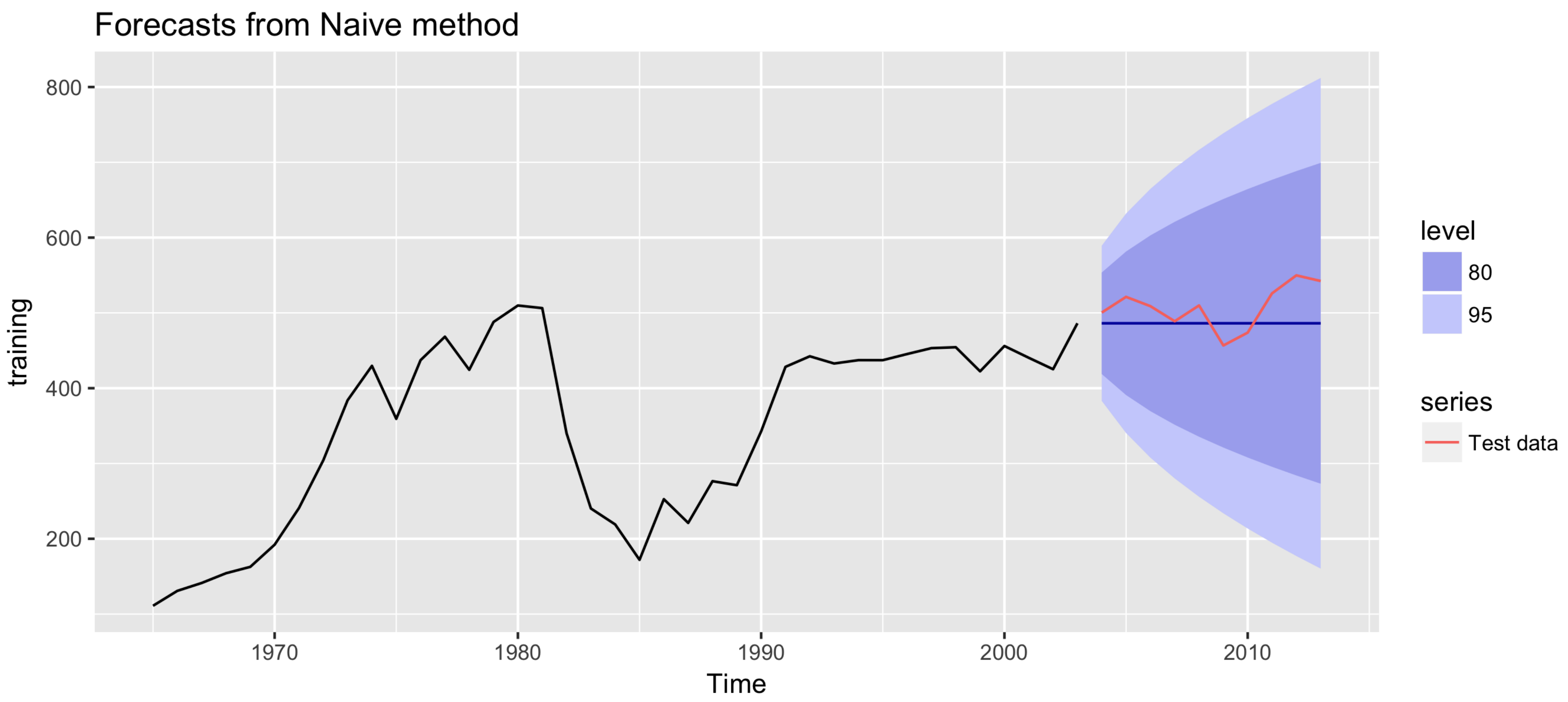
# Training and test sets


- 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

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

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|---|---|---|---|

| Accuracy measure | Calculation |
|---|---|
| Mean Absolute Error | $MAE = average(\|e_t\|)$ |
| Mean Squared Error | $MSE = average(e_t^2)$ |
| Mean Absolute Percentage Error | $MAPE = 100 \times average(\|\frac{e_t}{y_t}\|)$ |
| Mean Absolute Scaled Error | $MASE = MAE/Q$ |

* Where Q is a scaling constant.

