MONASH University

MONASH BUSINESS SCHOOL

Feature-based time series analysis

Rob J Hyndman

27 September 2019

Outline

Outline

1 Visualization

2 R packages

3 Anomaly detection

4 Forecast model selection

5 Foreast model averaging

M3 competition

ELSEVIER

International Journal of Forecasting 16 (2000) 451–476

international journal of forecasting

www.elsevier.com/locate/ijforecast

The M3-Competition: results, conclusions and implications

Spyros Makridakis, Michèle Hibon*

INSEAD, Boulevard de Constance, 77305 Fontainebleau, France

Abstract

This paper describes the M3-Competition, the latest of the M-Competitions. It explains the reasons for conducting the competition and summarizes its results and conclusions. In addition, the paper compares such results/conclusions with those of the previous two M-Competitions as well as with those of other major empirical studies. Finally, the implications of these results and conclusions are considered, their consequences for both the theory and practice of forecasting are explored and directions for future research are contemplated.

Keywords: Comparative methods — time series: univariate; Forecasting competitions; M-Competition; Forecasting methods, Forecasting accuracy

M3 competition

ELSEVIER

International Journal of Forecasting 16 (2000) 451–476

international journal of forecasting

www.elsevier.com/locate/ijforecast

etition: results, conclusions a s

Spyros Makridakis, Michèle Hibon*

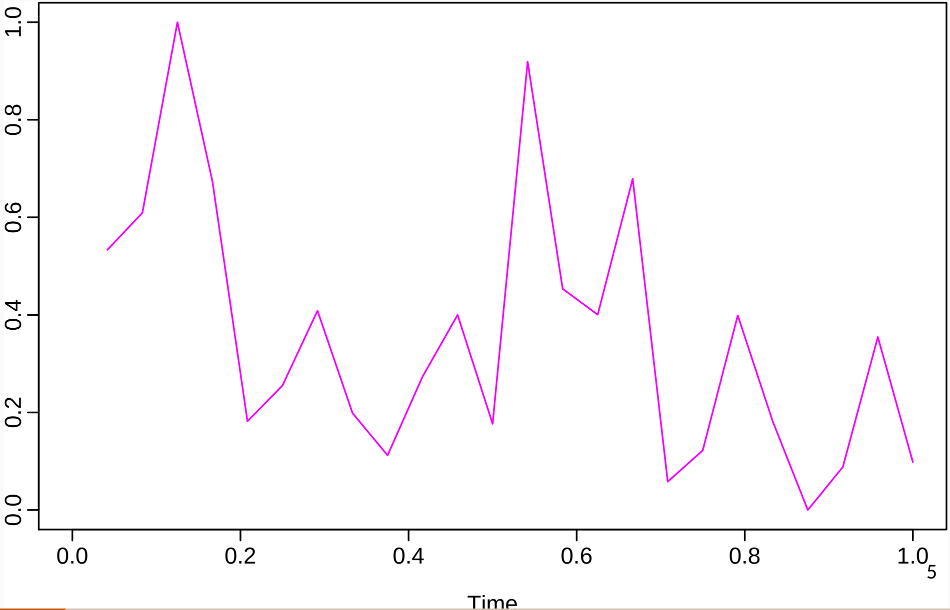
EAD, Boulevard de Constance, 77305 Fontainebleau, Fr

Abst

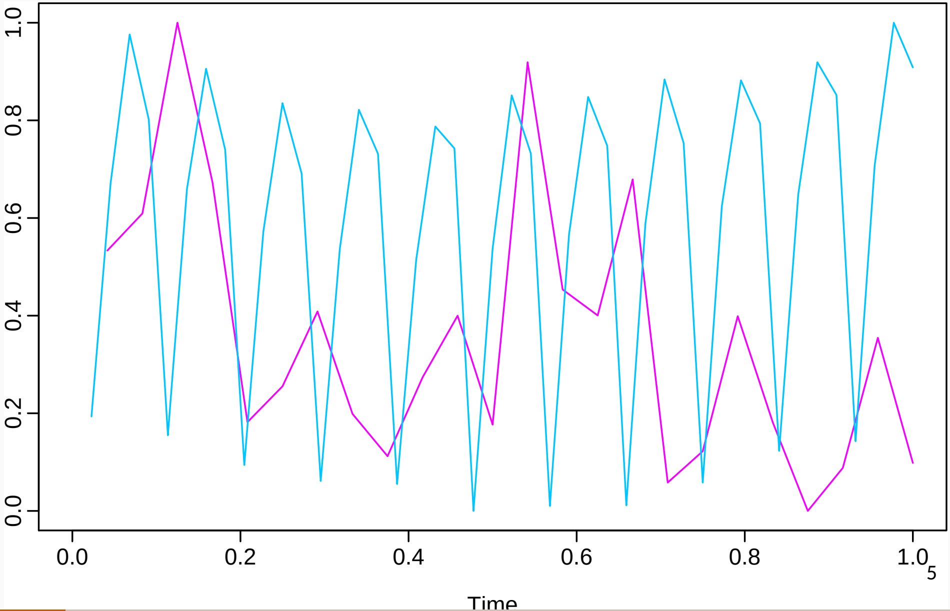
This paper describes the M3-Competition, the latest of the M-Competitions. It explains the reasons for conducting the competition and summarizes its results and conclusions. In addition, the paper compares such results/conclusions with those of the previous two M-Competitions as well as with those of other major empirical studies. Finally, the implications of these results and conclusions are considered, their consequences for both the theory and practice of forecasting are explored and directions for future research are contemplated.

