Exploratory time series analysis using R

bit.ly/etsa2022

3. Time series features

Outline

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

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

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

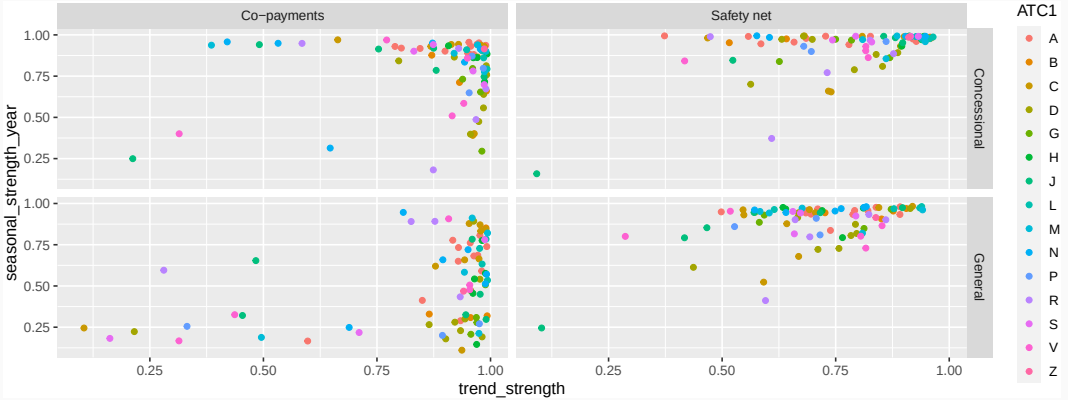
Feature extraction and statistics

```
PBS ▷
  features(Scripts, feat_stl)
```

```
## # A tibble: 336 x 13
##    Conces~1 Type  ATC1  ATC2  trend~2 seaso~3 seaso~4 seaso~5 spiki~6 linea~7 curva~8
##    <chr>    <chr> <chr> <chr>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>
##  1 Concess~ Co-p~ A     A01     0.845   0.918       9       7 2.03e 7 -2.22e4  -5165.
##  2 Concess~ Co-p~ A     A02     0.970   0.943      11       6 6.44e13  2.09e6  27300.
##  3 Concess~ Co-p~ A     A03     0.956   0.931       9       7 1.61e 9 -1.07e5 -56979.
##  4 Concess~ Co-p~ A     A04     0.790   0.930       9       7 3.85e 9 -5.95e4   5758.
##  5 Concess~ Co-p~ A     A05     0.950   0.888      11       6 3.18e 3  2.14e3   -695.
##  6 Concess~ Co-p~ A     A06     0.952   0.955       9       6 7.18e 8  9.46e4 -33858.
##  7 Concess~ Co-p~ A     A07     0.804   0.920       9       6 6.64e 8 -2.86e4 -34172.
##  8 Concess~ Co-p~ A     A09     0.900   0.901      11       6 2.29e 4  4.69e3  -1702.
##  9 Concess~ Co-p~ A     A10     0.975   0.952      11       6 3.40e12  1.06e6  21547.
## 10 Concess~ Co-p~ A     A11     0.963   0.881      11       7 1.35e 8 -5.66e4 -39186.
## #  ... with 326 more rows, 2 more variables: stl_e_acf1 <dbl>, stl_e_acf10 <dbl>, and
## #    abbreviated variable names 1: Concession, 2: trend strength
```

Feature extraction and statistics

```
PBS ▷ features(Scripts, feat_stl) ▷
  ggplot(aes(x = trend_strength, y = seasonal_strength_year, col=ATC1)) +
  geom_point() + facet_grid(Concession ~ Type)
```



Feature extraction and statistics

Find the most seasonal time series:

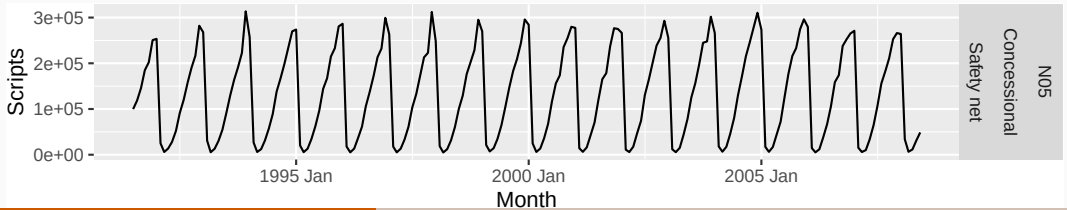
```
most_seasonal <- PBS ▷
  features(Scripts, feat_stl) ▷
  arrange(desc(seasonal_strength_year)) ▷
  head(1)
```