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# 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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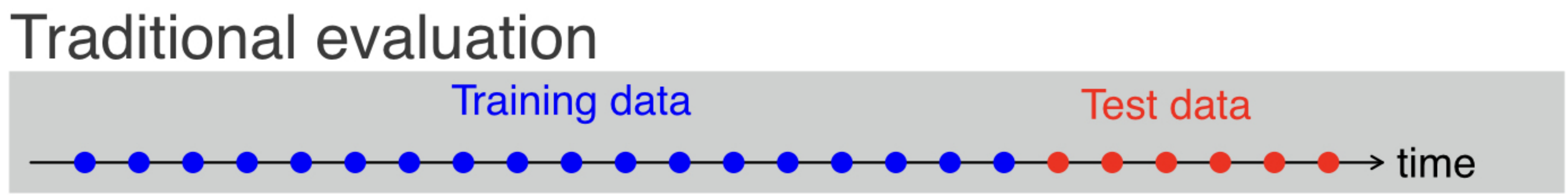
# Time series cross-validation



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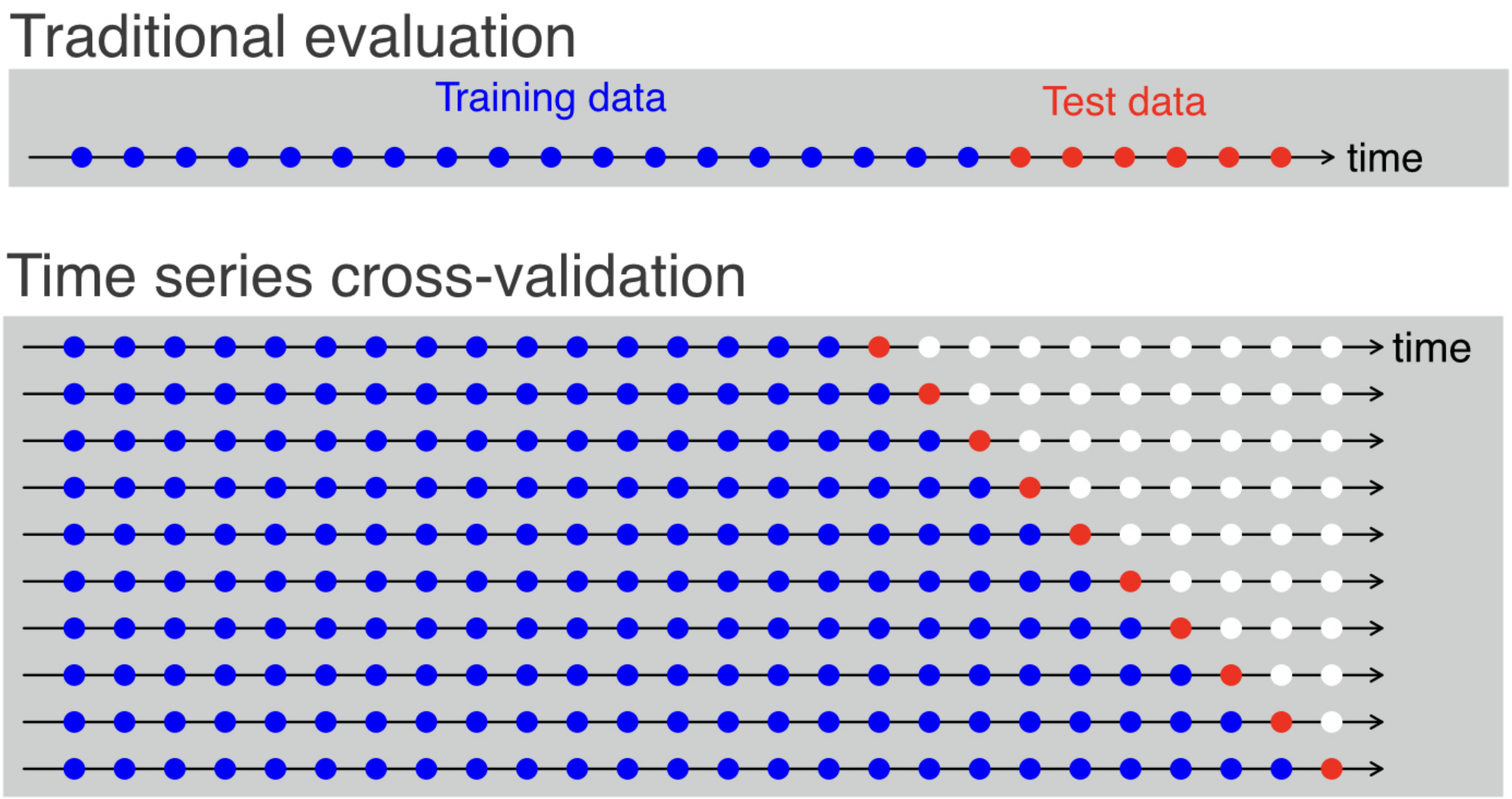

