Time Series Analysis & Forecasting Using R

5. Time series features

bit.ly/fable2023

tsibble
feasts
Fable

Outline

Outline

Strength of seasonality and trend

STL decomposition

$$y_t = T_t + S_t + R_t$$

Seasonal strength

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

Trend strength

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

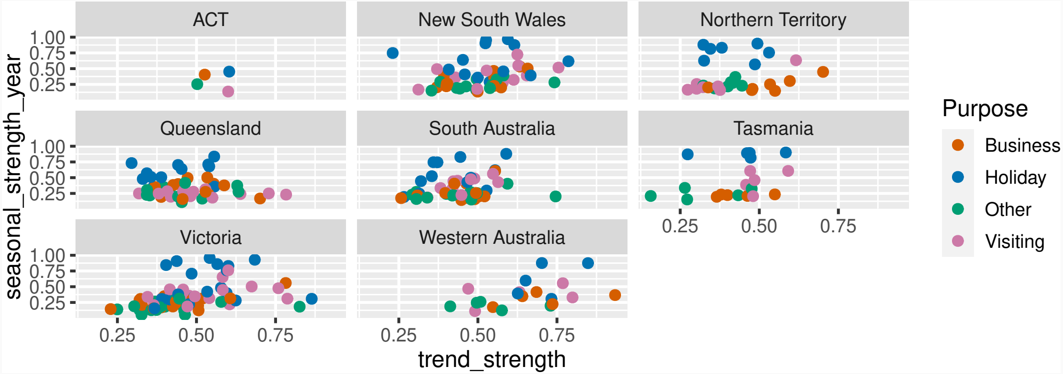
Feature extraction and statistics

```r
tourism |> features(Trips, feat_stl)
```

```
# A tibble: 304 x 12
   Region          State          Purpose trend_strength seasonal_strength_year
   <chr>           <chr>          <chr>            <dbl>                  <dbl>
 1 Adelaide        South Aust~ Busine~          0.464                  0.407
 2 Adelaide        South Aust~ Holiday          0.554                  0.619
 3 Adelaide        South Aust~ Other            0.746                  0.202
 4 Adelaide        South Aust~ Visiti~          0.435                  0.452
 5 Adelaide Hills South Aust~ Busine~          0.464                  0.179
 6 Adelaide Hills South Aust~ Holiday          0.528                  0.296
 7 Adelaide Hills South Aust~ Other            0.593                  0.404
 8 Adelaide Hills South Aust~ Visiti~          0.488                  0.254
 9 Alice Springs  Northern T~ Busine~          0.534                  0.251
10 Alice Springs  Northern T~ Holiday          0.381                  0.832
# i 294 more rows
# i 7 more variables: seasonal_peak_year <dbl>,
#   seasonal_trough_year <dbl>, spikiness <dbl>, linearity <dbl>,
#   curvature <dbl>, stl_e_acf1 <dbl>, stl_e_acf10 <dbl>
```

