
bit.ly/etsa2022
Exploratory time series analysis using R
3. Time series features

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

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

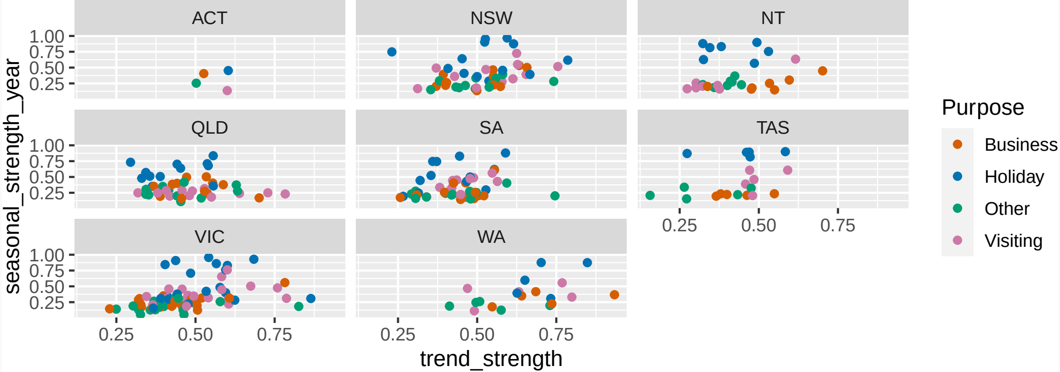
Feature extraction and statistics

```
tourism ▷ features(Trips, feat_stl)
```

```
## # A tibble: 304 x 12
##    Region         State Purpose trend~1 seaso~2 seaso~3 seaso~4 spiki~5 linea~6 curva~7
##    <chr>          <chr> <chr>     <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>
##  1 Adelaide       SA    Busine~   0.464   0.407       3       1 1.58e+2  -5.31   71.6
##  2 Adelaide       SA    Holiday   0.554   0.619       1       2 9.17e+0  49.0    78.7
##  3 Adelaide       SA    Other     0.746   0.202       2       1 2.10e+0  95.1    43.4
##  4 Adelaide       SA    Visiti~   0.435   0.452       1       3 5.61e+1  34.6    71.4
##  5 Adelaide Hi~ SA    Busine~   0.464   0.179       3       0 1.03e-1   0.968  -3.22
##  6 Adelaide Hi~ SA    Holiday   0.528   0.296       2       1 1.77e-1  10.5    24.0
##  7 Adelaide Hi~ SA    Other     0.593   0.404       2       2 4.44e-4   4.28    3.19
##  8 Adelaide Hi~ SA    Visiti~   0.488   0.254       0       3 6.50e+0  34.2    -0.529
##  9 Alice Sprin~ NT    Busine~   0.534   0.251       0       1 1.69e-1  23.8    19.5
## 10 Alice Sprin~ NT    Holiday   0.381   0.832       3       1 7.39e-1 -19.6    10.5
## # … with 294 more rows, 2 more variables: stl_e_acf1 <dbl>, stl_e_acf10 <dbl>, and
## #   abbreviated variable names 1: trend_strength, 2: seasonal_strength_year,
## #   3: seasonal_peak_year, 4: seasonal_trough_year, 5: spikiness, 6: linearity,
```