Keywords: Comparative methods — time series: univariate; Forecasting competitions; M-Competition; Forecasting methods, Forecasting accuracy

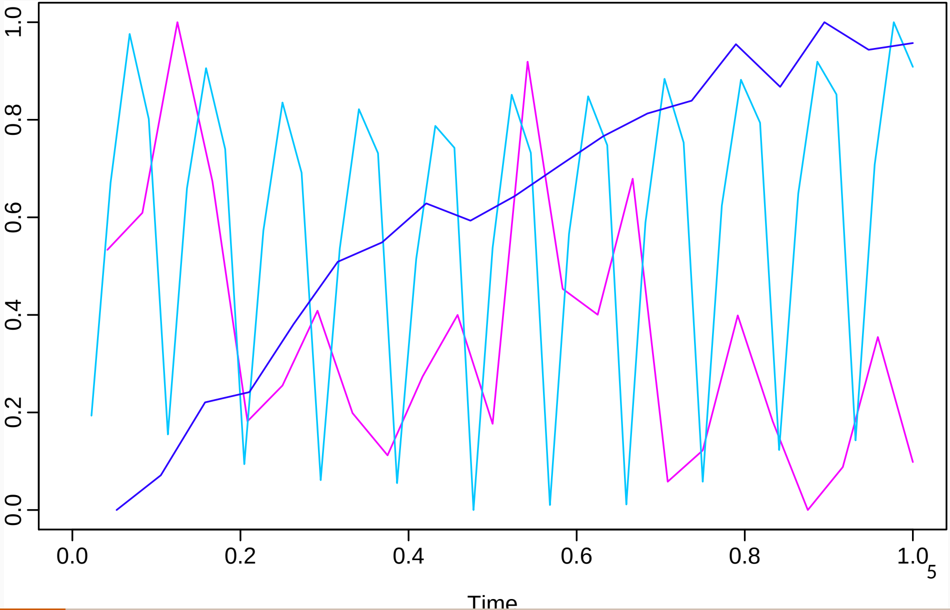
How to plot lots of time series?



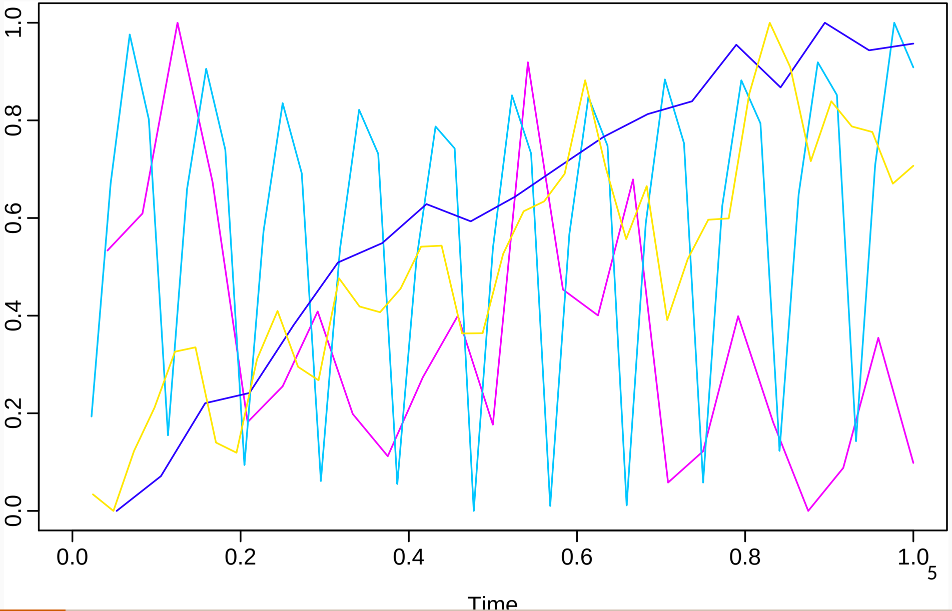
How to plot lots of time series?



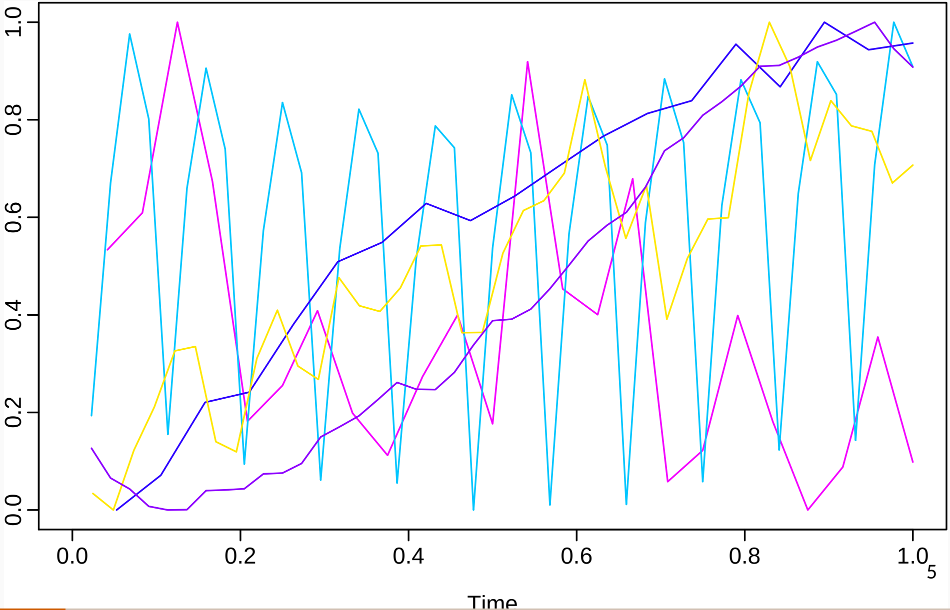
How to plot lots of time series?



