Tidy Time Series & Forecasting in R

5. 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)
```

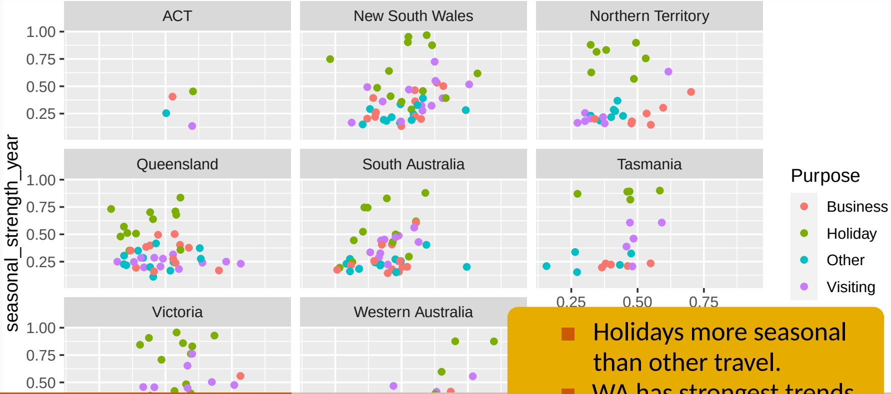
```
## # A tibble: 304 x 12
##    Region         State Purpose trend~1 seaso~2 seaso~3 seaso~4
##    <chr>          <chr> <chr>     <dbl>   <dbl>   <dbl>   <dbl>
##  1 Adelaide       Sout~ Busine~   0.464   0.407       3       1
##  2 Adelaide       Sout~ Holiday   0.554   0.619       1       2
##  3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

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:

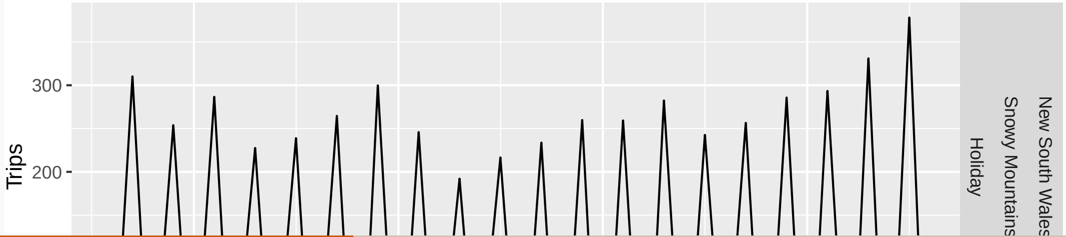
```
most_seasonal <- tourism %>%
  features(Trips, feat_stl) %>%
  filter(seasonal_strength_year == max(seasonal_strength_year))
```

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:

```
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 diff1~1 diff1~2
##    <chr>          <chr> <chr>      <dbl> <dbl>   <dbl>   <dbl>
##  1 Adelaide       Sout~ Busine~  0.0333  0.131  -0.520   0.463
##  2 Adelaide       Sout~ Holiday  0.0456  0.372  -0.343   0.614
##  3 Adelaide       Sout~ Other    0.517   1.15   -0.409   0.383
##  4 Adelaide       Sout~ Visiti~  0.0684  0.294  -0.394   0.452
##  5 Adelaide Hi~ Sout~ Busine~  0.0709  0.134  -0.580   0.415
##  6 Adelaide Hi~ Sout~ Holiday  0.131   0.313  -0.536   0.500
##  7 Adelaide Hi~ Sout~ Other    0.261   0.330  -0.253   0.317
##  8 Adelaide Hi~ Sout~ Visiti~  0.139   0.117  -0.472   0.239
##  9 Alice Sprin~ Nort~ Busine~  0.217   0.367  -0.500   0.381
## 10 Alice Sprin~ Nort~ Holiday -0.00660 2.11   -0.153   2.11
## # ... with 294 more rows, 3 more variables:
## #   diff2_acf1 <dbl>, diff2_acf10 <dbl>, season_acf1 <dbl>,
## #   and abbreviated variable names 1: diff1_acf1,
```

