

Feasts & fables

Modern tools for time series analysis

Rob J Hyndman

robjhyndman.com/whyR2021



MONASH University

Outline

- 1 What does modern time series data look like?
- 2 Feature-based time series analysis
- 3 Probabilistic forecasting for large time series
- 4 Evaluating probabilistic forecasts



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- 1 What does modern time series data look like?
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Australian electricity demand

```
## # A tibble: 420,864 x 6 [30m] <Australia/Melbourne>
```

```
## # Key:           State [8]
```

##	Time	State	Date	Holiday	Temperature	Demand
##	<dtm>	<fct>	<date>	<lgl>	<dbl>	<dbl>
##	1 2012-01-01 00:00:00	VIC	2012-01-01	TRUE	21.4	4383.
##	2 2012-01-01 00:30:00	VIC	2012-01-01	TRUE	21.0	4263.
##	3 2012-01-01 01:00:00	VIC	2012-01-01	TRUE	20.7	4049.
##	4 2012-01-01 01:30:00	VIC	2012-01-01	TRUE	20.6	3878.
##	5 2012-01-01 02:00:00	VIC	2012-01-01	TRUE	20.4	4036.
##	6 2012-01-01 02:30:00	VIC	2012-01-01	TRUE	20.2	3866.
##	7 2012-01-01 03:00:00	VIC	2012-01-01	TRUE	20.1	3694.
##	8 2012-01-01 03:30:00	VIC	2012-01-01	TRUE	19.6	3562.
##	9 2012-01-01 04:00:00	VIC	2012-01-01	TRUE	19.1	3433.
##	10 2012-01-01 04:30:00	VIC	2012-01-01	TRUE	19.0	3359.

```
## # ... with 420,854 more rows
```

Australian electricity demand

```
## # A tibble: 420,864 x 6 [30m] <Australia/Melbourne>
```

```
## # Key:           State [8]
```

```
##      Time                State Date      Holiday Temperature Demand
##      Index                <fct> <date>      <lgl>         <dbl>   <dbl>
##  1 2012-01-01 00:00:00 VIC    2012-01-01 TRUE         21.4   4383.
##  2 2012-01-01 00:30:00 VIC    2012-01-01 TRUE         21.0   4263.
##  3 2012-01-01 01:00:00 VIC    2012-01-01 TRUE         20.7   4049.
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## # ... with 420,854 more rows
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Australian electricity demand

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```
## # Key:           State [8]
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##	Time	State	Date	Holiday	Temperature	Demand
##	Index	Key	<date>	<lgl>	<dbl>	<dbl>
##	1	2012-01-01 00:00:00	VIC	2012-01-01	TRUE	21.4 4383.
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##	3	2012-01-01 01:00:00	VIC	2012-01-01	TRUE	20.7 4049.
##	4	2012-01-01 01:30:00	VIC	2012-01-01	TRUE	20.6 3878.
##	5	2012-01-01 02:00:00	VIC	2012-01-01	TRUE	20.4 4036.
##	6	2012-01-01 02:30:00	VIC	2012-01-01	TRUE	20.2 3866.
##	7	2012-01-01 03:00:00	VIC	2012-01-01	TRUE	20.1 3694.
##	8	2012-01-01 03:30:00	VIC	2012-01-01	TRUE	19.6 3562.
##	9	2012-01-01 04:00:00	VIC	2012-01-01	TRUE	19.1 3433.
##	10	2012-01-01 04:30:00	VIC	2012-01-01	TRUE	19.0 3359.
## #	... with 420,854 more rows					

Australian electricity demand

```
## # A tibble: 420,864 x 6 [30m] <Australia/Melbourne>
```

```
## # Key:      State [8]
```

```
##      Time                State Date      Holiday Temperature Demand
```

```
##      Index                Key      Measures
```

```
## 1 2012-01-01 00:00:00 VIC 2012-01-01 TRUE      21.4 4383.
```

```
## 2 2012-01-01 00:30:00 VIC 2012-01-01 TRUE      21.0 4263.
```

```
## 3 2012-01-01 01:00:00 VIC 2012-01-01 TRUE      20.7 4049.
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```
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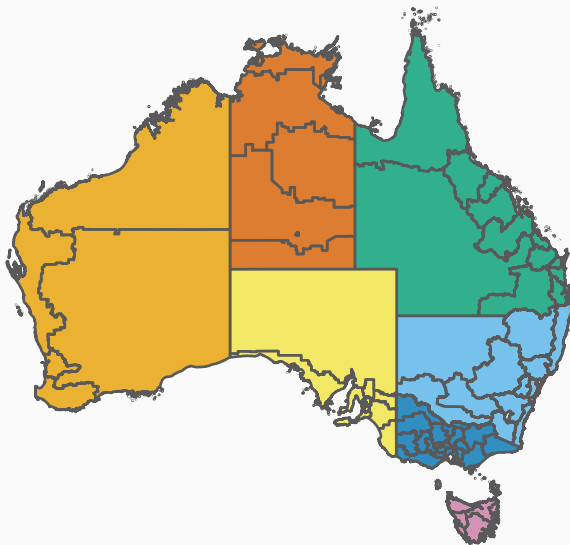
```
## 8 2012-01-01 03:30:00 VIC 2012-01-01 TRUE      19.6 3562.
```

```
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```
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```
## # ... with 420,854 more rows
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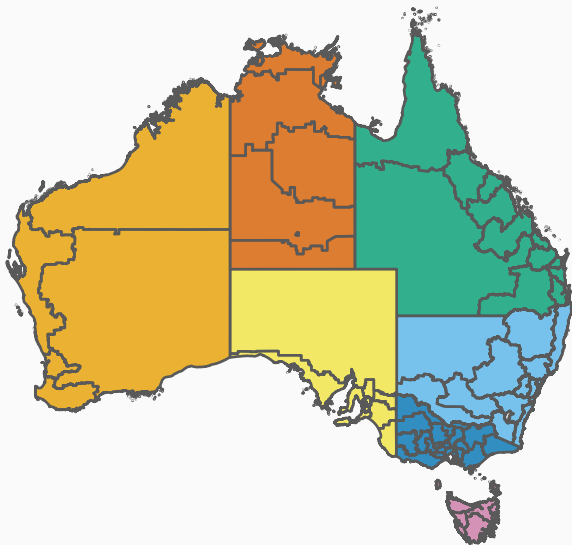

Australian tourism regions



State

- New South Wales
- Victoria
- Queensland
- South Australia
- Northern Territory
- Western Australia
- Tasmania
- Australian Capital Territory

Australian tourism regions



- Quarterly data on visitor nights: 1998 – 2017
- From *National Visitor Survey*, interviews of 120,000 Australians aged 15+.
- Geographical hierarchy split by
 - ▶ 8 states and territories
 - ▶ 76 regions
- Purpose:
 - ▶ Holidays
 - ▶ Business
 - ▶ Visiting friends & relatives
 - ▶ Other

Quarterly tourism data

```
## # A tsibble: 24,320 x 5 [1Q]
## # Key:           Region, State, Purpose [304]
##   Quarter Region  State Purpose  Trips
##   <qtr> <chr>    <chr> <chr>    <dbl>
## 1 1998 Q1 Adelaide SA      Business 135.
## 2 1998 Q2 Adelaide SA      Business 110.
## 3 1998 Q3 Adelaide SA      Business 166.
## 4 1998 Q4 Adelaide SA      Business 127.
## 5 1999 Q1 Adelaide SA      Business 137.
## 6 1999 Q2 Adelaide SA      Business 200.
## 7 1999 Q3 Adelaide SA      Business 169.
## 8 1999 Q4 Adelaide SA      Business 134.
## 9 2000 Q1 Adelaide SA      Business 154.
## 10 2000 Q2 Adelaide SA      Business 169.
## # ... with 24,310 more rows
```

Domestic visitor
nights in thousands
by state/region and
purpose.

Quarterly tourism data

```
## # A tibble: 24,320 x 5 [1Q]
## # Key:      Region, State, Purpose [304]
##   Quarter Region  State Purpose  Trips
##   Index      <chr>   <chr> <chr>   <dbl>
## 1 1998 Q1 Adelaide SA      Business 135.
## 2 1998 Q2 Adelaide SA      Business 110.
## 3 1998 Q3 Adelaide SA      Business 166.
## 4 1998 Q4 Adelaide SA      Business 127.
## 5 1999 Q1 Adelaide SA      Business 137.
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## 7 1999 Q3 Adelaide SA      Business 169.
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## # ... with 24,310 more rows
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Quarterly tourism data

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## # A tibble: 24,320 x 5 [1Q]
```

```
## # Key:      Region, State, Purpose [304]
```

```
##   Quarter Region  State Purpose  Trips
```

```
##   Index      Keys      Measure
```

```
## 1 1998 Q1 Adelaide SA      Business 135.
```

```
## 2 1998 Q2 Adelaide SA      Business 110.
```

```
## 3 1998 Q3 Adelaide SA      Business 166.
```

```
## 4 1998 Q4 Adelaide SA      Business 127.
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## 5 1999 Q1 Adelaide SA      Business 137.
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```

```
## 7 1999 Q3 Adelaide SA      Business 169.
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```
## 8 1999 Q4 Adelaide SA      Business 134.
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```