Feature extraction and statistics

Find the most seasonal time series:

```
most_seasonal <- PBS ▷
  features(Scripts, feat_stl) ▷
  arrange(desc(seasonal_strength_year)) ▷
  head(1)
```

```
PBS ▷
  right_join(most_seasonal, by = c("ATC1", "ATC2", "Concession", "Type")) ▷
  ggplot(aes(x = Month, y = Scripts)) +
  geom_line() + facet_grid(vars(ATC2, Concession, Type))
```



Feature extraction and statistics

Find the most trended time series:

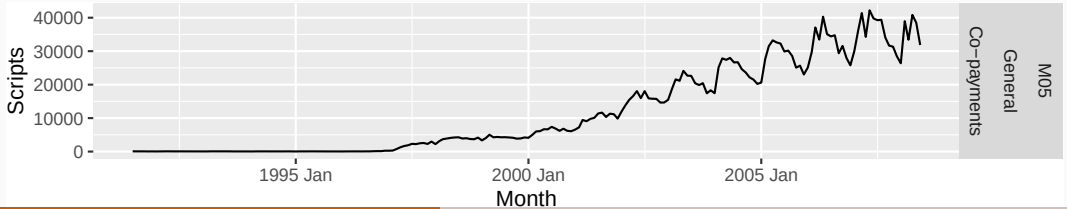
```
most_trended <- PBS ▷
  features(Scripts, feat_stl) ▷
  arrange(desc(trend_strength)) ▷
  head(1)
```

Feature extraction and statistics

Find the most trended time series:

```
most_trended <- PBS ▷
  features(Scripts, feat_stl) ▷
  arrange(desc(trend_strength)) ▷
  head(1)
```

```
PBS ▷
  right_join(most_trended, by = c("ATC1", "ATC2", "Concession", "Type")) ▷
  ggplot(aes(x = Month, y = Scripts)) +
  geom_line() + facet_grid(vars(ATC2, Concession, Type))
```



Outline

Feature extraction and statistics

```
PBS_features <- PBS |>
  features(Scripts, feature_set(pkgs = "feasts")) |>
  select(-`...26`) |>
  na.omit()
```

All features from the feasts package

```
## # A tibble: 333 x 52
##    Conces~1 Type  ATC1  ATC2  trend~2 seaso~3 seaso~4 seaso~5 spiki~6 linea~7 curva~8
##    <chr>    <chr> <chr> <chr>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>
##  1 Concess~ Co-p~ A     A01     0.845   0.918       9       7 2.03e 7 -2.22e4  -5165.
##  2 Concess~ Co-p~ A     A02     0.970   0.943      11       6 6.44e13  2.09e6  27300.
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##  4 Concess~ Co-p~ A     A04     0.790   0.930       9       7 3.85e 9 -5.95e4   5758.
##  5 Concess~ Co-p~ A     A05     0.950   0.888      11       6 3.18e 3  2.14e3   -695.
##  6 Concess~ Co-p~ A     A06     0.952   0.955       9       6 7.18e 8  9.46e4 -33858.
##  7 Concess~ Co-p~ A     A07     0.804   0.920       9       6 6.64e 8 -2.86e4 -34172.
##  8 Concess~ Co-p~ A     A09     0.900   0.901      11       6 2.29e 4  4.69e3  -1702.
##  9 Concess~ Co-p~ A     A10     0.975   0.952      11       6 3.40e12  1.06e6  21547.
## 10 Concess~ Co-p~ A     A11     0.963   0.881      11       7 1.35e 8 -5.66e4 -39186.
## #  ... with 323 more rows, 41 more variables: stl_e_acf1 <dbl>, stl_e_acf10 <dbl>,
```

Feature extraction and statistics

```
colnames(PBS_features)
```

```
##  [1] "Concession"          "Type"                "ATC1"
##  [4] "ATC2"                "trend_strength"      "seasonal_strength_year"
##  [7] "seasonal_peak_year"  "seasonal_trough_year" "spikiness"
## [10] "linearity"           "curvature"           "stl_e_acf1"
## [13] "stl_e_acf10"         "acf1"                "acf10"
## [16] "diff1_acf1"          "diff1_acf10"         "diff2_acf1"
## [19] "diff2_acf10"         "season_acf1"         "pacf5"
## [22] "diff1_pacf5"         "diff2_pacf5"         "season_pacf"
## [25] "zero_run_mean"       "nonzero_squared_cv"  "zero_start_prop"
## [28] "zero_end_prop"       "lambda_guerrero"     "kpss_stat"
## [31] "kpss_pvalue"         "pp_stat"             "pp_pvalue"
## [34] "ndiffs"              "nsdiffs"             "bp_stat"
## [37] "bp_pvalue"           "lb_stat"             "lb_pvalue"
## [40] "var_tiled_var"       "var_tiled_mean"      "shift_level_max"
## [43] "shift_level_index"   "shift_var_max"       "shift_var_index"
## [46] "shift_kl_max"        "shift_kl_index"      "spectral_entropy"
## [49] "n_crossing_points"   "longest_flat_spot"   "coef_hurst"
## [52] "stat_arch_lm"
```

