

Time Series Analysis & Forecasting Using R

5. Time series features



Outline

- 1 STL Features
- 2 Lab Session 9
- 3 Dimension reduction for features
- 4 Lab Session 10

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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_strength	seasonal_strength_year	seasonal_peak_year
	<chr>	<chr>	<chr>	<dbl>	<dbl>	<dbl>
1	Adelaide	SA	Busine~	0.464	0.407	3
2	Adelaide	SA	Holiday	0.554	0.619	1
3	Adelaide	SA	Other	0.746	0.202	2
4	Adelaide	SA	Visiti~	0.435	0.452	1
5	Adelaide Hills	SA	Busine~	0.464	0.179	3
6	Adelaide Hills	SA	Holiday	0.528	0.296	2
7	Adelaide Hills	SA	Other	0.593	0.404	2
8	Adelaide Hills	SA	Visiti~	0.488	0.254	0
9	Alice Springs	NT	Busine~	0.534	0.251	0
10	Alice Springs	NT	Holiday	0.381	0.832	3

```
# i 294 more rows
```

```
# i 6 more variables: seasonal_trough_year <dbl>, spikiness <dbl>, linearity <dbl>,
```

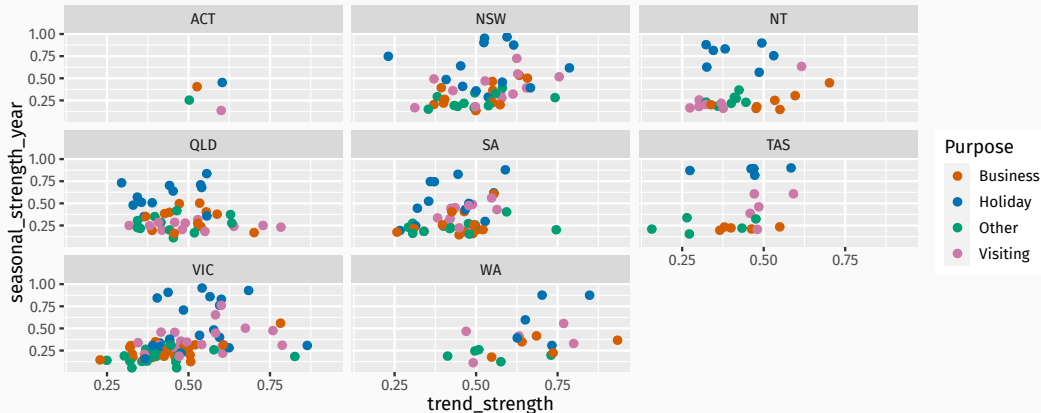
```
# curvature <dbl>, stl_e_acf1 <dbl>, stl_e_acf10 <dbl>
```

Feature extraction and statistics

```
tourism |>
```

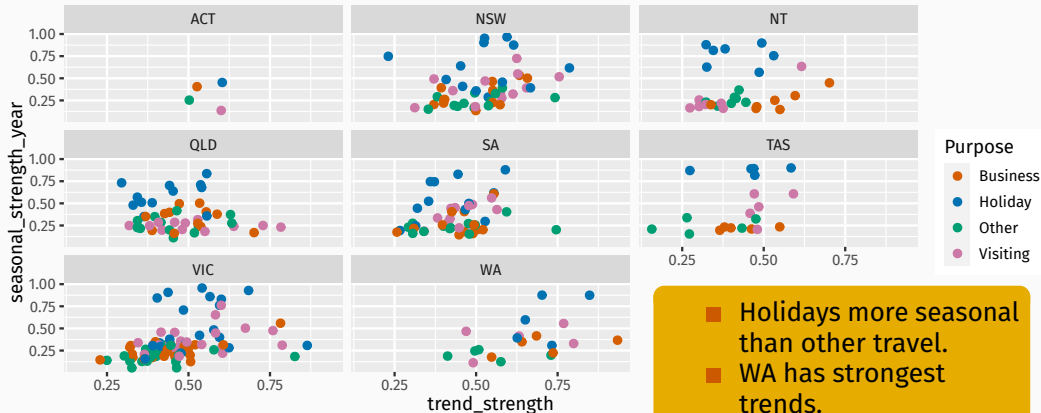
```
  features(Trips, feat_stl) |>
```

```
  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))
```



Feature extraction and statistics

Find the most seasonal time series:

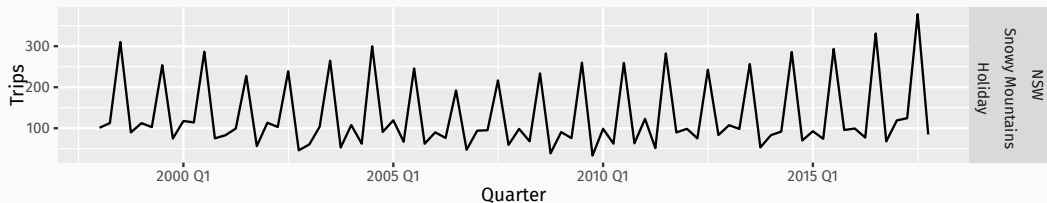
```
most_seasonal <- tourism |>  
  features(Trips, feat_stl) |>  
  filter(seasonal_strength_year == max(seasonal_strength_year))
```