```
## 10 2000 Q2 Adelaide SA      Business 169.
```

```
## # ... with 24,310 more rows
```

Domestic visitor
nights in thousands
by state/region and
purpose.

Characteristics of modern time series

- Often observed at sub-daily frequency over a long time.
- Multiple keys which may be nested.
- Multiple seasonal patterns.
- Multiple measures for each combination of index and keys.

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tsibble objects

- A `tsibble` allows storage and manipulation of multiple time series in R.
- It contains:
 - ▶ An index: time information about the observation
 - ▶ Key variable(s): optional unique identifiers for each series
 - ▶ Measured variable(s): numbers of interest and any other variable

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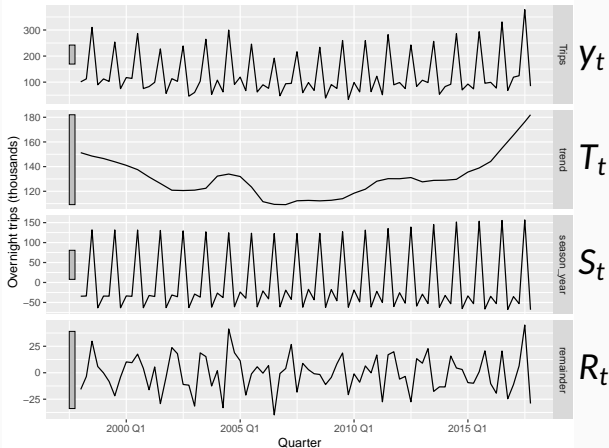
STL decomposition

STL decomposition

$$y_t = T_t + S_t + R_t$$

STL decomposition: Holidays in Snowy Mountains

Trips = trend + season_year + remainder



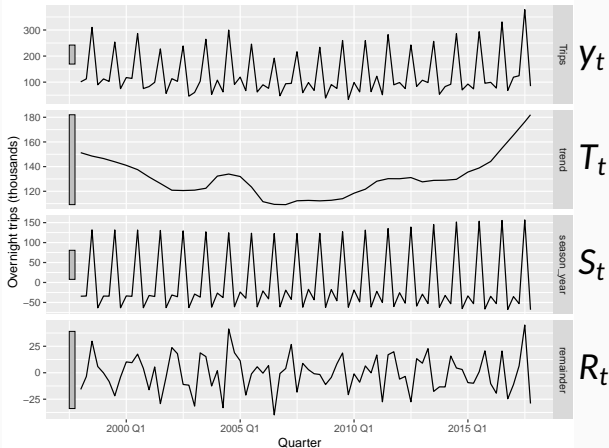
STL decomposition

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STL decomposition: Holidays in Snowy Mountains

Trips = trend + season_year + remainder



Trend strength

$$\max \left(0, 1 - \frac{\text{Var}(R_t)}{\text{Var}(T_t + R_t)} \right)$$

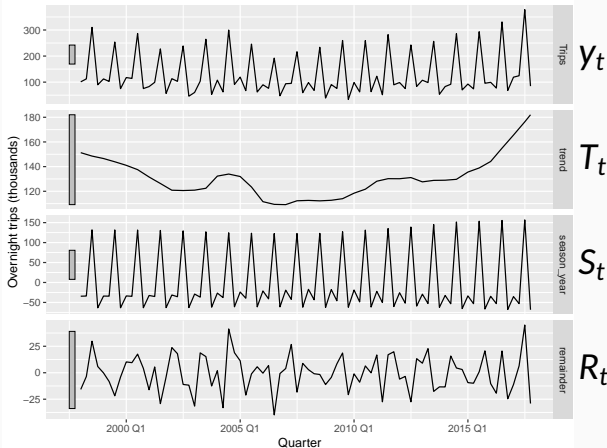
STL decomposition

STL decomposition

$$y_t = T_t + S_t + R_t$$

STL decomposition: Holidays in Snowy Mountains

Trips = trend + season_year + remainder



y_t

Trend strength

T_t

$$\max \left(0, 1 - \frac{\text{Var}(R_t)}{\text{Var}(T_t + R_t)} \right)$$

S_t

Seasonal strength

R_t

$$\max \left(0, 1 - \frac{\text{Var}(R_t)}{\text{Var}(S_t + R_t)} \right)$$

STL-based features

```
tourism %>%  
  features(Trips, feat_stl)
```

```
## # A tibble: 304 x 12  
##   Region State Purpose trend_strength seasonal_streng~ seasonal_peak_y~ seasonal_trough~  
##   <chr>   <chr> <chr>          <dbl>          <dbl>          <dbl>          <dbl>  
## 1 Adelai~ SA     Busine~      0.464          0.407             3             1  
## 2 Adelai~ SA     Holiday    0.554          0.619             1             2  
## 3 Adelai~ SA     Other      0.746          0.202             2             1  
## 4 Adelai~ SA     Visiti~    0.435          0.452             1             3  
## 5 Adelai~ SA     Busine~    0.464          0.179             3             0  
## 6 Adelai~ SA     Holiday    0.528          0.296             2             1  
## 7 Adelai~ SA     Other      0.593          0.404             2             2  
## 8 Adelai~ SA     Visiti~    0.488          0.254             0             3  
## 9 Alice ~ NT     Busine~    0.534          0.251             0             1  
## 10 Alice ~ NT     Holiday    0.381          0.832             3             1  
## # ... with 294 more rows, and 5 more variables: spikiness <dbl>, linearity <dbl>,  
## #   curvature <dbl>, stl_e_acf1 <dbl>, stl_e_acf10 <dbl>
```

STL-based features

```
tourism %>%  
  features(Trips, feat_stl) %>%  
  ggplot(aes(x = trend_strength, y = seasonal_strength_year, col = Purpose)) +  
  geom_point() + facet_wrap(vars(State))
```



STL-based features

```
tourism %>%  
  features(Trips, feat_stl) %>%  
  ggplot(aes(x = trend_strength, y = seasonal_strength_year, col = Purpose)) +  
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```

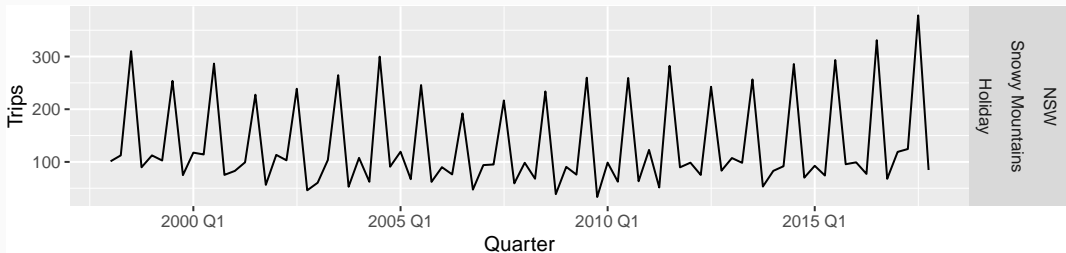


- Holidays more seasonal than other travel.
- WA has strongest trends.

STL-based features

Find the most seasonal time series:

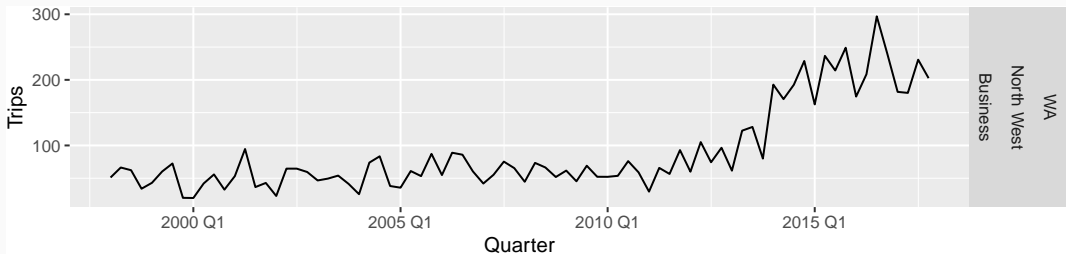
```
tourism %>%  
  features(Trips, feat_stl) %>%  
  filter(seasonal_strength_year == max(seasonal_strength_year)) %>%  
  left_join(tourism, by = c("State", "Region", "Purpose")) %>%  
  ggplot(aes(x = Quarter, y = Trips)) +  
  geom_line() +  
  facet_grid(vars(State, Region, Purpose))
```



STL-based features

Find the most trended time series:

```
tourism %>%  
  features(Trips, feat_stl) %>%  
  filter(trend_strength == max(trend_strength)) %>%  
  left_join(tourism, by = c("State", "Region", "Purpose")) %>%  
  ggplot(aes(x = Quarter, y = Trips)) +  
  geom_line() +  
  facet_grid(vars(State, Region, Purpose))
```



Time series features

```
tourism_features <- tourism %>%  
  features(Trips, feature_set(pkgs = "feasts"))
```