Feature extraction and statistics

```
pcs <- PBS_features |>
  select(-ATC1, -ATC2, -Type, -Concession) |>
  prcomp(scale = TRUE) |>
  broom::augment(PBS_features)
```

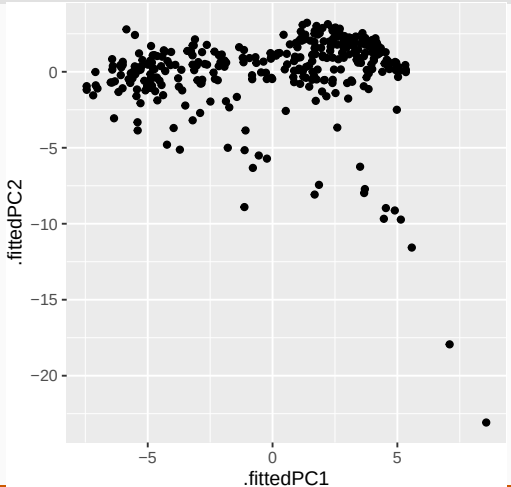
Principal components based on all features from the feasts package

```
## # A tibble: 333 x 101
##    .rowna~1 Conce~2 Type  ATC1  ATC2  trend~3 seaso~4 seaso~5 seaso~6 spiki~7 linea~8
##    <chr>    <chr>   <chr> <chr> <chr>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>
##  1 1        Conces~ Co-p~ A     A01     0.845   0.918       9       7 2.03e 7 -2.22e4
##  2 2        Conces~ Co-p~ A     A02     0.970   0.943      11       6 6.44e13  2.09e6
##  3 3        Conces~ Co-p~ A     A03     0.956   0.931       9       7 1.61e 9 -1.07e5
##  4 4        Conces~ Co-p~ A     A04     0.790   0.930       9       7 3.85e 9 -5.95e4
##  5 5        Conces~ Co-p~ A     A05     0.950   0.888      11       6 3.18e 3  2.14e3
##  6 6        Conces~ Co-p~ A     A06     0.952   0.955       9       6 7.18e 8  9.46e4
##  7 7        Conces~ Co-p~ A     A07     0.804   0.920       9       6 6.64e 8 -2.86e4
##  8 8        Conces~ Co-p~ A     A09     0.900   0.901      11       6 2.29e 4  4.69e3
##  9 9        Conces~ Co-p~ A     A10     0.975   0.952      11       6 3.40e12  1.06e6
## 10 10       Conces~ Co-p~ A     A11     0.963   0.881      11       7 1.35e 8 -5.66e4
## # ... with 323 more rows, 90 more variables: curvature <dbl>, stl_e_acf1 <dbl>,
```

Feature extraction and statistics

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

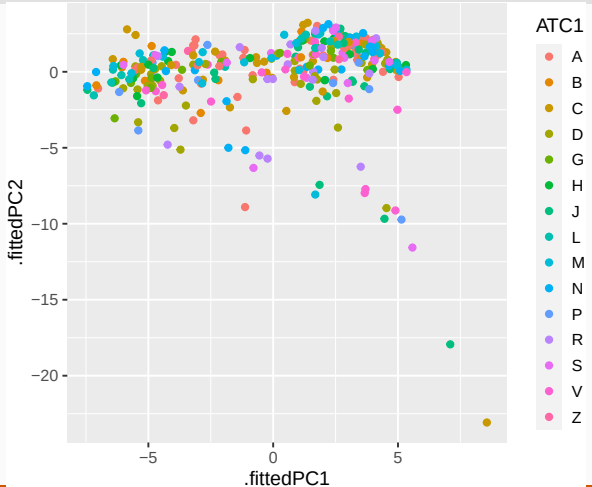
Principal components based on all features from the feasts package



Feature extraction and statistics

```
pcs ▷ ggplot(aes(x=.fittedPC1, y=.fittedPC2, col = ATC1)) +
  geom_point() + theme(aspect.ratio=1)
```

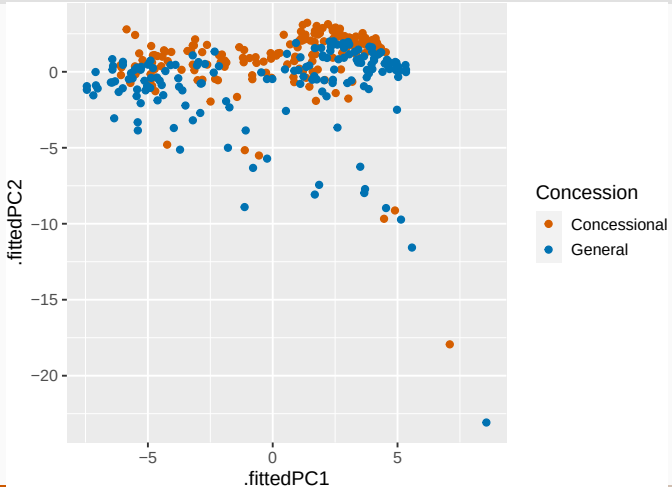
Principal components based on all features from the feasts package