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:

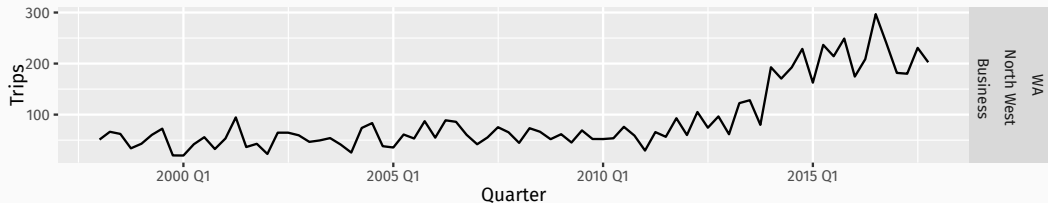
```
most_trended <- tourism |>  
  features(Trips, feat_stl) |>  
  filter(trend_strength == max(trend_strength))
```

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))
```



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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

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

```
# A tibble: 304 x 10
```

	Region	State	Purpose	acf1	acf10	diff1_acf1	diff1_acf10	diff2_acf1	diff2_acf10
	<chr>	<chr>	<chr>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
1	Adelaide	SA	Busine~	0.0333	0.131	-0.520	0.463	-0.676	0.741
2	Adelaide	SA	Holiday	0.0456	0.372	-0.343	0.614	-0.487	0.558
3	Adelaide	SA	Other	0.517	1.15	-0.409	0.383	-0.675	0.792
4	Adelaide	SA	Visiti~	0.0684	0.294	-0.394	0.452	-0.518	0.447
5	Adelaide ~	SA	Busine~	0.0709	0.134	-0.580	0.415	-0.750	0.746
6	Adelaide ~	SA	Holiday	0.131	0.313	-0.536	0.500	-0.716	0.906
7	Adelaide ~	SA	Other	0.261	0.330	-0.253	0.317	-0.457	0.392
8	Adelaide ~	SA	Visiti~	0.139	0.117	-0.472	0.239	-0.626	0.408
9	Alice Spr~	NT	Busine~	0.217	0.367	-0.500	0.381	-0.658	0.587
10	Alice Spr~	NT	Holiday	-0.00660	2.11	-0.153	2.11	-0.274	1.55

```
# i 294 more rows
```

```
# i 1 more variable: season_acf1 <dbl>
```

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Feature extraction and statistics

All features from the feasts package

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

```
# A tibble: 304 x 51
```

	Region <chr>	State <chr>	Purpose <chr>	trend_strength <dbl>	seasonal_strength_year <dbl>	seasonal_peak_year <dbl>
1	Adelaide	SA	Busine~	0.464	0.407	3
2	Adelaide	SA	Holiday	0.554	0.619	1
3	Adelaide	SA	Other	0.746	0.202	2
4	Adelaide	SA	Visiti~	0.435	0.452	1
5	Adelaide Hills	SA	Busine~	0.464	0.179	3
6	Adelaide Hills	SA	Holiday	0.528	0.296	2
7	Adelaide Hills	SA	Other	0.593	0.404	2
8	Adelaide Hills	SA	Visiti~	0.488	0.254	0
9	Alice Springs	NT	Busine~	0.534	0.251	0
10	Alice Springs	NT	Holiday	0.381	0.832	3

```
# i 294 more rows
```

```
# i 45 more variables: 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>, nonzero_squared_cv <dbl>,  
# zero_start_prop <dbl>, zero_end_prop <dbl>, lambda_guerrero <dbl>, ...
```


Feature extraction and statistics

Principal components based on all features from the feasts package

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

```
# A tibble: 304 x 100
```

	.rownames	Region	State	Purpose	trend_strength	seasonal_strength_year
	<chr>	<chr>	<chr>	<chr>	<dbl>	<dbl>
1	1	Adelaide	SA	Business	0.464	0.407
2	2	Adelaide	SA	Holiday	0.554	0.619
3	3	Adelaide	SA	Other	0.746	0.202
4	4	Adelaide	SA	Visiting	0.435	0.452
5	5	Adelaide Hills	SA	Business	0.464	0.179
6	6	Adelaide Hills	SA	Holiday	0.528	0.296
7	7	Adelaide Hills	SA	Other	0.593	0.404
8	8	Adelaide Hills	SA	Visiting	0.488	0.254
9	9	Alice Springs	NT	Business	0.534	0.251
10	10	Alice Springs	NT	Holiday	0.381	0.832

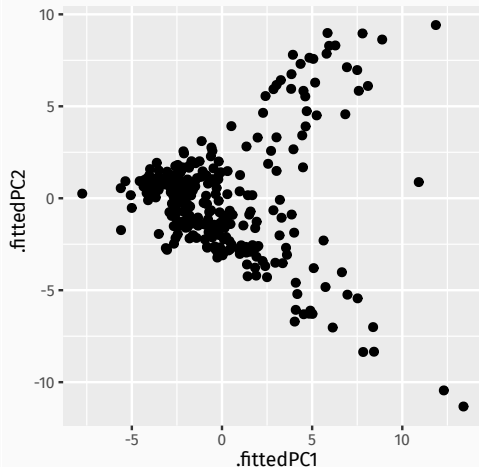
```
# i 294 more rows
```