All features from the feasts package

```
## # A tibble: 304 x 51  
##   Region State Purpose trend_strength seasonal_streng~ seasonal_peak_y~ seasonal_trough~  
##   <chr>   <chr> <chr>         <dbl>         <dbl>         <dbl>         <dbl>  
## 1 Adelai~ SA     Busine~      0.464         0.407           3           1  
## 2 Adelai~ SA     Holiday    0.554         0.619           1           2  
## 3 Adelai~ SA     Other      0.746         0.202           2           1  
## 4 Adelai~ SA     Visiti~    0.435         0.452           1           3  
## 5 Adelai~ SA     Busine~    0.464         0.179           3           0  
## 6 Adelai~ SA     Holiday    0.528         0.296           2           1  
## 7 Adelai~ SA     Other      0.593         0.404           2           2  
## 8 Adelai~ SA     Visiti~    0.488         0.254           0           3  
## 9 Alice ~ NT     Busine~    0.534         0.251           0           1  
## 10 Alice ~ NT     Holiday    0.381         0.832           3           1  
## # ... with 294 more rows, and 44 more variables: spikiness <dbl>, linearity <dbl>,  
## #   curvature <dbl>, stl_e_acf1 <dbl>, stl_e_acf10 <dbl>, acf1 <dbl>, acf10 <dbl>,  
## #   diff1_acf1 <dbl>, diff1_acf10 <dbl>, diff2_acf1 <dbl>, diff2_acf10 <dbl>,  
## #   season_acf1 <dbl>, pacf5 <dbl>, diff1_pacf5 <dbl>, diff2_pacf5 <dbl>,  
## #   season_pacf <dbl>, zero_run_mean <dbl>, nonzero_squared_cv <dbl>,  
## #   zero_start_prop <dbl>, zero_end_prop <dbl>, lambda_guerrero <dbl>, kpss_stat <dbl>,  
## #   kpss_pvalue <dbl>, pp_stat <dbl>, pp_pvalue <dbl>, ndiffs <int>, nsdifs <int>. ...
```

Reduced feature space

```
pcs <- tourism_features %>%  
  select(-State, -Region, -Purpose) %>%  
  prcomp(scale = TRUE) %>%  
  augment(tourism_features)
```

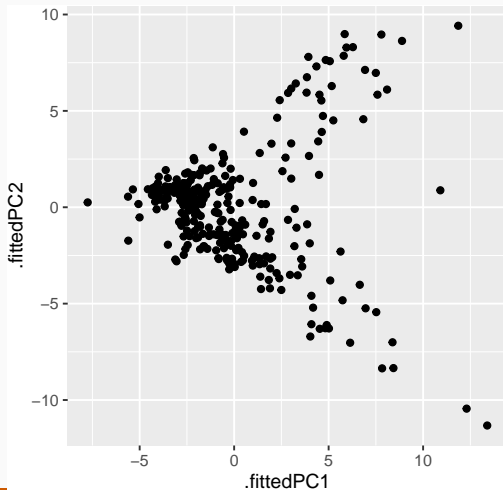
Principal components based on all features from the feasts package

```
## # A tibble: 304 x 100  
##   .rownames Region      State Purpose trend_strength seasonal_streng~ seasonal_peak_y~  
##   <chr>      <chr>      <chr> <chr>      <dbl>          <dbl>          <dbl>  
## 1 1      Adelaide      SA      Busine~      0.464          0.407          3  
## 2 2      Adelaide      SA      Holiday     0.554          0.619          1  
## 3 3      Adelaide      SA      Other       0.746          0.202          2  
## 4 4      Adelaide      SA      Visiti~      0.435          0.452          1  
## 5 5      Adelaide Hills SA      Busine~      0.464          0.179          3  
## 6 6      Adelaide Hills SA      Holiday     0.528          0.296          2  
## 7 7      Adelaide Hills SA      Other       0.593          0.404          2  
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## 9 9      Alice Springs NT      Busine~      0.534          0.251          0  
## 10 10     Alice Springs NT      Holiday     0.381          0.832          3  
## # ... with 294 more rows, and 93 more variables: seasonal_trough_year <dbl>,  
## #   spikiness <dbl>, linearity <dbl>, curvature <dbl>, stl_e_acf1 <dbl>,  
## #   stl_e_acf10 <dbl>, acf1 <dbl>, acf10 <dbl>, diff1_acf1 <dbl>, diff1_acf10 <dbl>,  
## #   diff2_acf1 <dbl>, diff2_acf10 <dbl>, season_acf1 <dbl>, pacf5 <dbl>,  
## #   diff1_pacf5 <dbl>, diff2_pacf5 <dbl>, season_pacf <dbl>, zero_run_mean <dbl>
```

Reduced feature space

```
pcs %>% ggplot(aes(x=.fittedPC1, y=.fittedPC2)) +  
  geom_point() + theme(aspect.ratio=1)
```

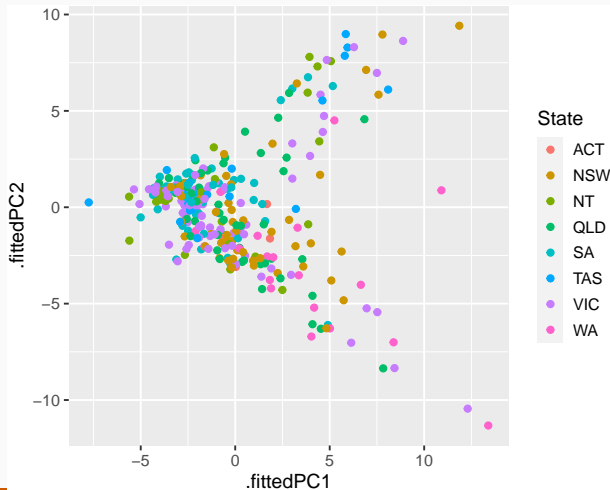
Principal components
based on all features
from the feasts
package



Reduced feature space

```
pcs %>% ggplot(aes(x=.fittedPC1, y=.fittedPC2, col=State)) +  
  geom_point() + theme(aspect.ratio=1)
```

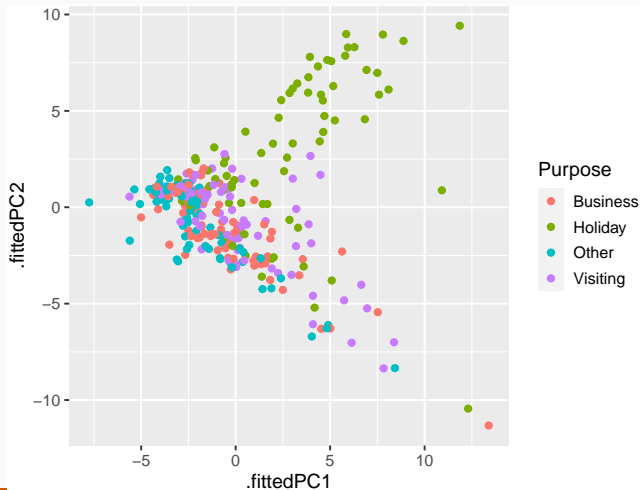
Principal components
based on all features
from the feasts
package



Reduced feature space

```
pcs %>% ggplot(aes(x=.fittedPC1, y=.fittedPC2, col=Purpose)) +  
  geom_point() + theme(aspect.ratio=1)
```

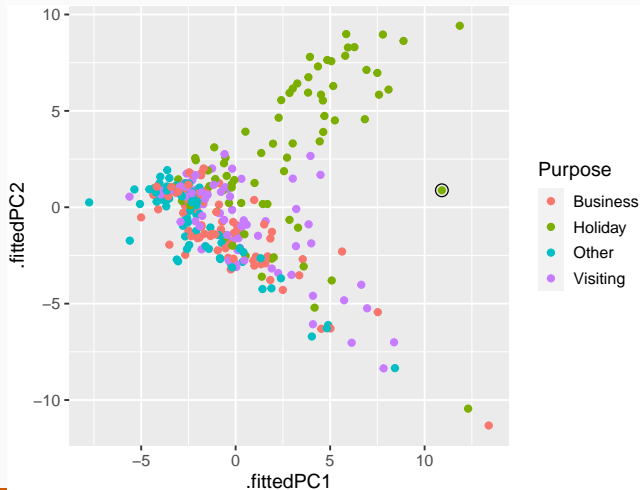
Principal components
based on all features
from the feasts
package



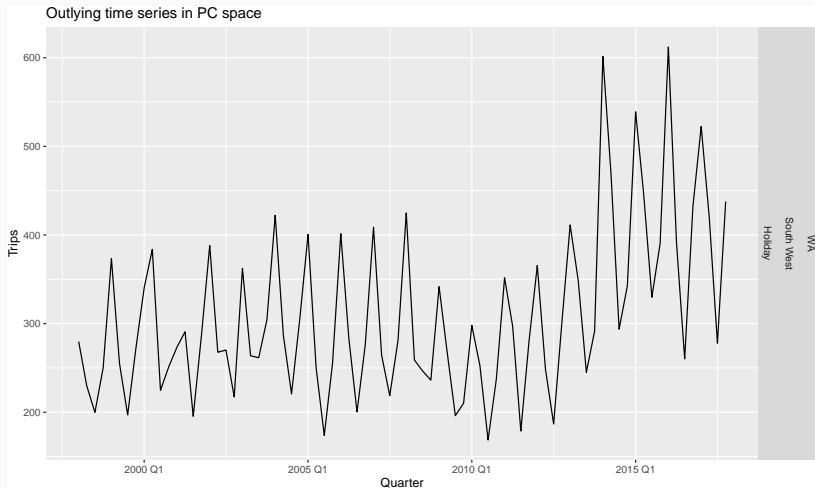
Anomaly detection using time series features

```
pcs %>% ggplot(aes(x=.fittedPC1, y=.fittedPC2, col=Purpose)) +  
  geom_point() + theme(aspect.ratio=1)
```