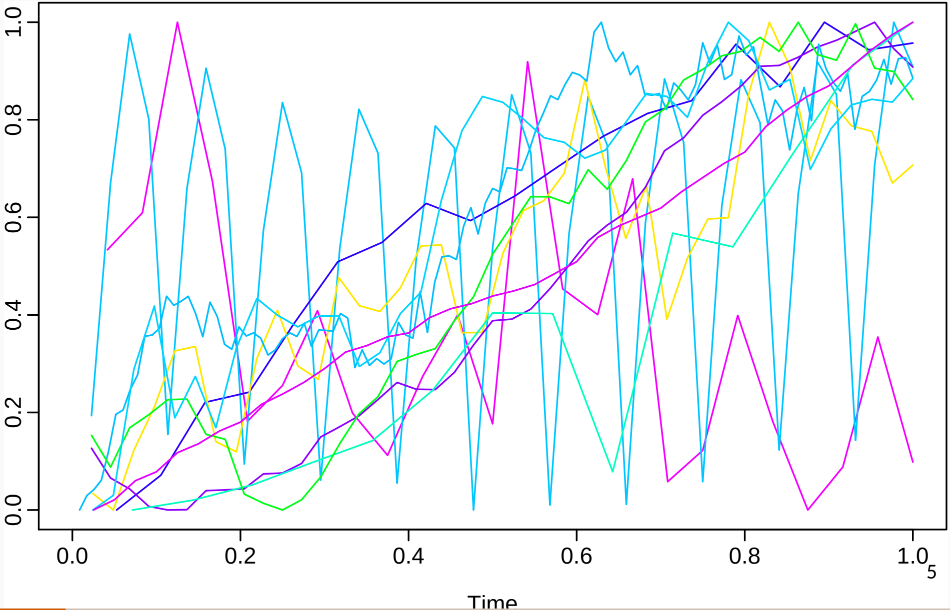
How to plot lots of time series?



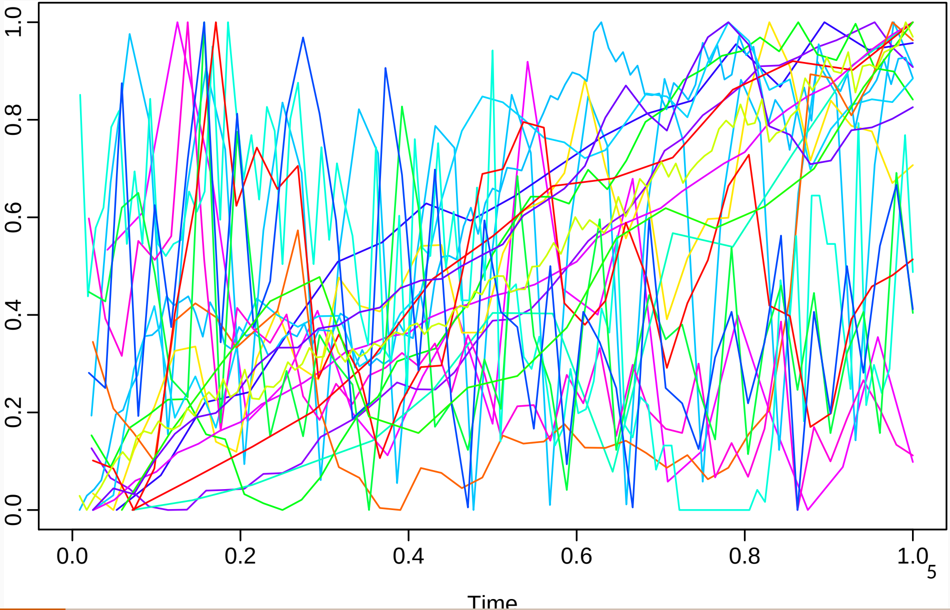
How to plot lots of time series?



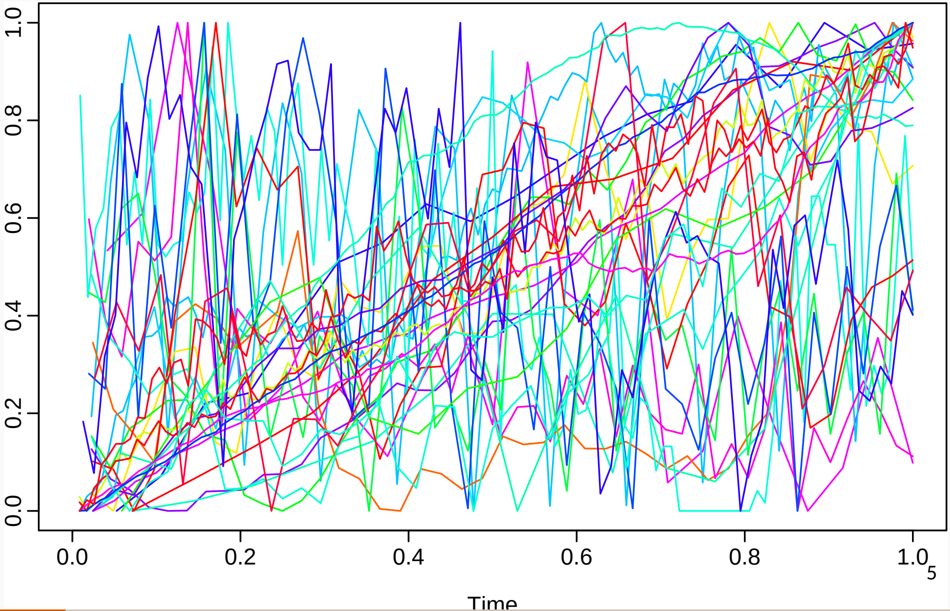
How to plot lots of time series?