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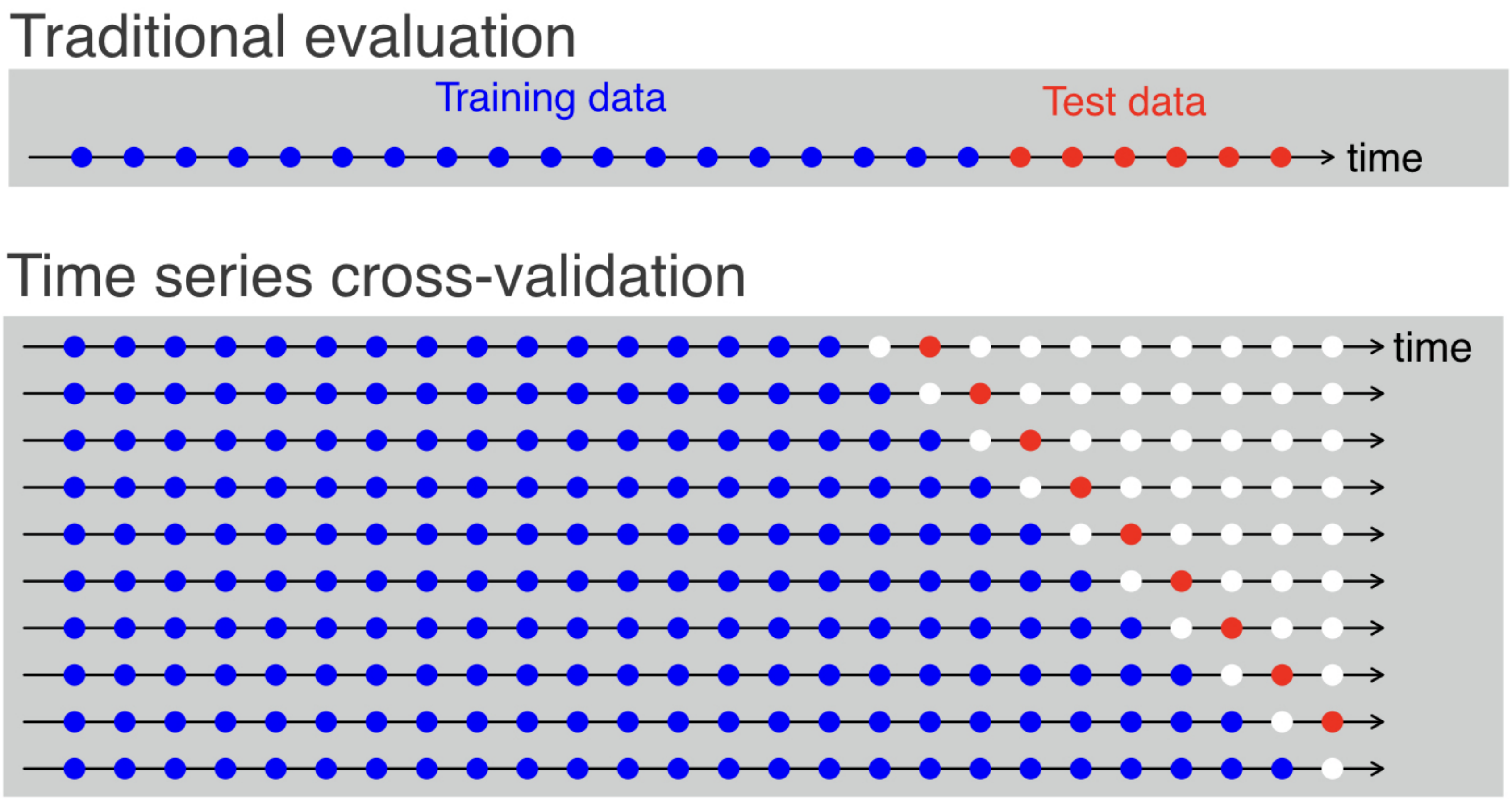