Principal components
based on all features
from the feasts
package



Anomaly detection using time series features



Outline

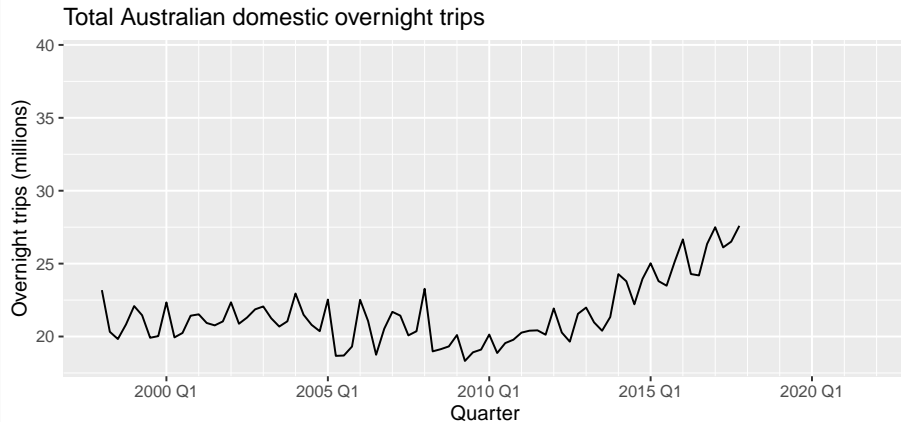
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Random futures

A forecast is an estimate of the probability distribution of a variable to be observed in the future.

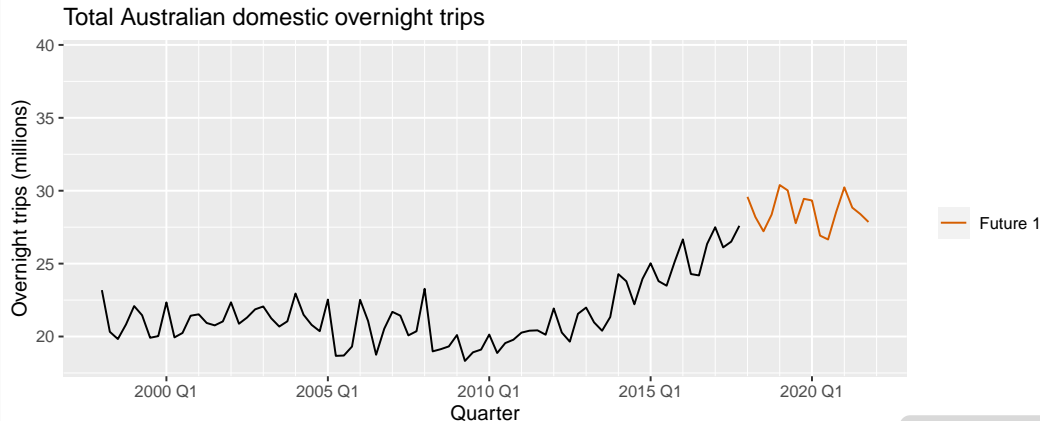
Random futures

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Random futures

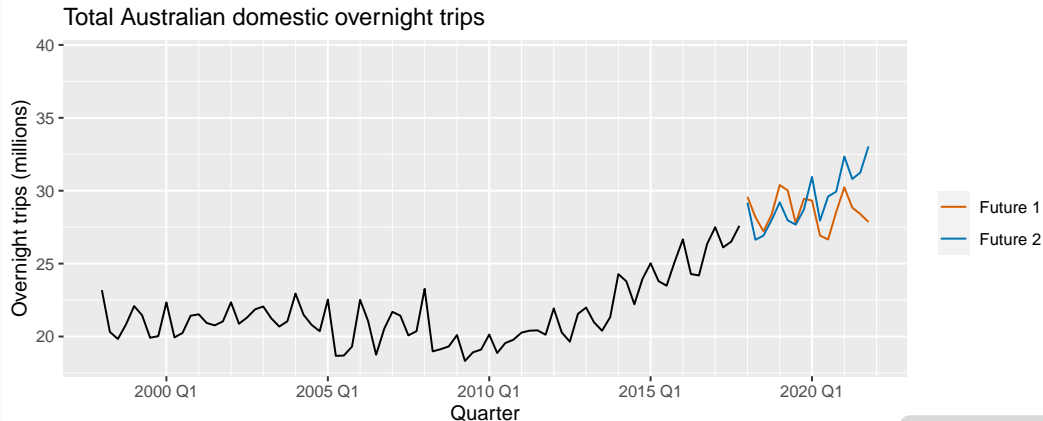
A forecast is an estimate of the probability distribution of a variable to be observed in the future.



Simulated futures
from an ETS model

Random futures

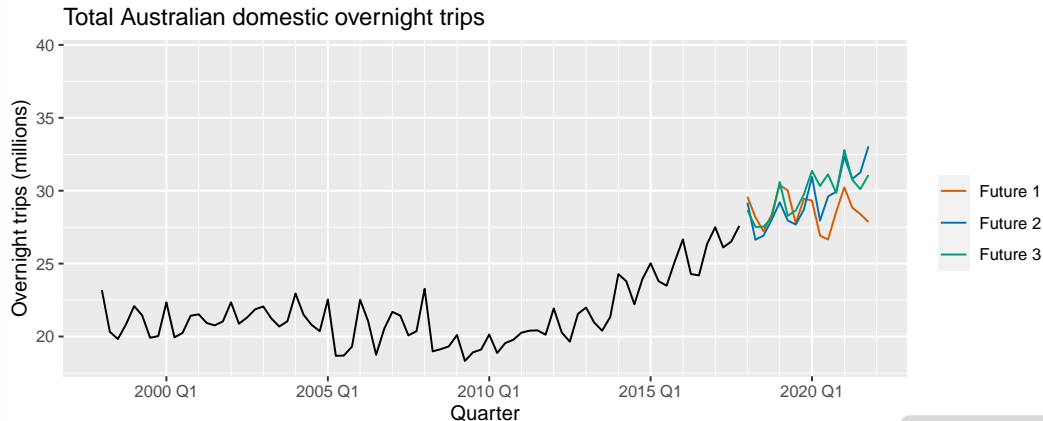
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Simulated futures
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Random futures

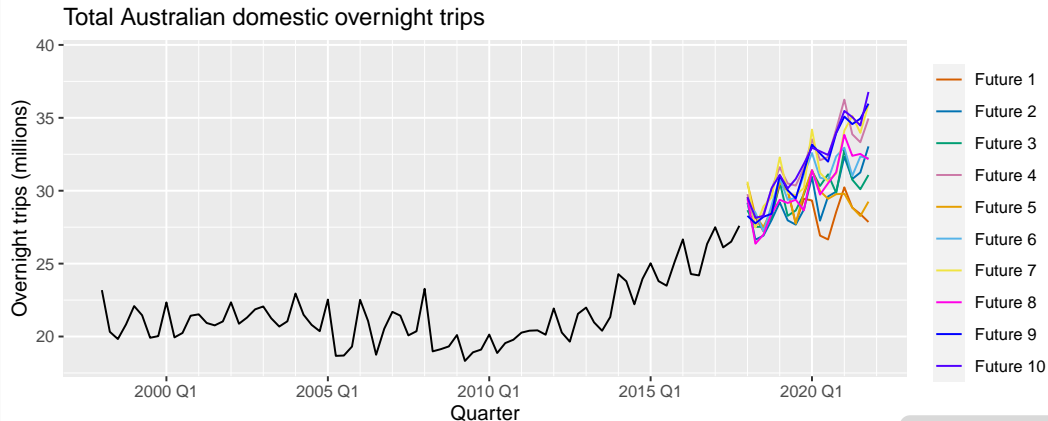
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Random futures

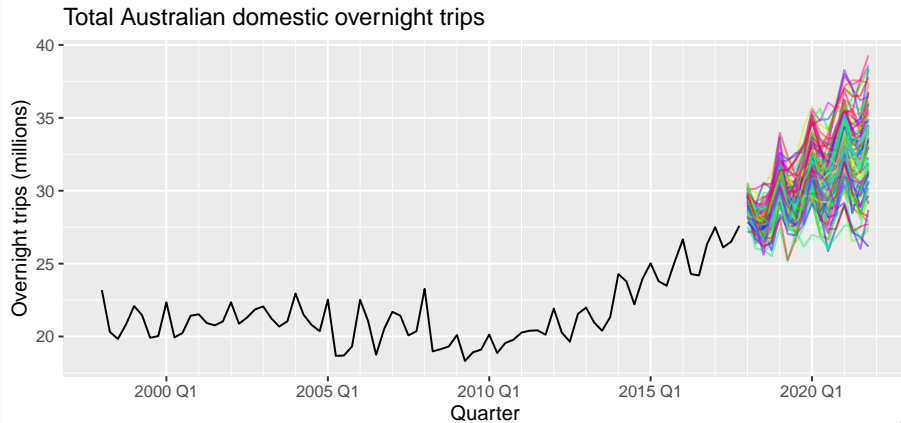
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Simulated futures
from an ETS model