```
# 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_acf10 <dbl>, diff2_acf10 <dbl>, season_acf10 <dbl>, pacf5 <dbl>
```

Feature extraction and statistics

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

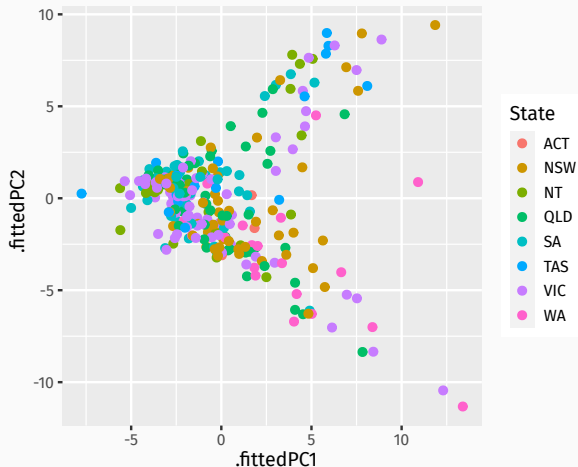
Principal
components based
on all features from
the feasts package



Feature extraction and statistics

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

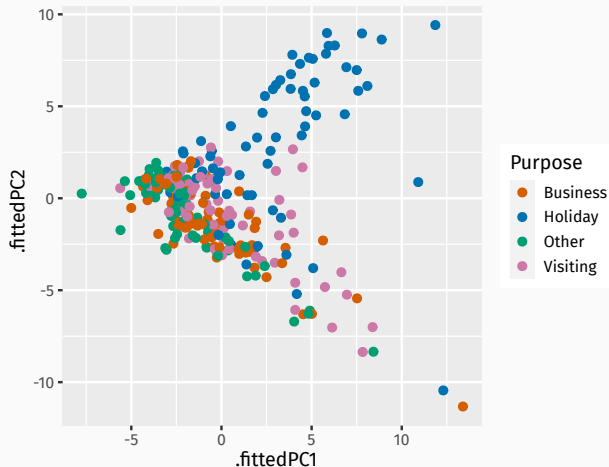
Principal
components based
on all features from
the feasts package



Feature extraction and statistics

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

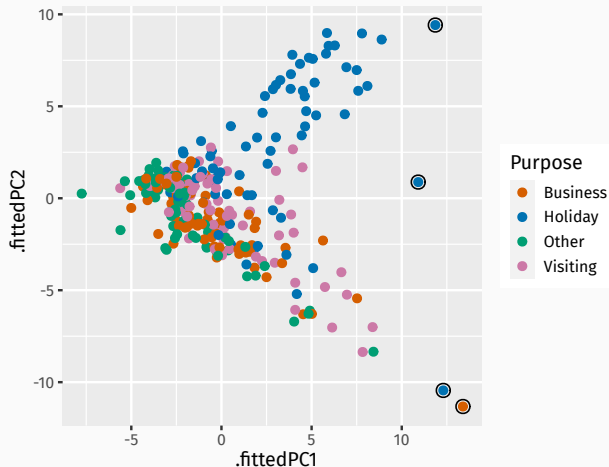
Principal
components based
on all features from
the feasts package



Feature extraction and statistics

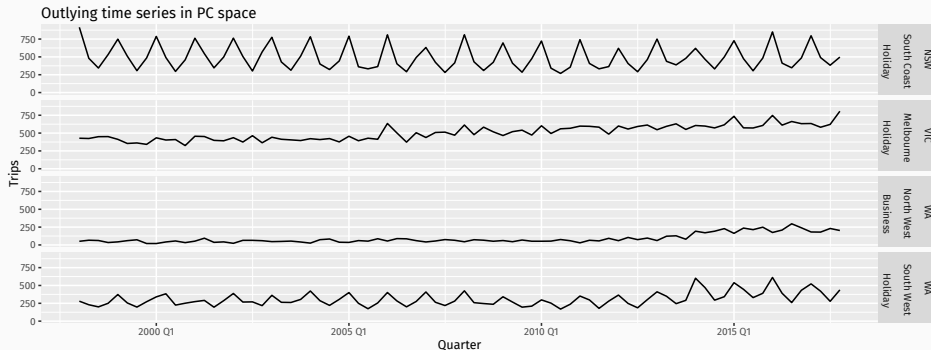
```
pcs |> ggplot(aes(x=.fittedPC1, y=.fittedPC2, col=Purpose)) +  
  geom_point() + theme(aspect.ratio=1)
```

Principal
components based
on all features from
the feasts package



Feature extraction and statistics

```
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")
```



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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?