workshop.nectric.com.au/tidyfc2024

Time Series Analysis & Forecasting Using R

5. Time series features

tsibble

feasts

Fable

Outline

Outline

Notice: Material planned to change

This material is planned to be updated to better align with the training needs of the Department of Education.

In particular, this section will be removed to make time for:

- econometric concepts
- multivariate models.

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)
```

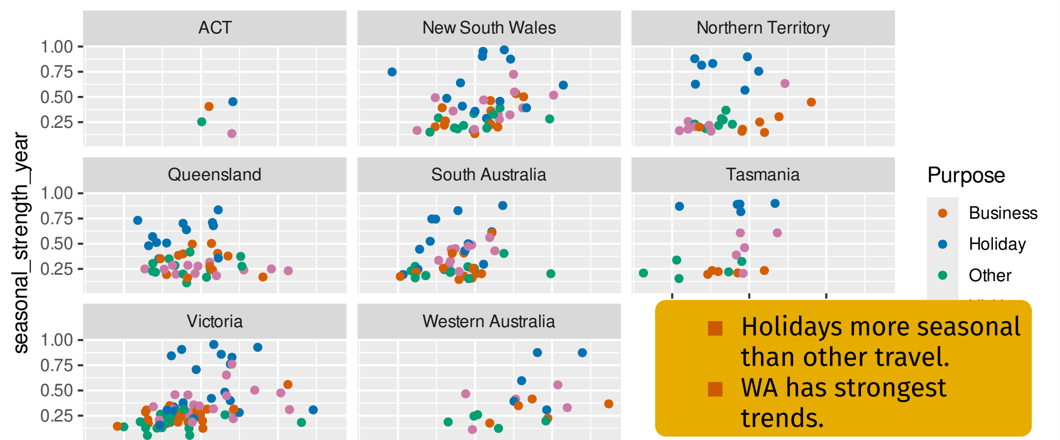
```
# A tibble: 304 x 12
   Region         State        Purpose trend_strength seasonal_strength_year
   <chr>          <chr>        <chr>            <dbl>                  <dbl>
 1 Adelaide       South Aust~ Busine~           0.464                  0.407
 2 Adelaide       South Aust~ Holiday           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

```r
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

```r
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

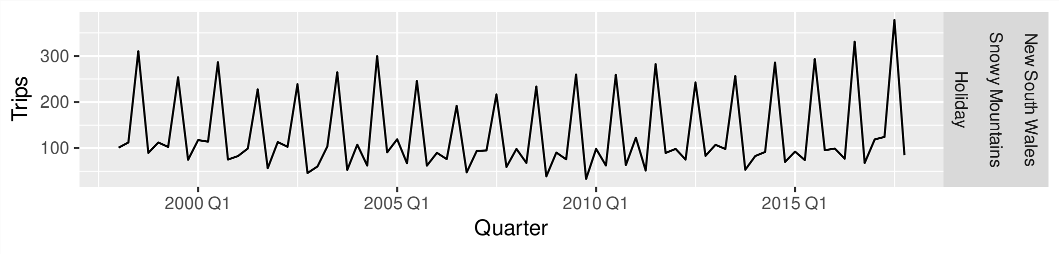
Find the most seasonal time series:

```
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:

```r
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

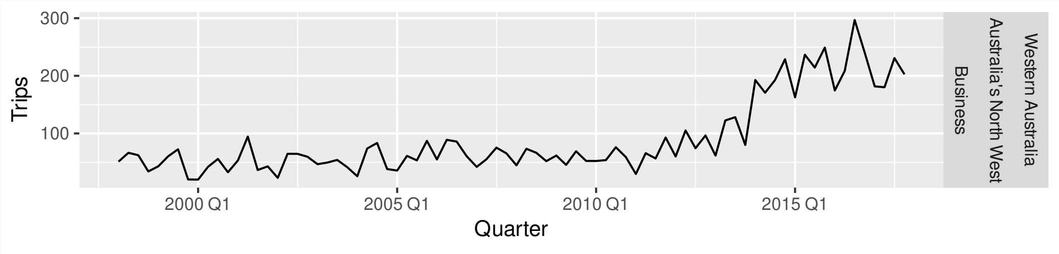
Find the most trended time series:

```
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

All features from the feasts package

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

```
# 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>,
#   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>, ...
```

Feature extraction and statistics

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

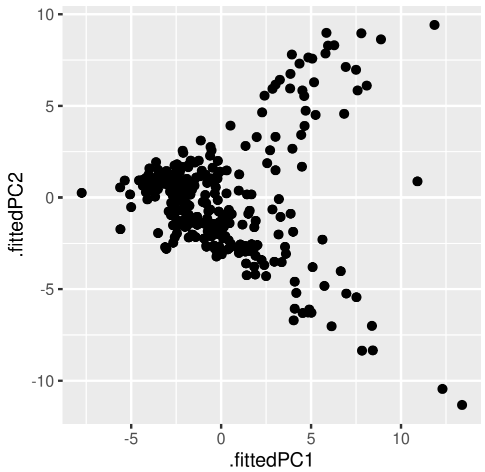
Principal components based on all features from the feasts package