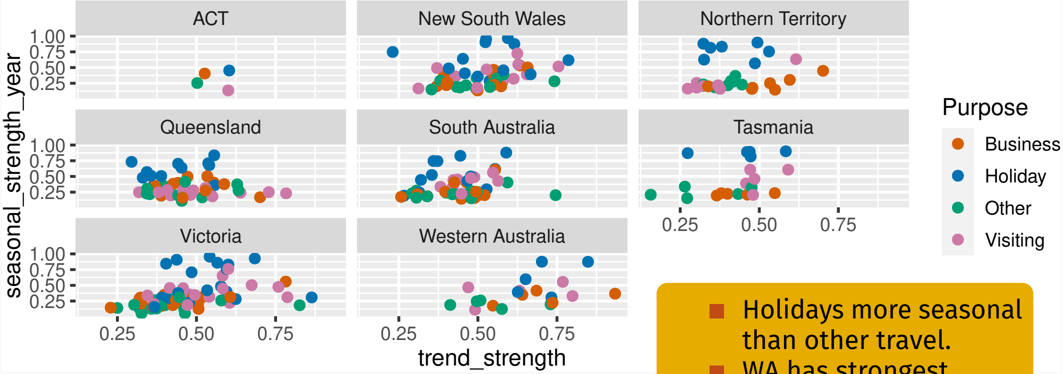
Feature extraction and statistics

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



Feature extraction and statistics

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



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

Feature extraction and statistics

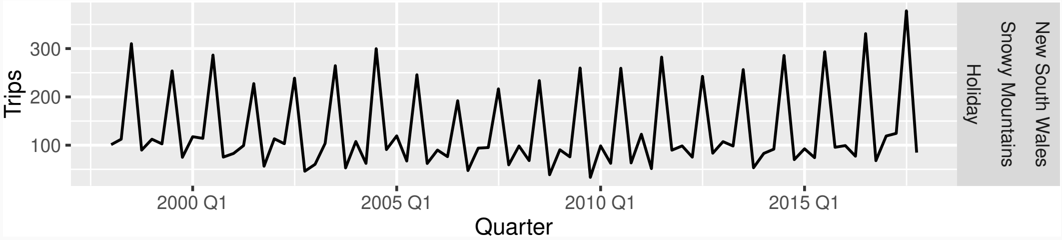
Find the most seasonal time series:

```
most_seasonal <- tourism |>
  features(Trips, feat_stl) |>
  filter(seasonal_strength_year == max(seasonal_strength_year))
```

Feature extraction and statistics

Find the most seasonal time series:

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



Feature extraction and statistics

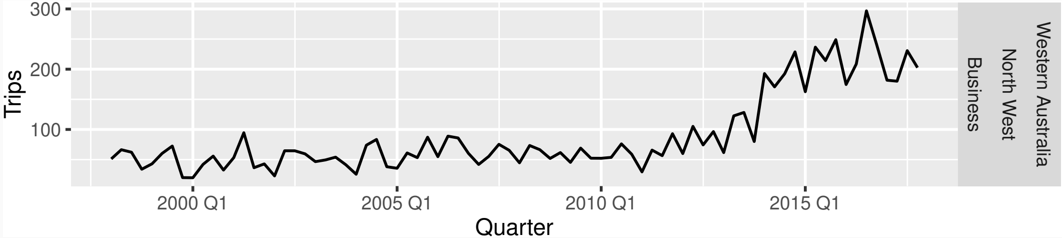
Find the most trended time series:

```r
most_trended <- tourism |>
  features(Trips, feat_stl) |>
  filter(trend_strength == max(trend_strength))
```

Feature extraction and statistics

Find the most trended time series:

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



Outline

Lab Session 9

- Use `GGally::ggpairs()` to look at the relationships between the STL-based features. You might wish to change `seasonal_peak_year` and `seasonal_trough_year` to factors.
- Which is the peak quarter for holidays in each state?

Feature extraction and statistics

```r
tourism |> features(Trips, feat_acf)
```

```
# A tibble: 304 x 10
   Region     State Purpose     acf1 acf10 diff1_acf1 diff1_acf10 diff2_acf1
   <chr>      <chr> <chr>      <dbl> <dbl>      <dbl>       <dbl>      <dbl>
 1 Adelaide   Sout~ Busine~  0.0333  0.131     -0.520       0.463     -0.676
 2 Adelaide   Sout~ Holiday  0.0456  0.372     -0.343       0.614     -0.487
 3 Adelaide   Sout~ Other    0.517   1.15      -0.409       0.383     -0.675
 4 Adelaide   Sout~ Visiti~  0.0684  0.294     -0.394       0.452     -0.518
 5 Adelaide~  Sout~ Busine~  0.0709  0.134     -0.580       0.415     -0.750
 6 Adelaide~  Sout~ Holiday  0.131   0.313     -0.536       0.500     -0.716
 7 Adelaide~  Sout~ Other    0.261   0.330     -0.253       0.317     -0.457
 8 Adelaide~  Sout~ Visiti~  0.139   0.117     -0.472       0.239     -0.626
 9 Alice Sp~  Nort~ Busine~  0.217   0.367     -0.500       0.381     -0.658
10 Alice Sp~  Nort~ Holiday -0.00660 2.11      -0.153       2.11      -0.274
# i 294 more rows
# i 2 more variables: diff2_acf10 <dbl>, season_acf1 <dbl>
```