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
##    <chr>          <chr> <chr>     <dbl>   <dbl>   <dbl>   <dbl>
##  1 Adelaide       Sout~ Busine~   0.464   0.407       3       1
##  2 Adelaide       Sout~ Holiday   0.554   0.619       1       2
##  3 Adelaide       Sout~ Other     0.746   0.202       2       1
##  4 Adelaide       Sout~ Visiti~   0.435   0.452       1       3
##  5 Adelaide H~    Sout~ Busine~   0.464   0.179       3       0
##  6 Adelaide H~    Sout~ Holiday   0.528   0.296       2       1
##  7 Adelaide H~    Sout~ Other     0.593   0.404       2       2
##  8 Adelaide H~    Sout~ Visiti~   0.488   0.254       0       3
##  9 Alice Spri~    Nort~ Busine~   0.534   0.251       0       1
## 10 Alice Spri~    Nort~ Holiday   0.381   0.832       3       1
## # ... with 294 more rows, 44 more variables:
## #   spikiness <dbl>, linearity <dbl>, curvature <dbl>,
## #   stl_e_acf1 <dbl>, stl_e_acf10 <dbl>, acf1 <dbl>,
```

Feature extraction and statistics

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

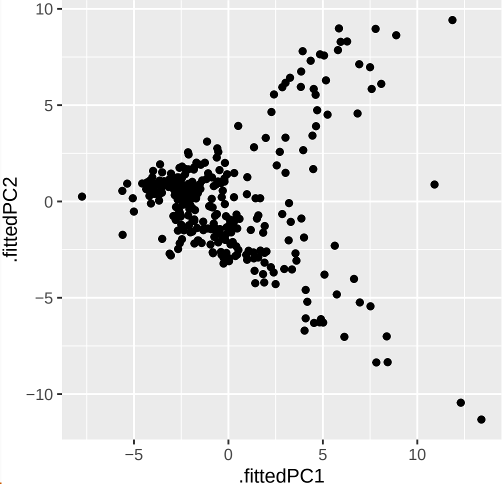
```
## # A tibble: 304 x 100
##    .rownames Region    State Purpose trend~1 seaso
##    <chr>     <chr>     <chr> <chr>     <dbl>    <db
##  1 1         Adelaide  Sout~ Busine~   0.464    0.4
##  2 2         Adelaide  Sout~ Holiday   0.554    0.6
##  3 3         Adelaide  Sout~ Other     0.746    0.202              2
##  4 4         Adelaide  Sout~ Visiti~   0.435    0.452              1
##  5 5         Adelaide~ Sout~ Busine~   0.464    