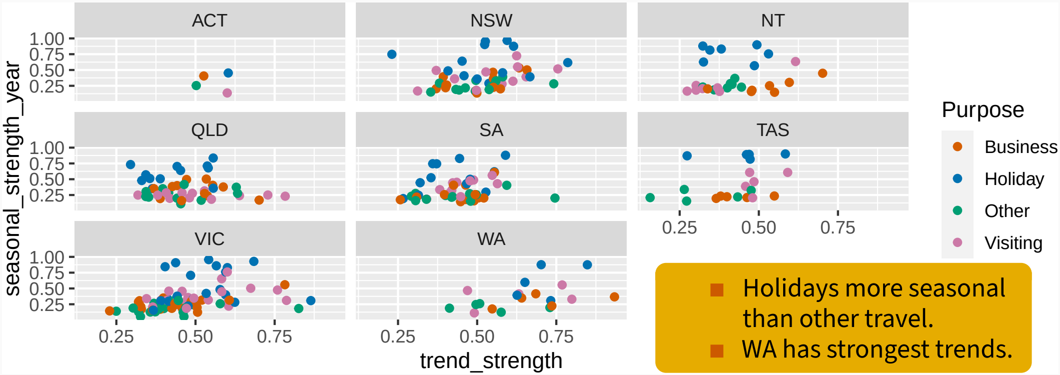
Feature extraction and statistics

```
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:

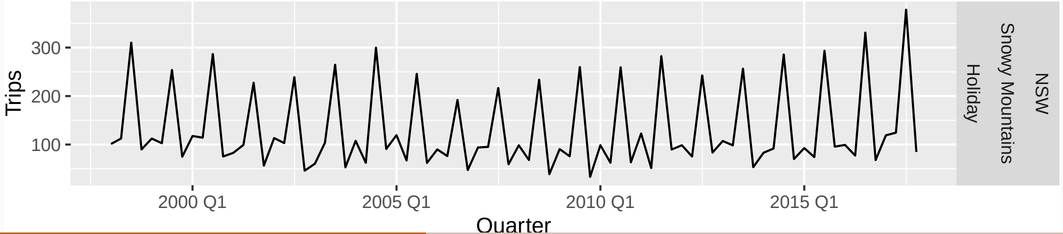
```
most_seasonal <- tourism |>
  features(Trips, feat_stl) |>
  filter(seasonal_strength_year == max(seasonal_strength_year))
```

Feature extraction and statistics

Find the most seasonal time series:

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

```r
tourism |>
  right_join(most_seasonal, by = c("State", "Region", "Purpose")) |>
  ggplot(aes(x = Quarter, y = Trips)) +
  geom_line() + facet_grid(vars(State, Region, Purpose))
```



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~1 seaso~2 seaso~3 seaso~4 spiki~5 linea~6 curva~7
##    <chr>          <chr> <chr>     <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>
##  1 Adelaide       SA    Busine~   0.464   0.407       3       1 1.58e+2  -5.31    71.6
##  2 Adelaide       SA    Holiday   0.554   0.619       1       2 9.17e+0  49.0     78.7
##  3 Adelaide       SA    Other     0.746   0.202       2       1 2.10e+0  95.1     43.4
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##  5 Adelaide Hi~   SA    Busine~   0.464   0.179       3       0 1.03e-1   0.968  -3.22
##  6 Adelaide Hi~   SA    Holiday   0.528   0.296       2       1 1.77e-1  10.5     24.0
##  7 Adelaide Hi~   SA    Other     0.593   0.404       2       2 4.44e-4   4.28     3.19
##  8 Adelaide Hi~   SA    Visiti~   0.488   0.254       0       3 6.50e+0  34.2     -0.529
##  9 Alice Sprin~   NT    Busine~   0.534   0.251       0       1 1.69e-1  23.8     19.5
## 10 Alice Sprin~   NT    Holiday   0.381   0.832       3       1 7.39e-1 -19.6     10.5
## # ... with 294 more rows, 41 more variables: 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