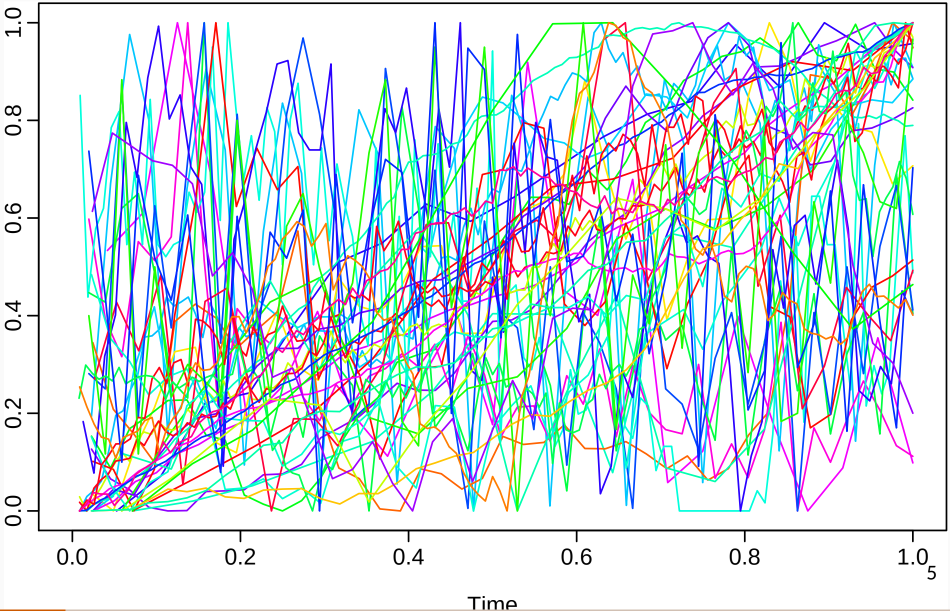
How to plot lots of time series?



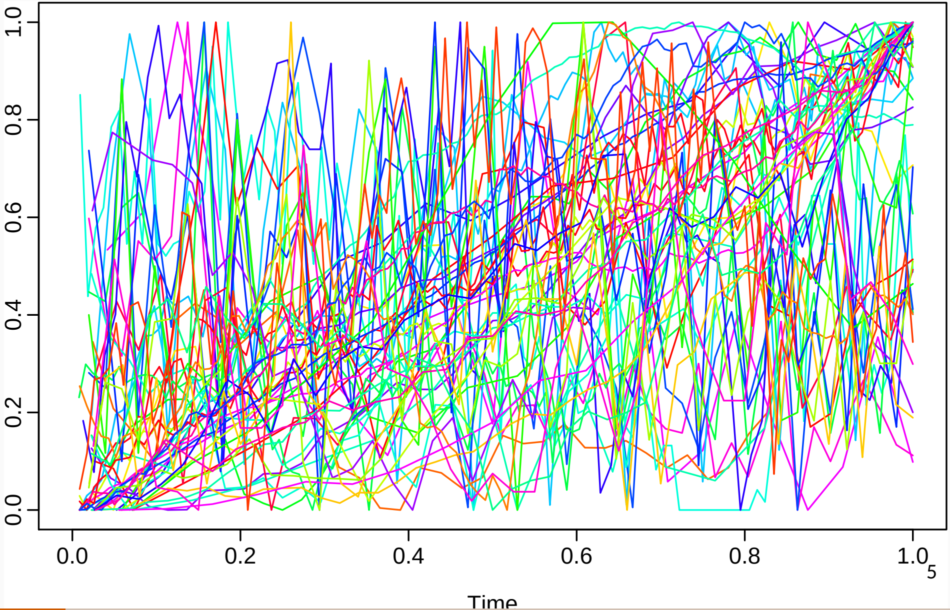
How to plot lots of time series?