0.179              3
##  6 6         Adelaide~ Sout~ Holiday   0.528    0.296              2
##  7 7         Adelaide~ Sout~ Other     0.593    0.404              2
##  8 8         Adelaide~ Sout~ Visiti~   0.488    0.254              0
##  9 9         Alice Sp~ Nort~ Busine~   0.534    0.251              0
## 10 10        Alice Sp~ Nort~ Holiday   0.381    0.832              3
## # ... with 294 more rows, 93 more variables:
```

Principal components based on all features from the feasts package

Feature extraction and statistics

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

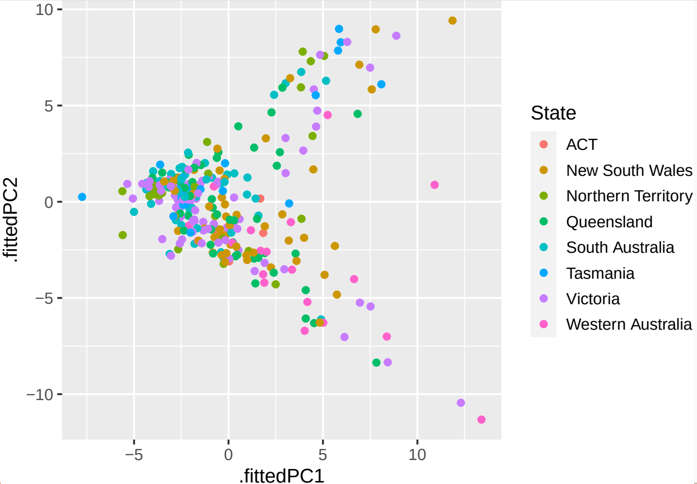
Principal components based on all features from the feasts package



Feature extraction and statistics

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

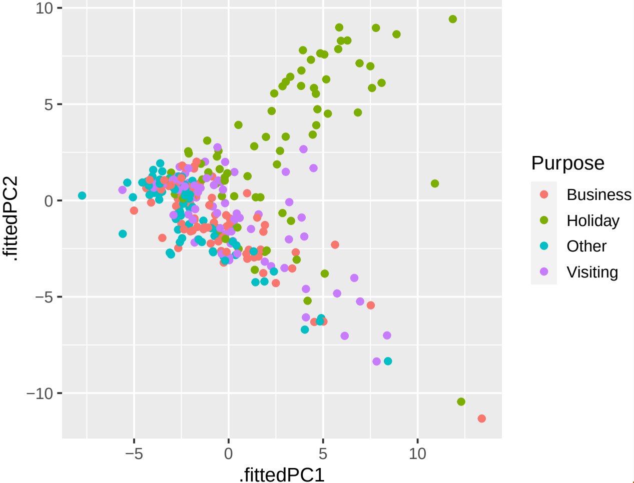
Principal components based on all features from the feasts package



Feature extraction and statistics

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

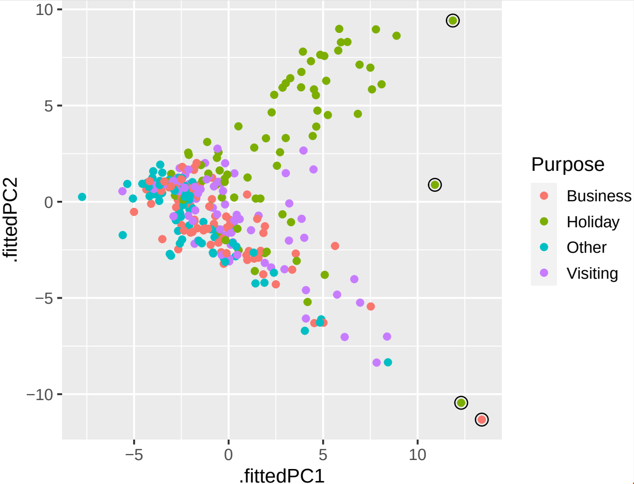
Principal components based on all features from the feasts package



Feature extraction and statistics

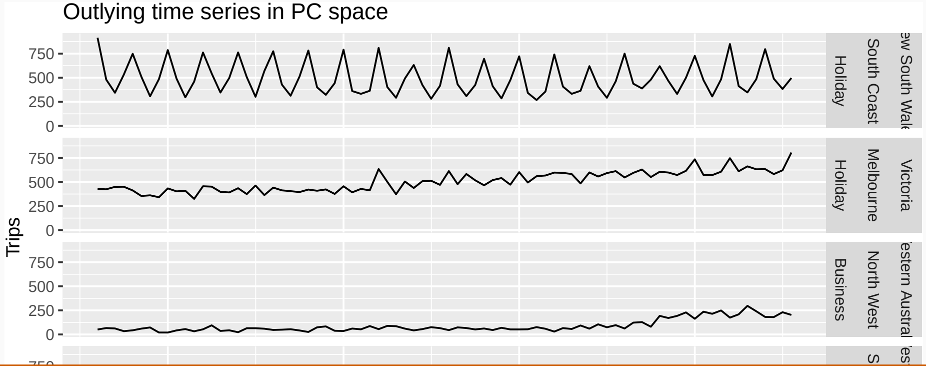
```r
pcs %>% ggplot(aes(x=.fittedPC1, y=.fittedPC2, col=Purpose)) +
  geom_point() + theme(aspect.ratio=1)
```

Principal components based on all features from the feasts package



Feature extraction and statistics

```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 ~ .) + ggtitle("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?