```r
colnames(tourism_features)
```

```
##  [1] "Region"                "State"                 "Purpose"
##  [4] "trend_strength"        "seasonal_strength_year" "seasonal_peak_year"
##  [7] "seasonal_trough_year"  "spikiness"             "linearity"
## [10] "curvature"             "stl_e_acf1"            "stl_e_acf10"
## [13] "acf1"                  "acf10"                 "diff1_acf1"
## [16] "diff1_acf10"           "diff2_acf1"            "diff2_acf10"
## [19] "season_acf1"           "pacf5"                 "diff1_pacf5"
## [22] "diff2_pacf5"           "season_pacf"           "zero_run_mean"
## [25] "nonzero_squared_cv"    "zero_start_prop"       "zero_end_prop"
## [28] "lambda_guerrero"       "kpss_stat"             "kpss_pvalue"
## [31] "pp_stat"               "pp_pvalue"             "ndiffs"
## [34] "nsdiffs"               "bp_stat"               "bp_pvalue"
## [37] "lb_stat"               "lb_pvalue"             "var_tiled_var"
## [40] "var_tiled_mean"        "shift_level_max"       "shift_level_index"
## [43] "shift_var_max"         "shift_var_index"       "shift_kl_max"
## [46] "shift_kl_index"        "spectral_entropy"      "n_crossing_points"
## [49] "longest_flat_spot"     "coef_hurst"            "stat_arch_lm"
```

Feature extraction and statistics

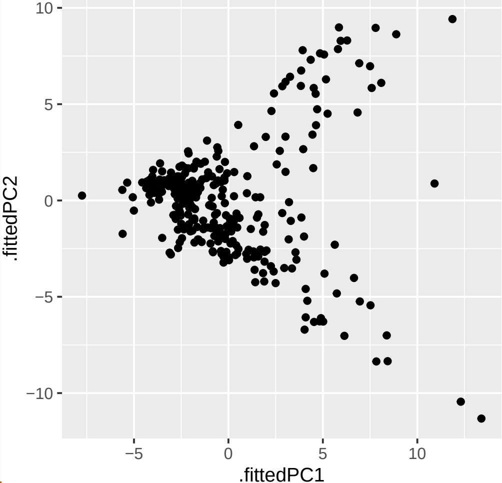
```r
pcs <- tourism_features ▷
  select(-State, -Region, -Purpose) ▷
  prcomp(scale = TRUE) ▷
  broom::augment(tourism_features)
```

Principal components based on all features from the feasts package

