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FORECASTING

PRINCIPLES AND PRACTICE

A comprehensive introduction to the latest forecasting methods using R. Learn to improve your forecast accuracy using dozens of real data examples.



3RD EDITION

 **OTexts**
OPEN TEXTS FOR PRACTICE

7. Time series regression models

7.7 Nonlinear regression

OTexts.org/fpp3/

Nonlinear regression

A log-log functional form

$$\log y = \beta_0 + \beta_1 \log x + \varepsilon$$

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- alternative specifications: log-linear, linear-log.
- use $\log(x + 1)$ if required.

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- In general, **linear regression splines**

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- Need to select knots: can be difficult and arbitrary.
- Automatic knot selection algorithms very slow.
- Using piecewise cubics achieves a smoother result.

Warning: better fit but forecasting outside the range of the historical data is even more unreliable.

Nonlinear trends

Piecewise linear trend with bend at τ

$$x_{1,t} = t$$

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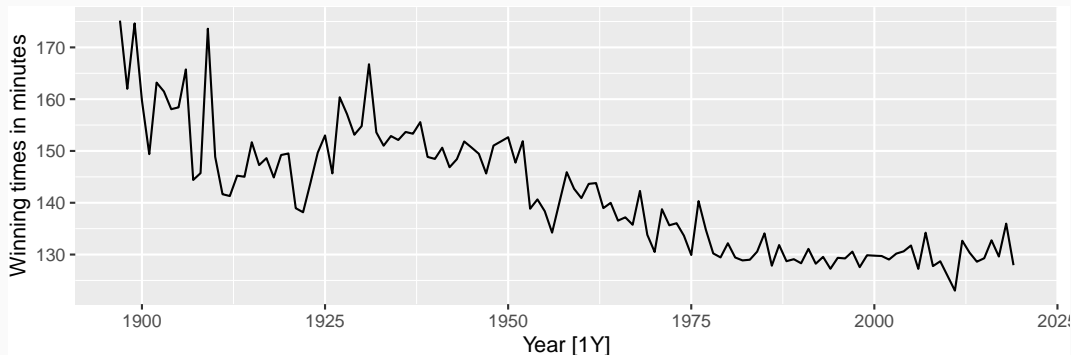
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NOT RECOMMENDED!

Example: Boston marathon winning times

```
marathon <- boston_marathon |>  
  filter(Event == "Men's open division") |>  
  select(-Event) |>  
  mutate(Minutes = as.numeric(Time) / 60)  
marathon |> autoplot(Minutes) + labs(y = "Winning times in minutes")
```



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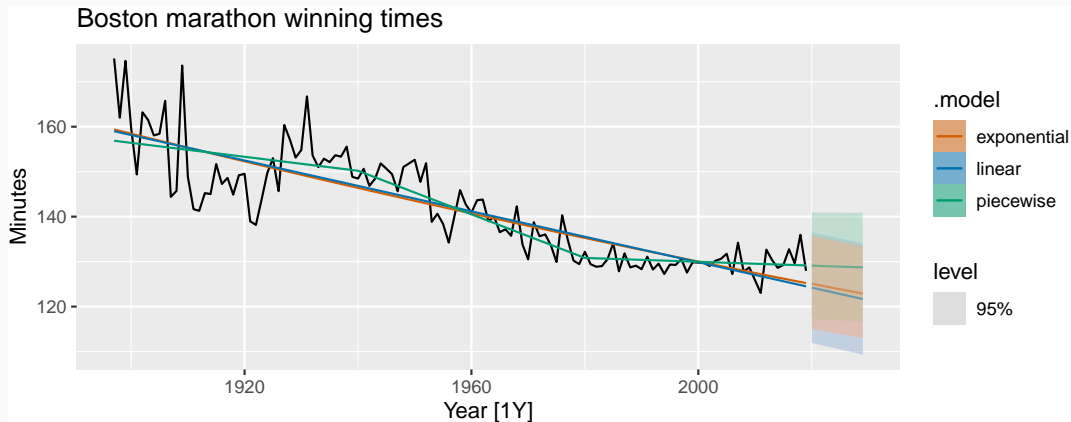
```
fit_trends <- marathon |>
  model(
    # Linear trend
    linear = TSLM(Minutes ~ trend()),
    # Exponential trend
    exponential = TSLM(log(Minutes) ~ trend()),
    # Piecewise linear trend
    piecewise = TSLM(Minutes ~ trend(knots = c(1940, 1980)))
  )
```

```
fit_trends
```

```
## # A mable: 1 x 3
##   linear exponential piecewise
##   <model>      <model>    <model>
## 1  <TSLM>      <TSLM>    <TSLM>
```

Example: Boston marathon winning times

```
fit_trends |>  
  forecast(h = 10) |>  
  autoplot(marathon)
```



Example: Boston marathon winning times

```
fit_trends |>  
  select(piecewise) |>  
  gg_tsresiduals()
```