```
# 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>,
#   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>,
```

Feature extraction and statistics

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

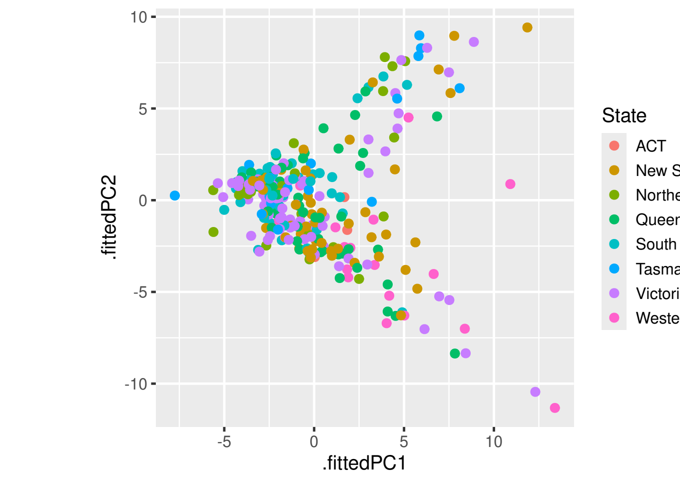
Principal components based on all features from the feasts package



Feature extraction and statistics

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

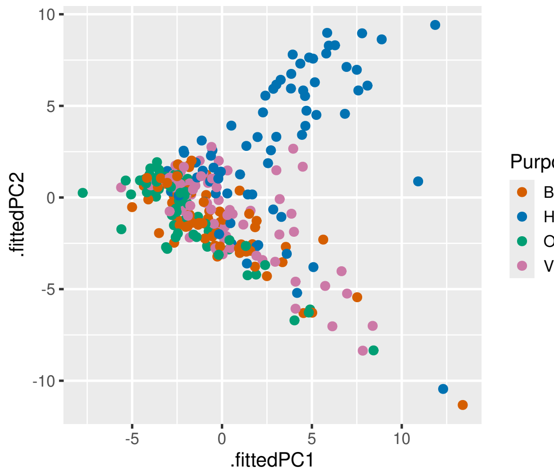
Principal components based on all features from the feasts package



Feature extraction and statistics

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

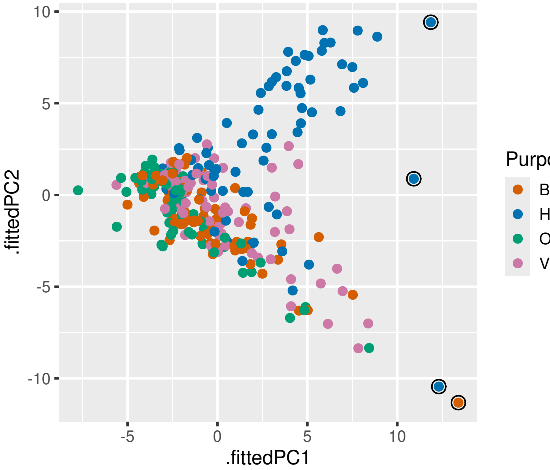
Principal components based on all features from the feasts package



Feature extraction and statistics

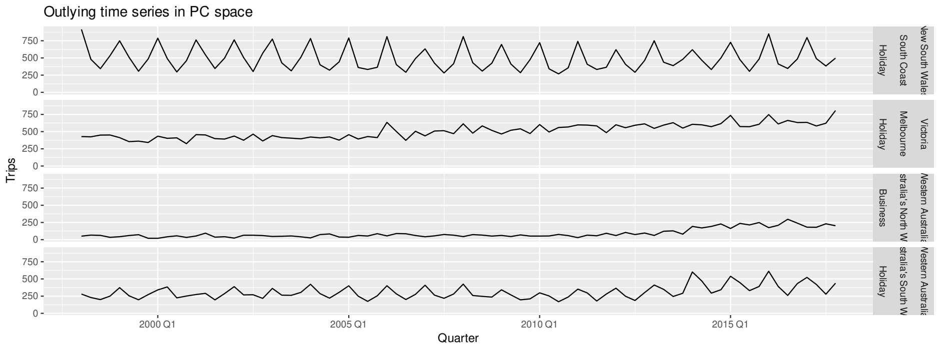
```
pcs |> ggplot(aes(x=.fittedPC1, y=.fittedPC2, col=Purpose)) +
  geom_point() + theme(aspect.ratio=1)
```

Principal components based on all features from the feasts package



Feature extraction and statistics

```r
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?