Feature extraction and statistics

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

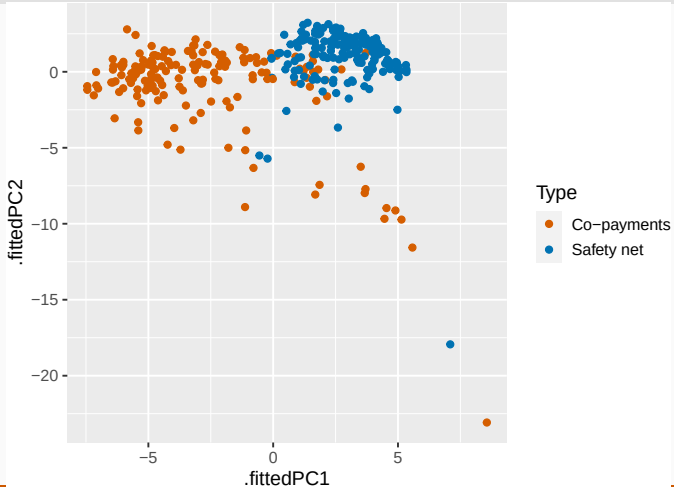
Principal components based on all features from the feasts package



Feature extraction and statistics

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

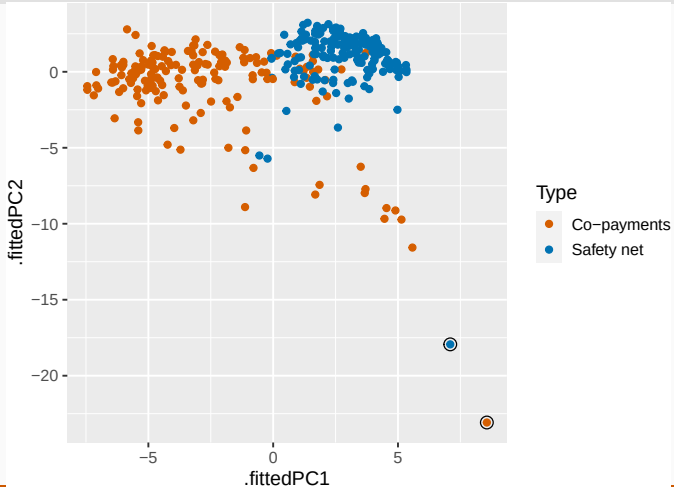
Principal components based on all features from the feasts package



Feature extraction and statistics

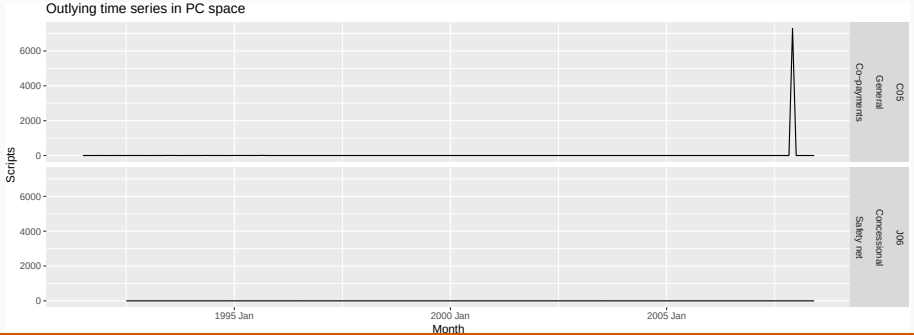
```
pcs ▷ ggplot(aes(x=.fittedPC1, y=.fittedPC2, col=Type)) +
  geom_point() + theme(aspect.ratio=1)
```

Principal components based on all features from the feasts package



Feature extraction and statistics

```
outliers <- filter(pcs, .fittedPC2 < -15)
semi_join(PBS, outliers, by = c("ATC1", "ATC2", "Concession", "Type")) ▷
  mutate(Series = glue("{ATC2}", "{Concession}", "{Type}", .sep = "\n\n")) ▷
  ggplot(aes(x = Month, y = Scripts)) +
  geom_line() + facet_grid(Series ~ .) +
  labs(title = "Outlying time series in PC space")
```



Outline

Lab Session 4

- Find the most seasonal time series in the tourism data.
- Which state has the strongest trends?
- Use a feature-based approach to look for outlying series in `tourism`.
- What is unusual about the series you identify as outliers?