Random futures

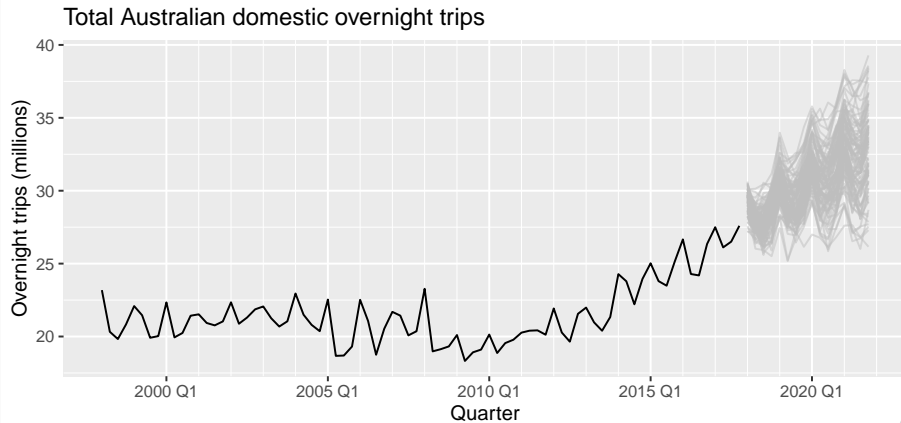
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Simulated futures
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Random futures

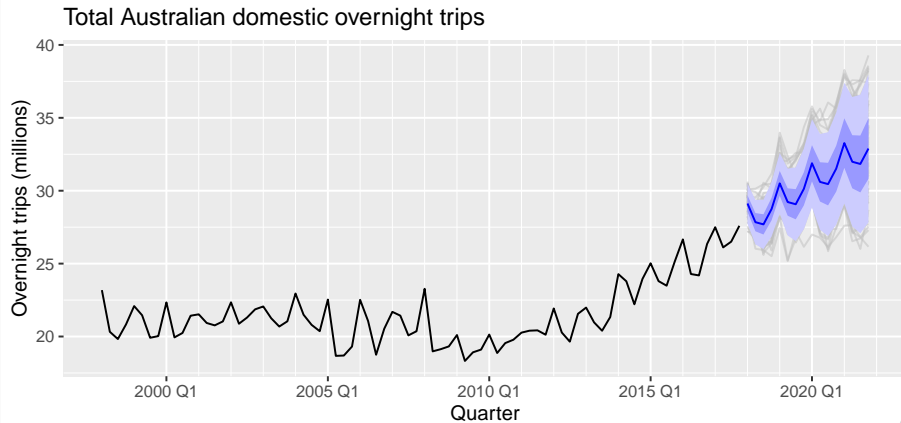
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Random futures

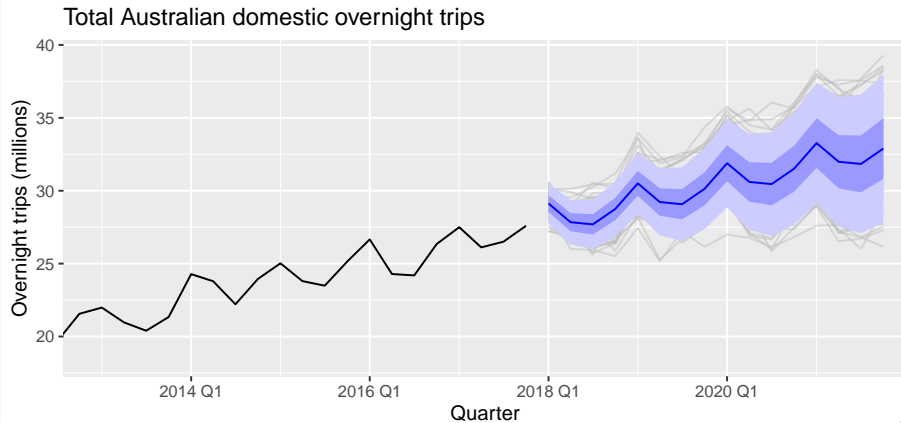
A forecast is an estimate of the probability distribution of a variable to be observed in the future.



Simulated futures
from an ETS model

Random futures

A forecast is an estimate of the probability distribution of a variable to be observed in the future.



Simulated futures
from an ETS model

Model fitting

```
tourism_fit <- tourism %>%
  filter(year(Quarter) <= 2015) %>%
  model(ets = ETS(Trips), arima = ARIMA(Trips)) %>%
  mutate(ensemble = (ets + arima)/2)
```

```
## # A mable: 304 x 6
```

```
## # Key:      Region, State, Purpose [304]
```

##	Region	State	Purpose	ets	arima	ensemble
##	<chr>	<chr>	<chr>	<model>	<model>	<model>
## 1	Adelaide	SA	Busine~	<ETS(M,N,A)>	<ARIMA(0,0,0)(1,0,1)[4] w/ mean>	<COMBINATION>
## 2	Adelaide	SA	Holiday	<ETS(M,N,A)>	<ARIMA(0,0,0)(2,0,0)[4] w/ mean>	<COMBINATION>
## 3	Adelaide	SA	Other	<ETS(M,A,N)>	<ARIMA(0,1,1) w/ drift>	<COMBINATION>
## 4	Adelaide	SA	Visiti~	<ETS(A,N,A)>	<ARIMA(0,0,0)(1,0,1)[4] w/ mean>	<COMBINATION>
## 5	Adelaide Hil~	SA	Busine~	<ETS(A,N,N)>	<ARIMA(0,0,0) w/ mean>	<COMBINATION>
## 6	Adelaide Hil~	SA	Holiday	<ETS(A,A,N)>	<ARIMA(0,0,0) w/ mean>	<COMBINATION>
## 7	Adelaide Hil~	SA	Other	<ETS(A,N,N)>	<ARIMA(2,1,1)(2,0,0)[4]>	<COMBINATION>
## 8	Adelaide Hil~	SA	Visiti~	<ETS(M,A,A)>	<ARIMA(0,1,1)>	<COMBINATION>
## 9	Alice Springs	NT	Busine~	<ETS(A,N,N)>	<ARIMA(0,0,0)(0,0,1)[4] w/ mean>	<COMBINATION>
## 10	Alice Springs	NT	Holiday	<ETS(M,N,A)>	<ARIMA(0,0,0)(0,1,2)[4]>	<COMBINATION>

with 294 more rows

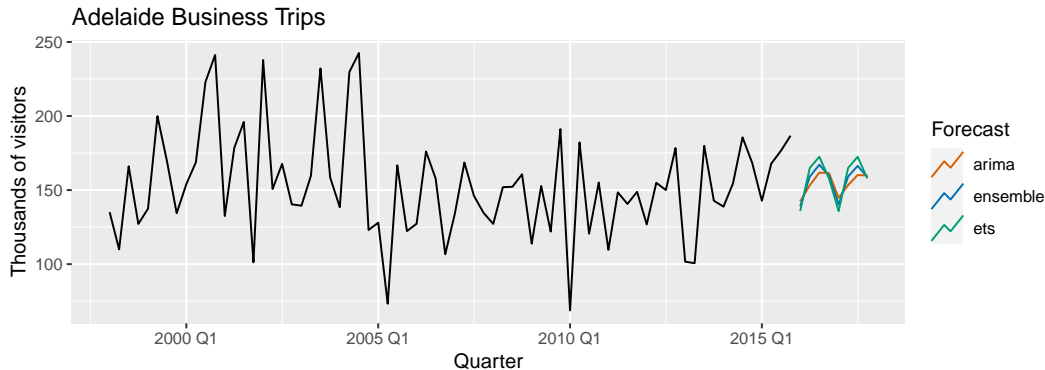
Producing forecasts

```
tourism_fc <- tourism_fit %>%  
  forecast(h = "2 years")
```

```
## # A tibble: 7,296 x 7 [1Q]  
## # Key:      Region, State, Purpose, .model [912]  
##   Region    State Purpose  .model Quarter      Trips .mean  
##   <chr>     <chr> <chr>    <chr>    <qtr>      <dist> <dbl>  
## 1 Adelaide SA      Business ets      2016 Q1  N(136, 902) 136.  
## 2 Adelaide SA      Business ets      2016 Q2  N(165, 1344) 165.  
## 3 Adelaide SA      Business ets      2016 Q3  N(173, 1490) 173.  
## 4 Adelaide SA      Business ets      2016 Q4  N(158, 1277) 158.  
## 5 Adelaide SA      Business ets      2017 Q1  N(136, 979) 136.  
## 6 Adelaide SA      Business ets      2017 Q2  N(165, 1422) 165.  
## 7 Adelaide SA      Business ets      2017 Q3  N(173, 1569) 173.  
## 8 Adelaide SA      Business ets      2017 Q4  N(158, 1356) 158.  
## 9 Adelaide SA      Business arima    2016 Q1  N(142, 1232) 142.  
## 10 Adelaide SA      Business arima    2016 Q2  N(153, 1232) 153.  
## # ... with 7,286 more rows
```