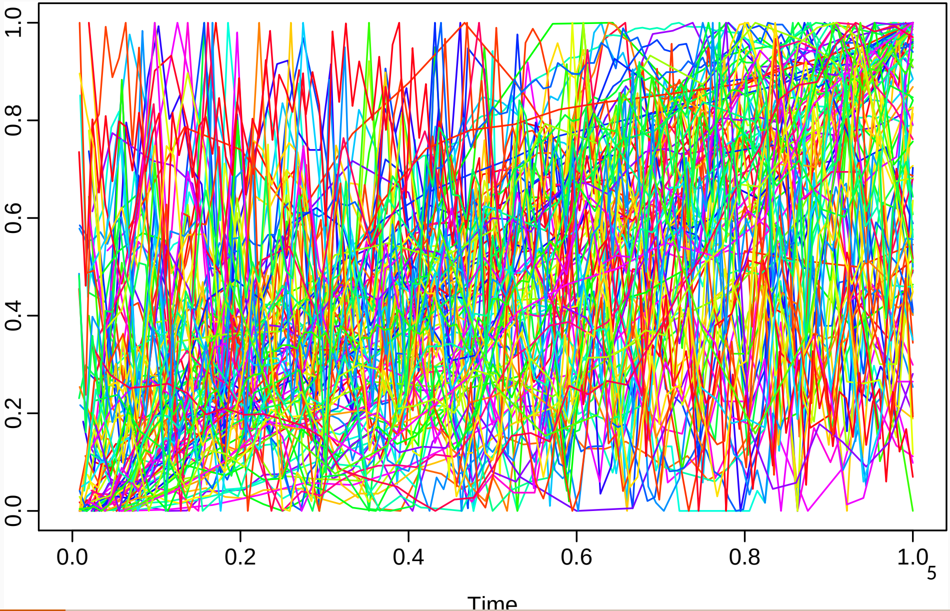
How to plot lots of time series?



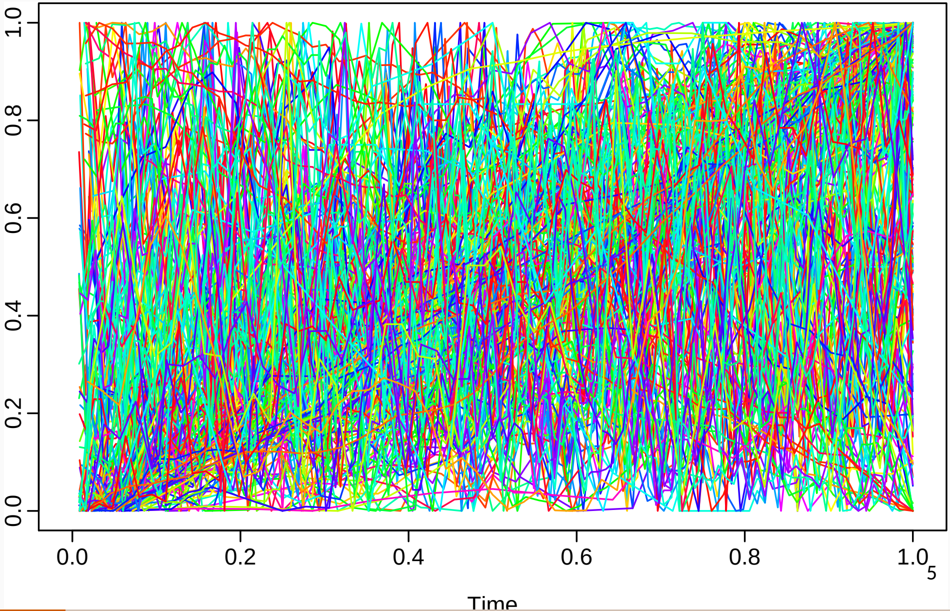
How to plot lots of time series?



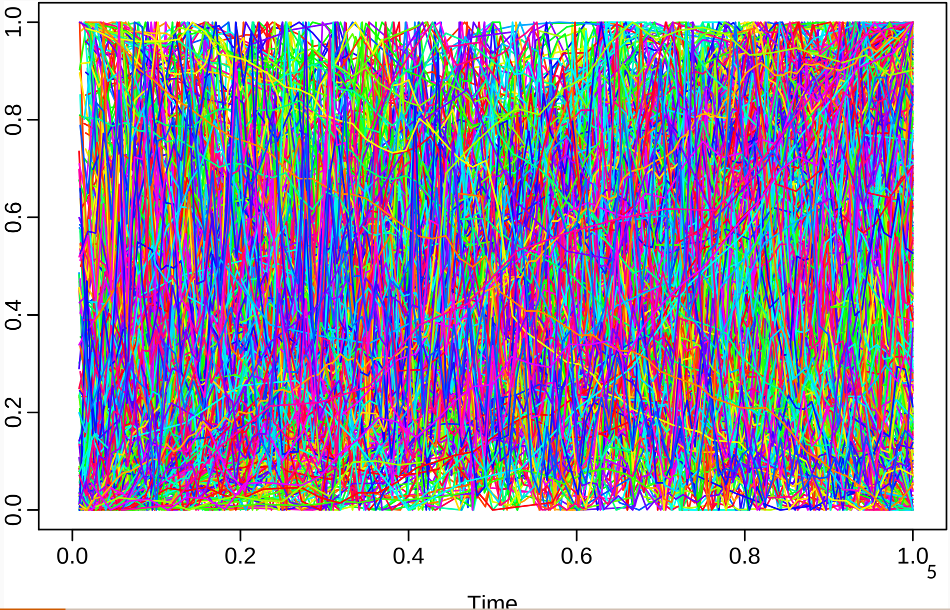
How to plot lots of time series?