Outline

Feature extraction and statistics

```r
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_strength_year
   <chr>          <chr>        <chr>            <dbl>                  <dbl>
 1 Adelaide       South Aust~ Busine~          0.464                  0.407
 2 Adelaide       South Aust~ Holiday          0.554                  0.619
 3 Adelaide       South Aust~ Other            0.746                  0.202
 4 Adelaide       South Aust~ Visiti~          0.435                  0.452
 5 Adelaide Hills South Aust~ Busine~          0.464                  0.179
 6 Adelaide Hills South Aust~ Holiday          0.528                  0.296
 7 Adelaide Hills South Aust~ Other            0.593                  0.404
 8 Adelaide Hills South Aust~ Visiti~          0.488                  0.254
 9 Alice Springs  Northern T~ Busine~          0.534                  0.251
10 Alice Springs  Northern T~ Holiday          0.381                  0.832
# i 294 more rows
# i 46 more variables: seasonal_peak_year <dbl>,
#   seasonal_trough_year <dbl>, spikiness <dbl>, linearity <dbl>,
#   curvature <dbl>, stl_e_acf1 <dbl>, stl_e_acf10 <dbl>, acf1 <dbl>,
```

Feature extraction and statistics

```r
pcs <- tourism_features |>
  select(-State, -Region, -Purpose) |>
  prcomp(scale = TRUE) |>
  broom::augment(tourism_features)
```

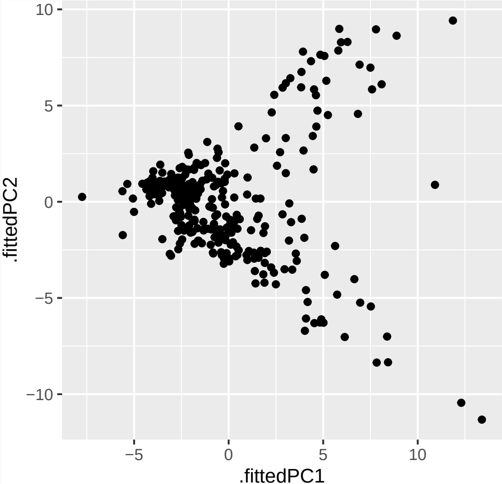
Principal components based on all features from the feasts package

```
# A tibble: 304 x 100
   .rownames Region     State Purpose trend_strength seasonal_strength_year
   <chr>     <chr>      <chr> <chr>            <dbl>                  <dbl>
 1 1         Adelaide   Sout~ Busine~          0.464                  0.407
 2 2         Adelaide   Sout~ Holiday          0.554                  0.619
 3 3         Adelaide   Sout~ Other            0.746                  0.202
 4 4         Adelaide   Sout~ Visiti~          0.435                  0.452
 5 5         Adelaide ~ Sout~ Busine~          0.464                  0.179
 6 6         Adelaide ~ Sout~ Holiday          0.528                  0.296
 7 7         Adelaide ~ Sout~ Other            0.593                  0.404
 8 8         Adelaide ~ Sout~ Visiti~          0.488                  0.254
 9 9         Alice Spr~ Nort~ Busine~          0.534                  0.251
10 10        Alice Spr~ Nort~ Holiday          0.381                  0.832
# i 294 more rows
# i 94 more variables: seasonal_peak_year <dbl>,
```

Feature extraction and statistics

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

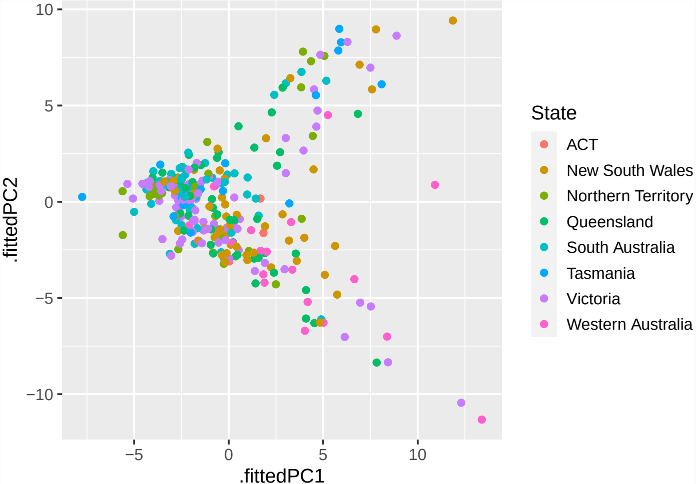
Principal components based on all features from the feasts package