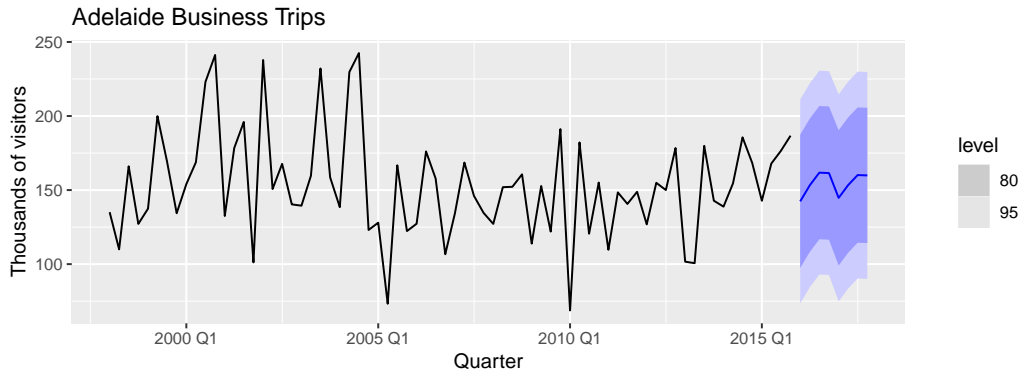
Visualising forecasts

```
tourism_fc %>%  
  filter(Region == "Adelaide", Purpose=="Business") %>%  
  autoplot(tourism, level = NULL) +  
  labs(title = "Adelaide Business Trips", y = "Thousands of visitors") +  
  guides(color = guide_legend(title = "Forecast"))
```



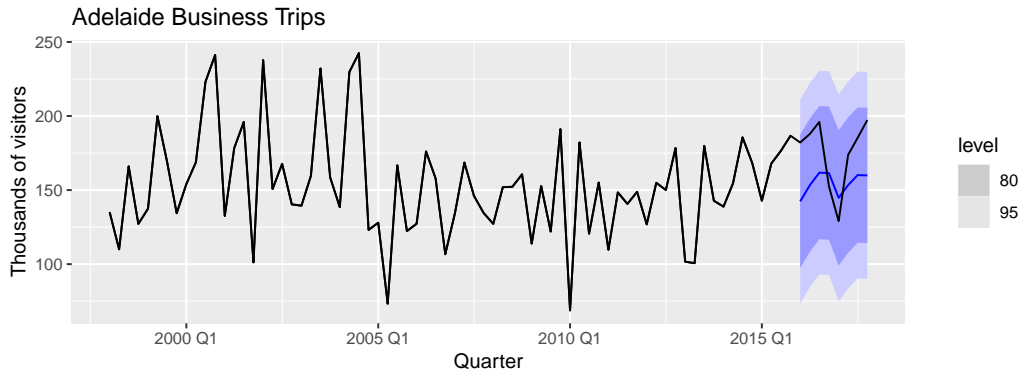
Visualising forecasts

```
tourism_fc %>%  
  filter(Region == "Adelaide", Purpose=="Business", .model == "arima") %>%  
  autoplot(tourism) +  
  labs(title = "Adelaide Business Trips", y = "Thousands of visitors") +  
  guides(color = guide_legend(title = "Forecast"))
```



Visualising forecasts

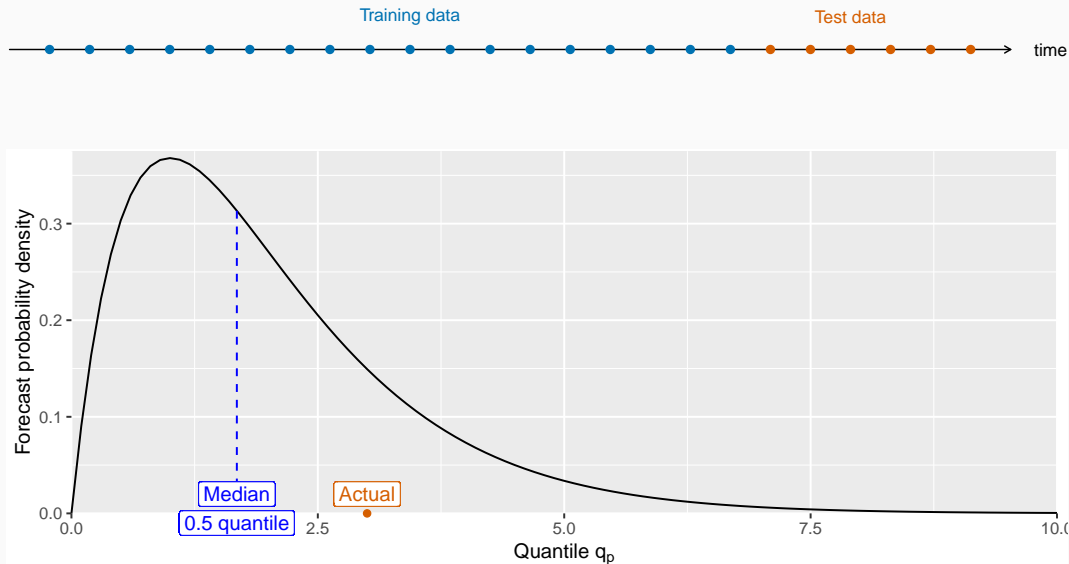
```
tourism_fc %>%  
  filter(Region == "Adelaide", Purpose=="Business", .model == "arima") %>%  
  autoplot(tourism) +  
  labs(title = "Adelaide Business Trips", y = "Thousands of visitors") +  
  guides(color = guide_legend(title = "Forecast"))
```



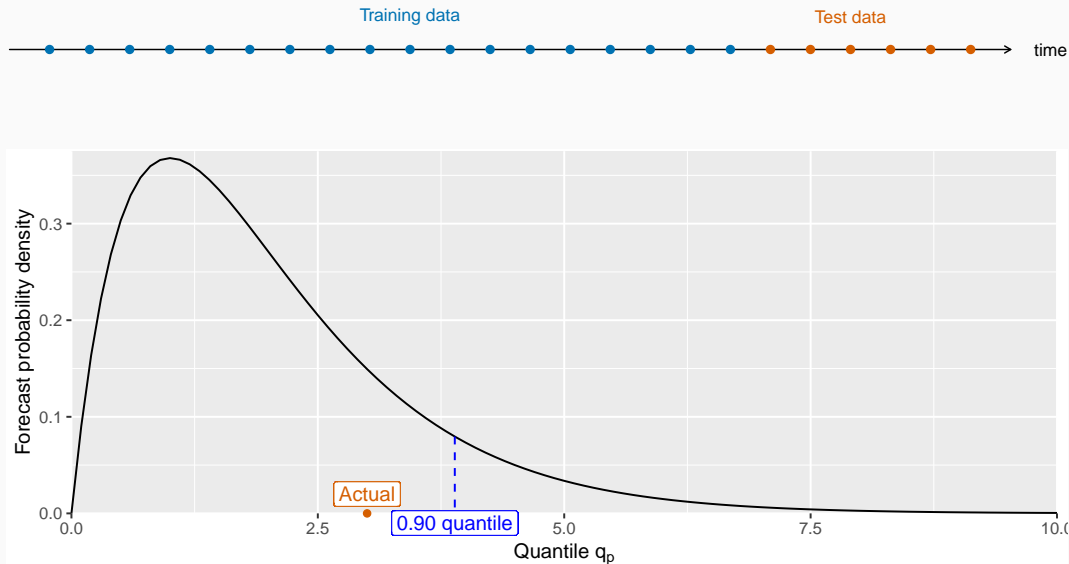
Outline

- 1 What does modern time series data look like?
- 2 Feature-based time series analysis
- 3 Probabilistic forecasting for large time series
- 4 Evaluating probabilistic forecasts

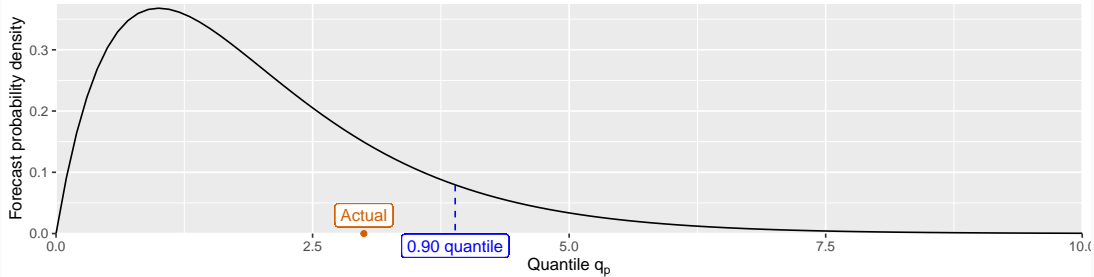
Evaluating probabilistic forecasts



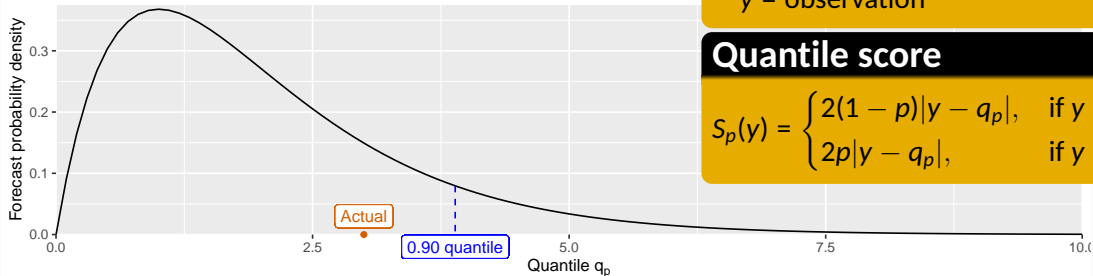
Evaluating probabilistic forecasts



Evaluating probabilistic forecasts



Evaluating probabilistic forecasts



q_p = quantile forecast with prob. p

y = observation

Quantile score

$$S_p(y) = \begin{cases} 2(1-p)|y - q_p|, & \text{if } y < q_p \\ 2p|y - q_p|, & \text{if } y \geq q_p \end{cases}$$