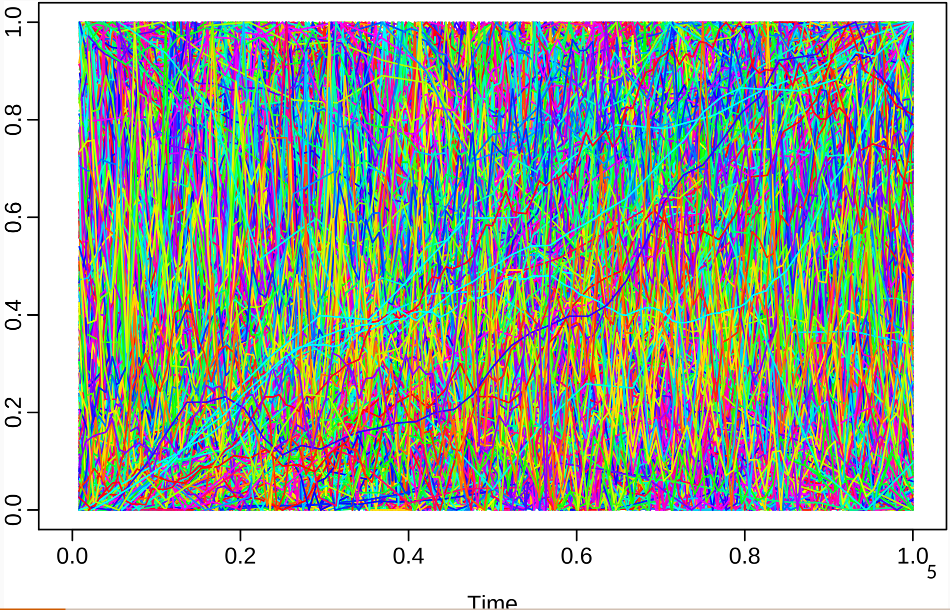
How to plot lots of time series?



How to plot lots of time series?



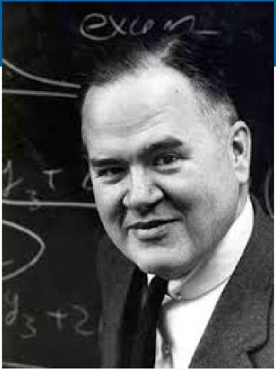
How to plot lots of time series?



Key idea

Cognostics

Computer-produced diagnostics (Tukey and Tukey, 1985).

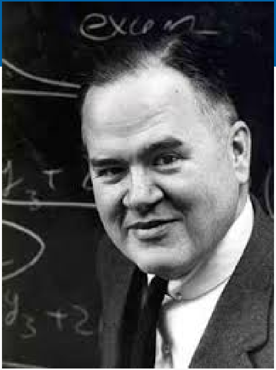


John W Tukey

Key idea

Cognostics

Computer-produced diagnostics (Tukey and Tukey, 1985).



John W Tukey

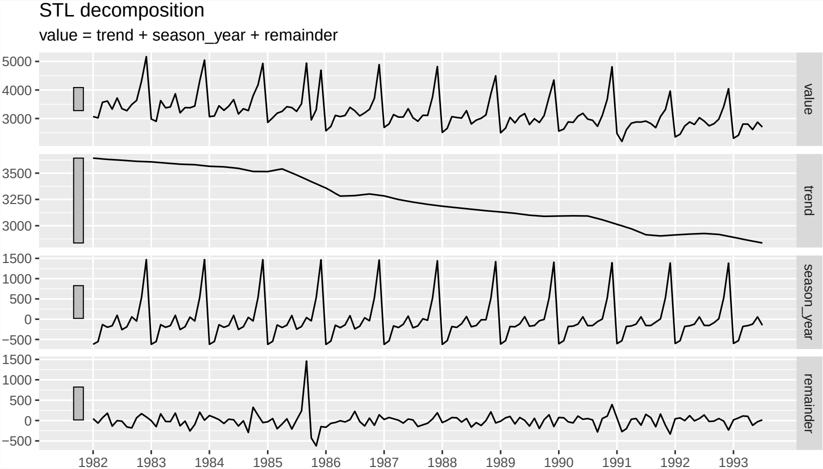
Examples for time series

- lag correlation
- size and direction of trend
- strength of seasonality
- timing of peak seasonality
- spectral entropy

Called "features" in the machine learning literature.

An STL decomposition: N2096

$Y_t = S_t + T_t + R_t$ $\qquad$ S_t is periodic with mean 0



Candidate features

STL decomposition

$$Y_t = S_t + T_t + R_t$$

Candidate features

STL decomposition

$$Y_t = S_t + T_t + R_t$$

- Seasonal period
- Autocorrelations of data $(Y_1, \dots, Y_T)$
- Autocorrelations of data $(R_1, \dots, R_T)$
- Strength of seasonality: $\max\left(0, 1 - \frac{\text{Var}(R_t)}{\text{Var}(Y_t - T_t)}\right)$
- Strength of trend: $\max\left(0, 1 - \frac{\text{Var}(R_t)}{\text{Var}(Y_t - S_t)}\right)$
- Spectral entropy: $H = -\int_{-\pi}^{\pi} f_y(\lambda) \log f_y(\lambda) d\lambda$, where $f_y(\lambda)$ is spectral density of Y_t.
  Low values of H suggest a time series that is easier to forecast (more signal).
- Optimal Box-Cox transformation of data

Feature properties

For series with different lengths, scales, domains, etc., we need features that are:

- scale-independent
- ergodic

Feature properties

For series with different lengths, scales, domains, etc., we need features that are:

- scale-independent
- ergodic

1. Seasonal period
2. Strength of seasonality
3. Strength of trend
4. First autocorrelation of STL remainder series
5. Spectral entropy
6. Optimal MLE Box-Cox transformation of data