```
## # A tibble: 304 x 100
##    .rownames Region     State Purpose trend~1 seaso~2 seaso~3 seaso~4 spiki~5 linea~6
##    <chr>     <chr>      <chr> <chr>     <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>
##  1 1         Adelaide   SA    Busine~   0.464   0.407       3       1 1.58e+2  -5.31
##  2 2         Adelaide   SA    Holiday   0.554   0.619       1       2 9.17e+0  49.0
##  3 3         Adelaide   SA    Other     0.746   0.202       2       1 2.10e+0  95.1
##  4 4         Adelaide   SA    Visiti~   0.435   0.452       1       3 5.61e+1  34.6
##  5 5         Adelaide ~ SA    Busine~   0.464   0.179       3       0 1.03e-1   0.968
##  6 6         Adelaide ~ SA    Holiday   0.528   0.296       2       1 1.77e-1  10.5
##  7 7         Adelaide ~ SA    Other     0.593   0.404       2       2 4.44e-4   4.28
##  8 8         Adelaide ~ SA    Visiti~   0.488   0.254       0       3 6.50e+0  34.2
##  9 9         Alice Spr~ NT    Busine~   0.534   0.251       0       1 1.69e-1  23.8
## 10 10        Alice Spr~ NT    Holiday   0.381   0.832       3       1 7.39e-1 -19.6
## # ... with 294 more rows, 90 more variables: curvature <dbl>, stl_e_acf1 <dbl>,
```

Feature extraction and statistics

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

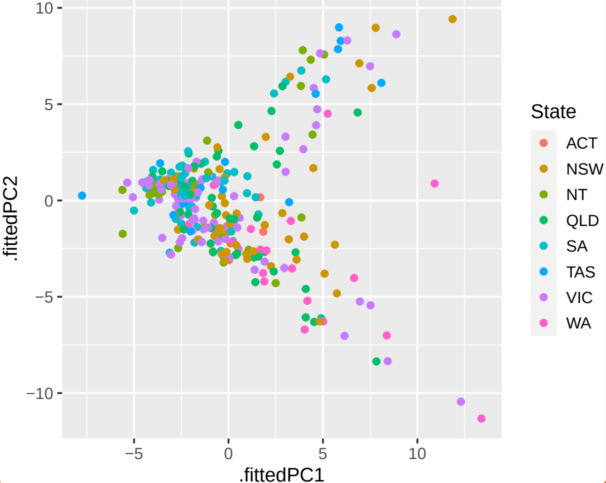


Principal components based on all features from the feasts package

Feature extraction and statistics

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

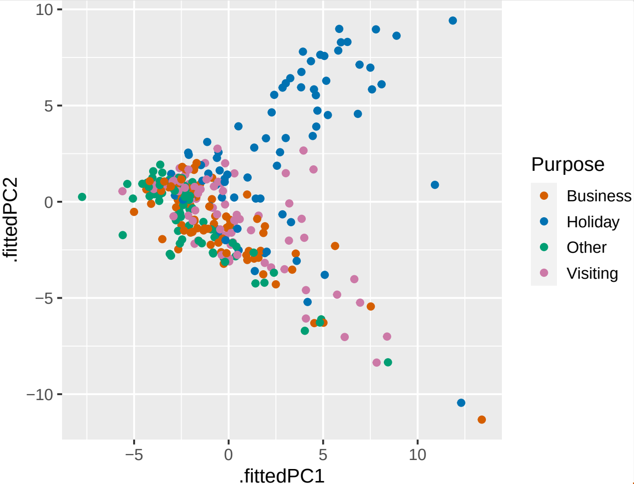
Principal components based on all features from the feasts package



Feature extraction and statistics

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

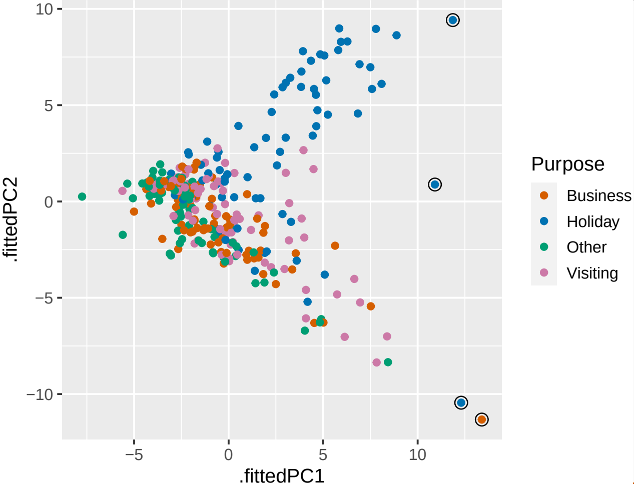
Principal components based on all features from the feasts package



Feature extraction and statistics

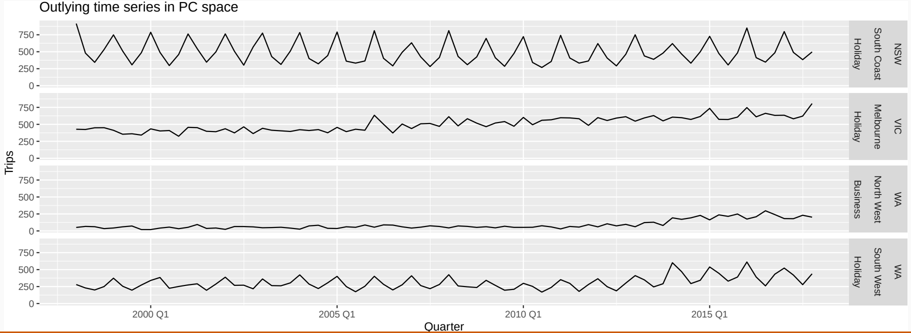
```
pcs |> ggplot(aes(x=.fittedPC1, y=.fittedPC2, col=Purpose)) +
  geom_point() + theme(aspect.ratio=1)
```

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

1. STL Features
2. Dimension reduction for features
3. Lab Session 4

Lab Session 4

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