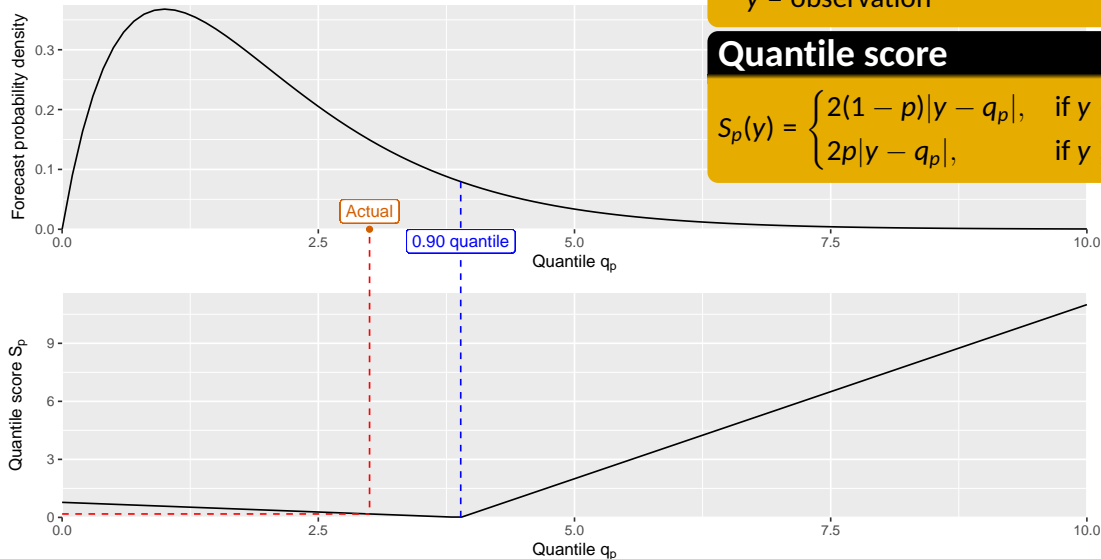
Evaluating probabilistic forecasts

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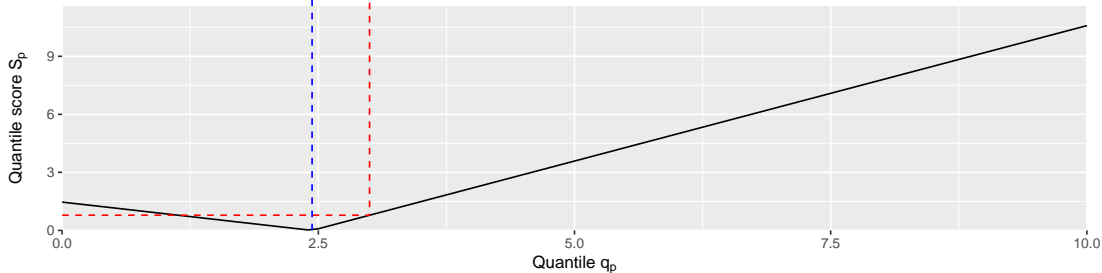
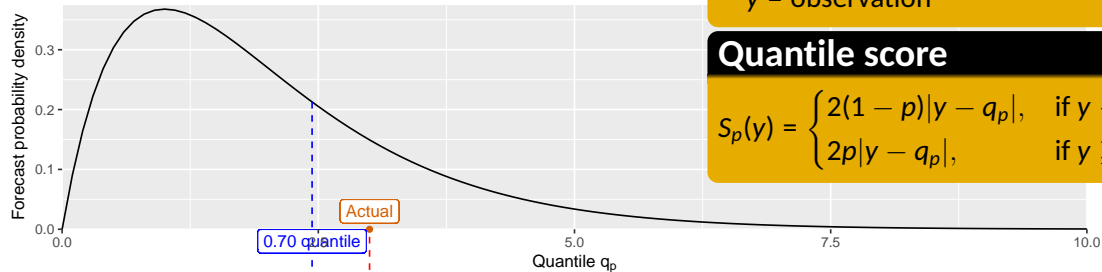
Evaluating probabilistic forecasts

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$$S_p(y) = \begin{cases} 2(1-p)|y - q_p|, & \text{if } y < q_p \\ 2p|y - q_p|, & \text{if } y \geq q_p \end{cases}$$



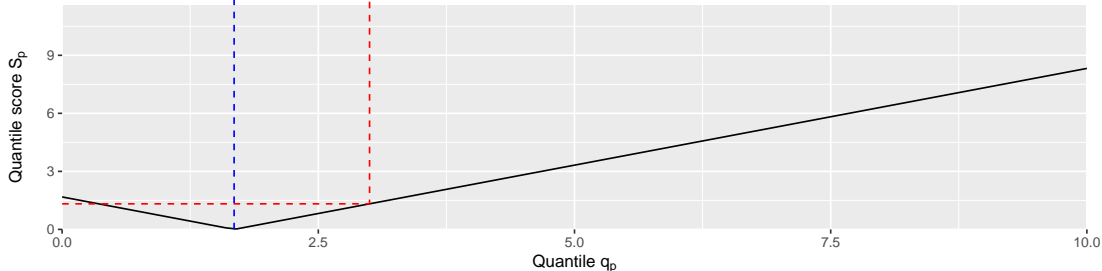
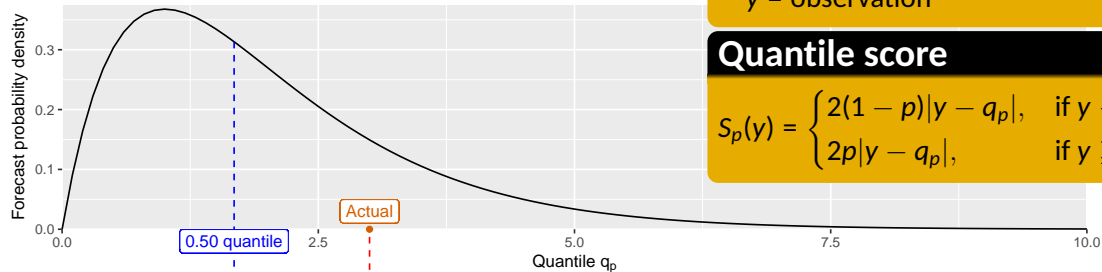
Evaluating probabilistic forecasts

q_p = quantile forecast with prob. p

y = observation

Quantile score

$$S_p(y) = \begin{cases} 2(1-p)|y - q_p|, & \text{if } y < q_p \\ 2p|y - q_p|, & \text{if } y \geq q_p \end{cases}$$

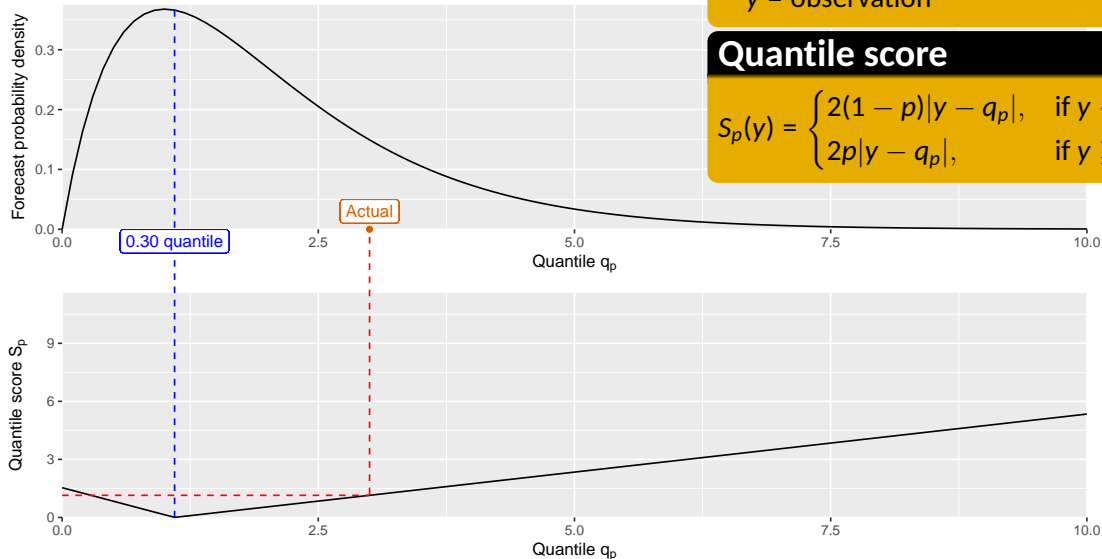


Evaluating probabilistic forecasts

q_p = quantile forecast with prob. p
 y = observation

Quantile score

$$S_p(y) = \begin{cases} 2(1-p)|y - q_p|, & \text{if } y < q_p \\ 2p|y - q_p|, & \text{if } y \geq q_p \end{cases}$$