Feature properties

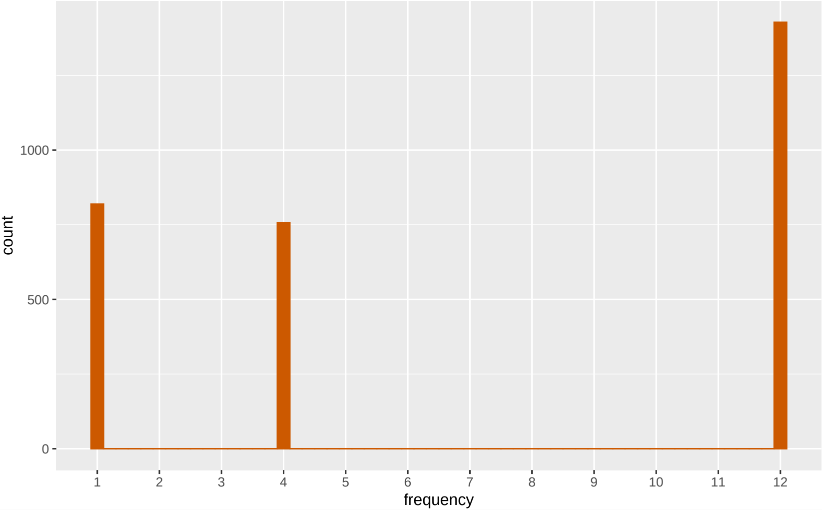
For series with different lengths, scales, domains, etc., we need features that are:

- scale-independent
- ergodic

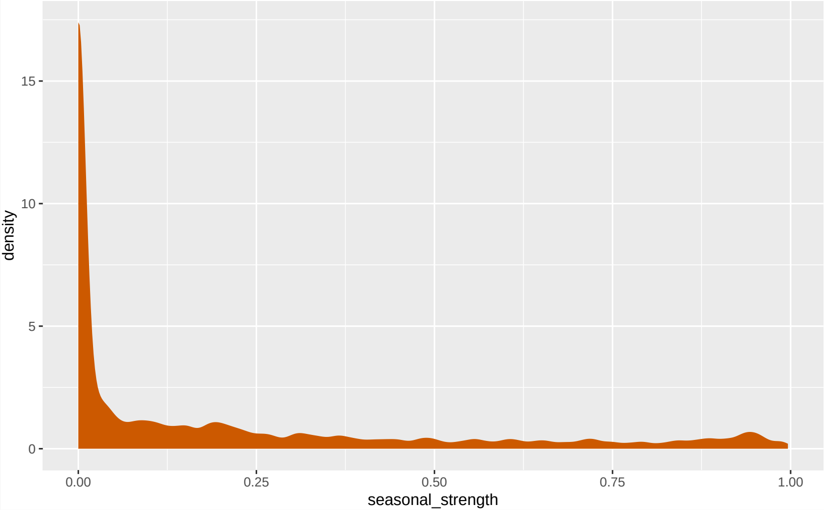
1. Seasonal period
2. Strength of seasonality
3. Strength of trend
4. First autocorrelation of STL remainder series
5. Spectral entropy
6. Optimal MLE Box-Cox transformation of data

For other analyses, it may be appropriate to have different requirements.