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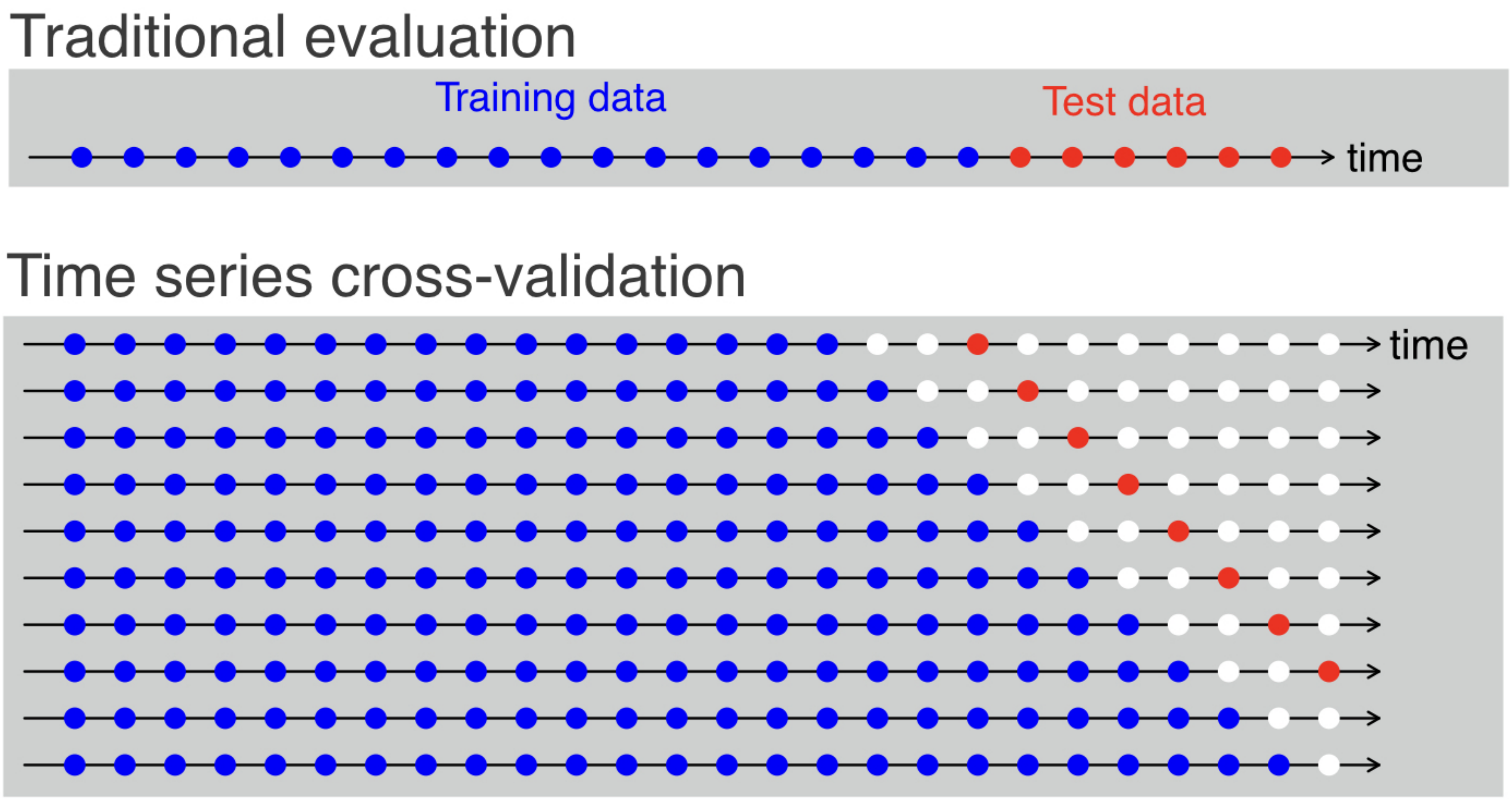

# tsCV function

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}
for(h in 1:10)
  {
    oil %>% tsCV(forecastfunction = naive, h = h) %>%
      sq() %>% mean(na.rm = TRUE) %>% print()
  }
```

```
2355.753
5734.838
9842.239
14300
18560.89
23264.41
26932.8
30766.14
32892.2
32986.21
```

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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