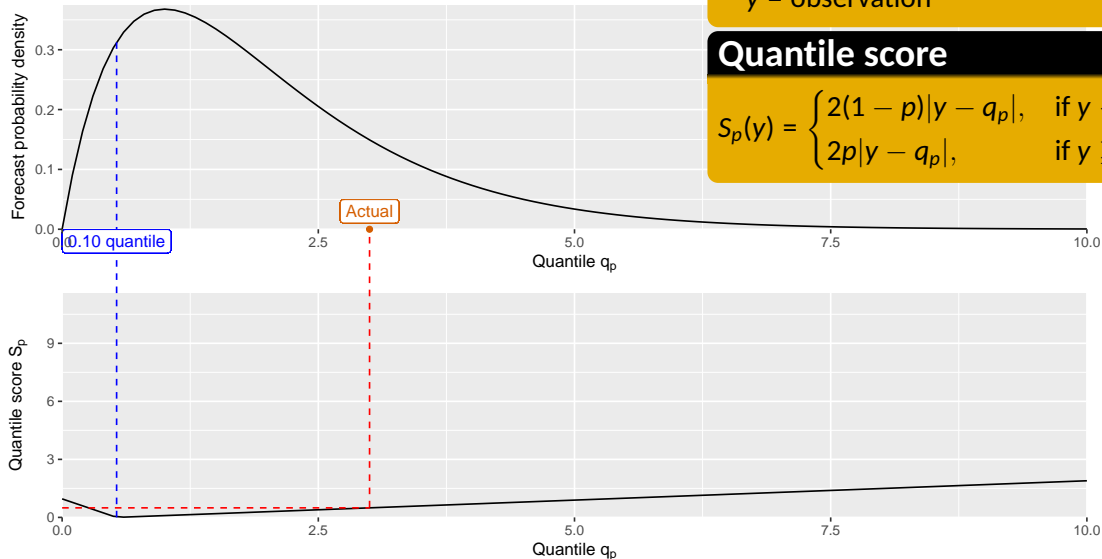
Evaluating probabilistic forecasts

q_p = quantile forecast with prob. p

y = observation

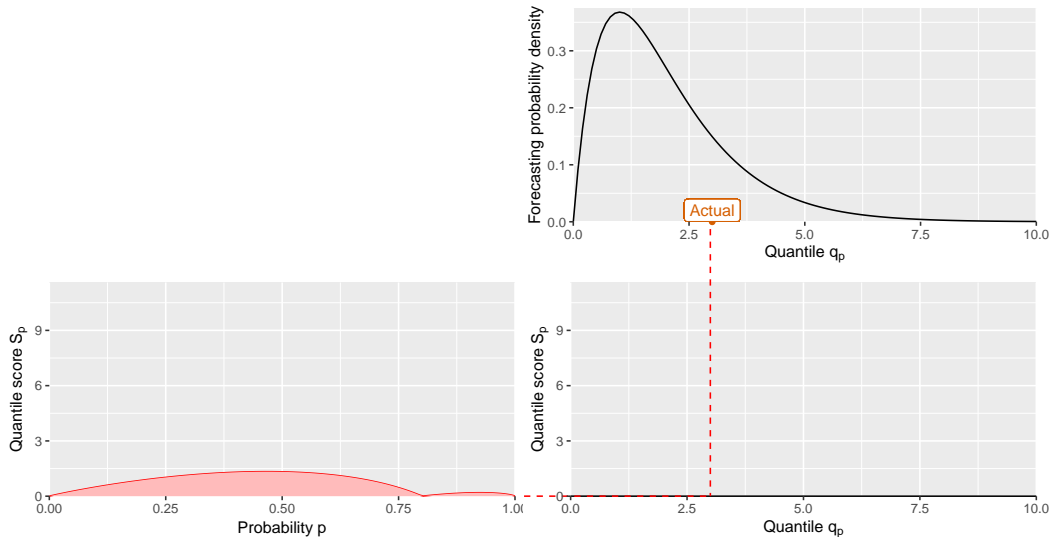
Quantile score

$$S_p(y) = \begin{cases} 2(1-p)|y - q_p|, & \text{if } y < q_p \\ 2p|y - q_p|, & \text{if } y \geq q_p \end{cases}$$

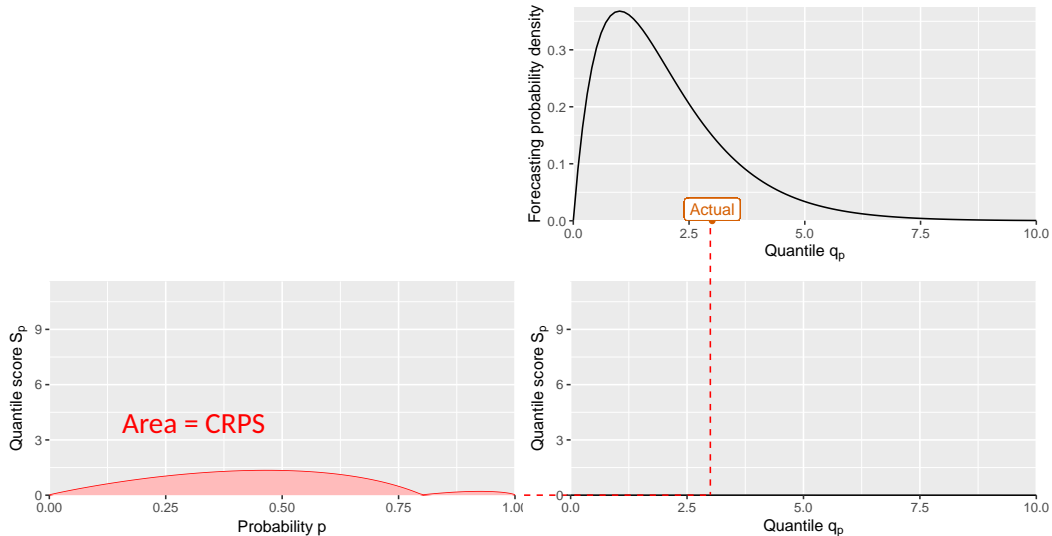


Evaluating probabilistic forecasts

Evaluating probabilistic forecasts



Evaluating probabilistic forecasts



Evaluating probabilistic forecasts

```
tourism_fc %>%  
  accuracy(tourism, measures = list(MSE=MSE, CRPS=CRPS))
```

```
## # A tibble: 912 x 7
```

```
##   .model Region      State Purpose .type      MSE      CRPS  
##   <chr>  <chr>      <chr> <chr>  <chr>   <dbl>   <dbl>  
## 1 arima  Adelaide      SA    Business Test    840.    17.1  
## 2 arima  Adelaide      SA    Holiday  Test    968.    18.1  
## 3 arima  Adelaide      SA    Other    Test    188.     7.95  
## 4 arima  Adelaide      SA    Visiting Test   1302.    21.4  
## 5 arima  Adelaide Hills SA    Business Test     21.7    2.39  
## 6 arima  Adelaide Hills SA    Holiday  Test     52.4    4.18  
## 7 arima  Adelaide Hills SA    Other    Test      2.31   0.893  
## 8 arima  Adelaide Hills SA    Visiting Test    144.     7.08  
## 9 arima  Alice Springs NT    Business Test    150.     7.78  
## 10 arima Alice Springs NT    Holiday  Test     93.2    5.59  
## # ... with 902 more rows
```

Evaluating probabilistic forecasts

```
tourism_fc %>%  
  accuracy(tourism, measures = list(SS_MSE=skill_score(MSE), SS_CRPS=skill_score(CRPS)))
```

```
## # A tibble: 912 x 7  
##   .model Region      State Purpose .type SS_MSE SS_CRPS  
##   <chr>   <chr>      <chr> <chr>   <chr>  <dbl>   <dbl>  
## 1 arima  Adelaide      SA     Business Test  -0.719 -0.00789  
## 2 arima  Adelaide      SA     Holiday  Test   0.394  0.212  
## 3 arima  Adelaide      SA     Other    Test   0.787  0.578  
## 4 arima  Adelaide      SA     Visiting Test  -1.01  -0.354  
## 5 arima  Adelaide Hills SA     Business Test   0.693  0.508  
## 6 arima  Adelaide Hills SA     Holiday  Test  -0.568 -0.136  
## 7 arima  Adelaide Hills SA     Other    Test   0.834  0.565  
## 8 arima  Adelaide Hills SA     Visiting Test   0.120  0.0788  
## 9 arima  Alice Springs NT      Business Test  -1.43  -0.696  
## 10 arima Alice Springs NT      Holiday  Test   0.468  0.186  
## # ... with 902 more rows
```

Evaluating probabilistic forecasts

```
tourism_fc %>%  
  accuracy(tourism, measures = list(SS_MSE=skill_score(MSE), SS_CRPS=skill_score(CRPS))) %>%  
  group_by(.model) %>%  
  summarise(SS_MSE = mean(SS_MSE), SS_CRPS=mean(SS_CRPS)) %>%  
  arrange(desc(SS_CRPS))
```

```
## # A tibble: 3 x 3  
##   .model  SS_MSE SS_CRPS  
##   <chr>    <dbl>  <dbl>  
## 1 ets      0.155    0.138  
## 2 ensemble 0.141    0.138  
## 3 arima    0.0636   0.0999
```


Tidyverts developers

Earo Wang



Mitchell O'Hara-Wild



More information

- Slides and papers: **robjhyndman.com**
- Packages: **tidyverts.org**
- Forecasting textbook using tidyverts package:
OTexts.com/fpp3

Find me at ...



@robjhyndman



@robjhyndman



robjhyndman.com



rob.hyndman@monash.edu