Feature extraction and statistics

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

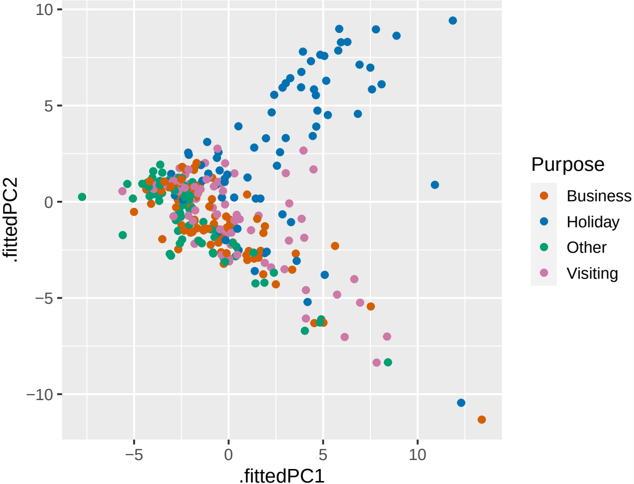
Principal components based on all features from the feasts package



Feature extraction and statistics

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

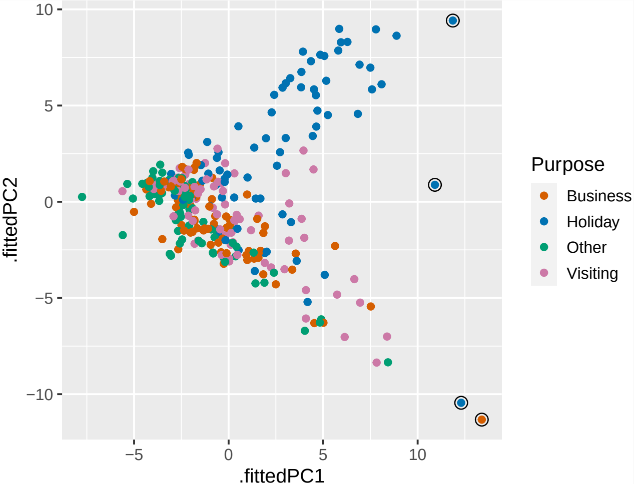
Principal components based on all features from the feasts package



Feature extraction and statistics

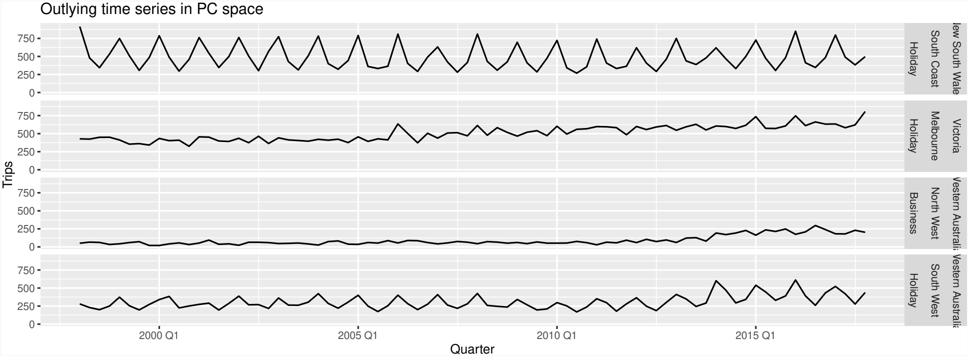
```r
pcs |> ggplot(aes(x=.fittedPC1, y=.fittedPC2, col=Purpose)) +
  geom_point() + theme(aspect.ratio=1)
```

Principal components based on all features from the feasts package



Feature extraction and statistics

```
outliers |>
  left_join(tourism, by = c("State", "Region", "Purpose")) |>
  mutate(Series = glue("{State}", "{Region}", "{Purpose}", .sep = "\n\n")) |>
  ggplot(aes(x = Quarter, y = Trips)) +
  geom_line() + facet_grid(Series ~ .) +
  labs(title = "Outlying time series in PC space")
```



Outline

Lab Session 10

- Use a feature-based approach to look for outlying series in PBS.
- What is unusual about the series you identify as outliers?