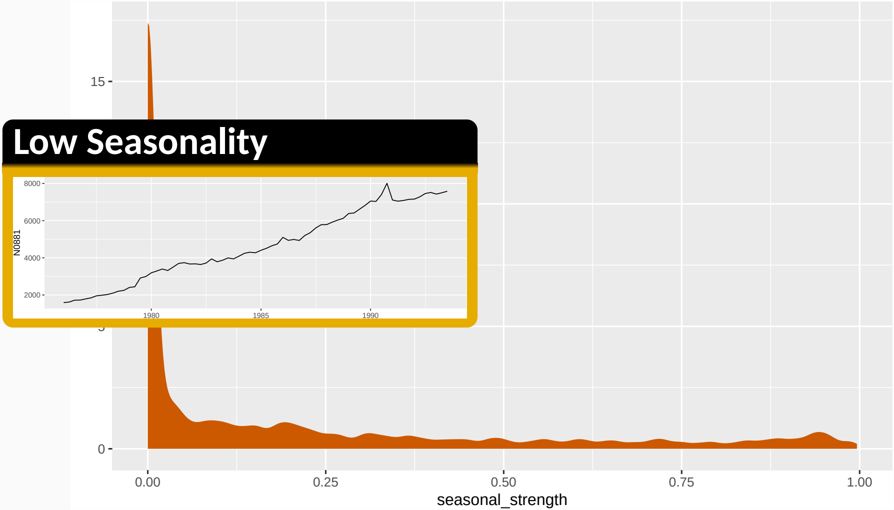
Distribution of Period for M3



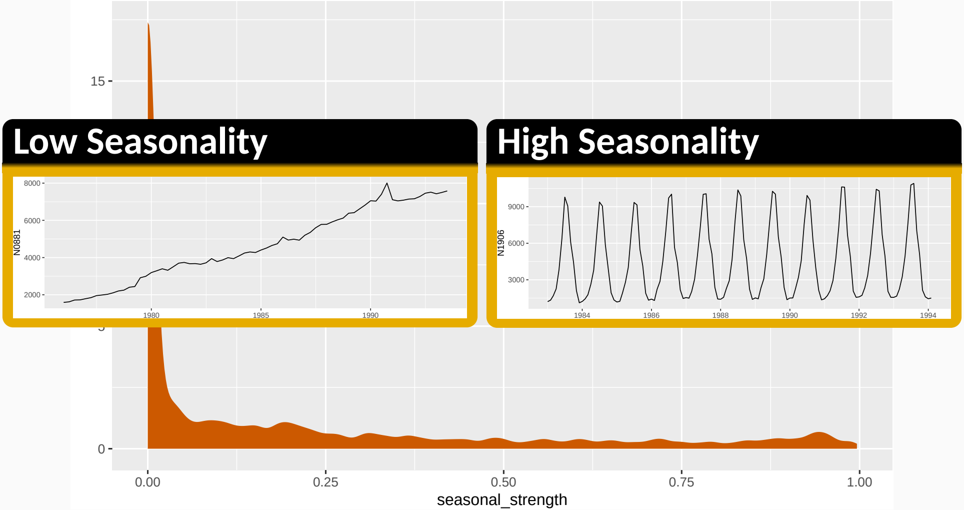
Distribution of Seasonality for M3



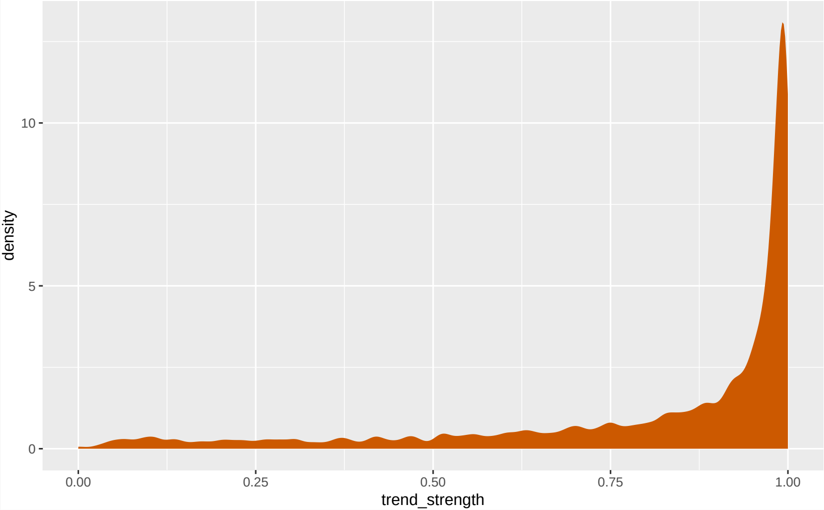
Distribution of Seasonality for M3



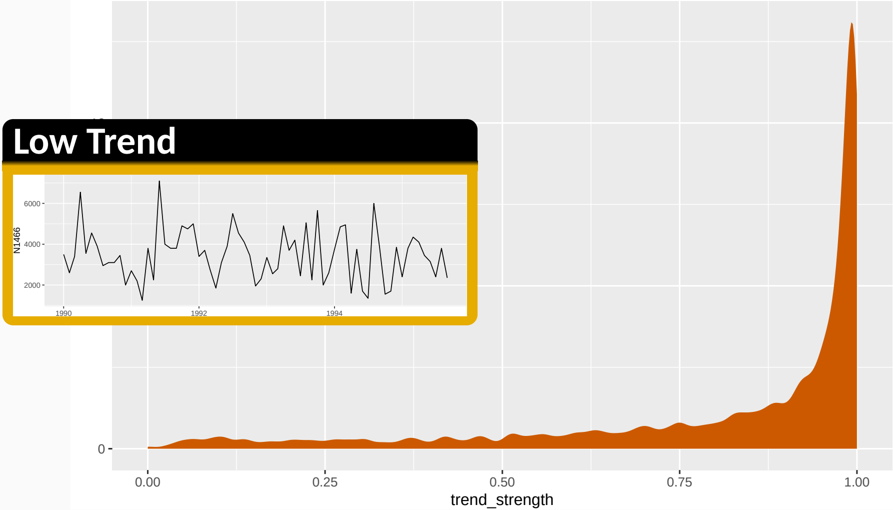
Distribution of Seasonality for M3



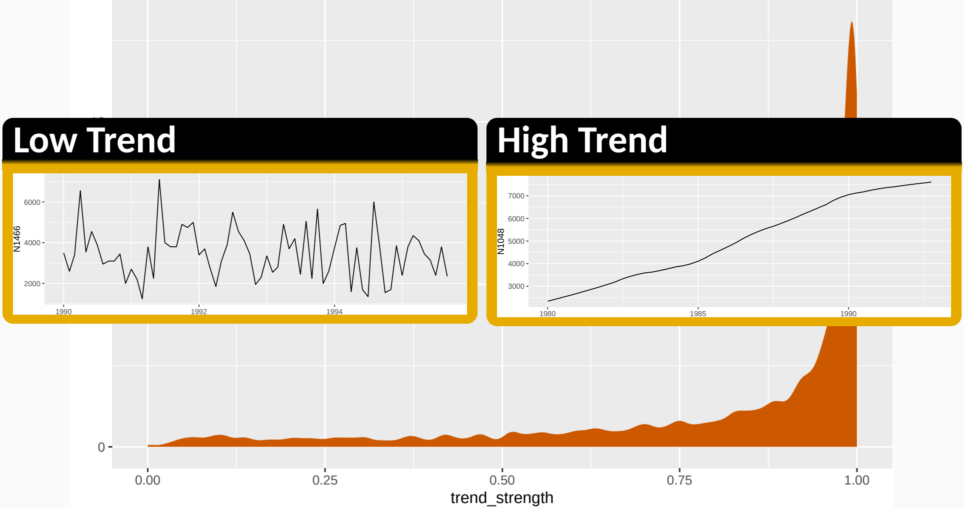
Distribution of Trend for M3



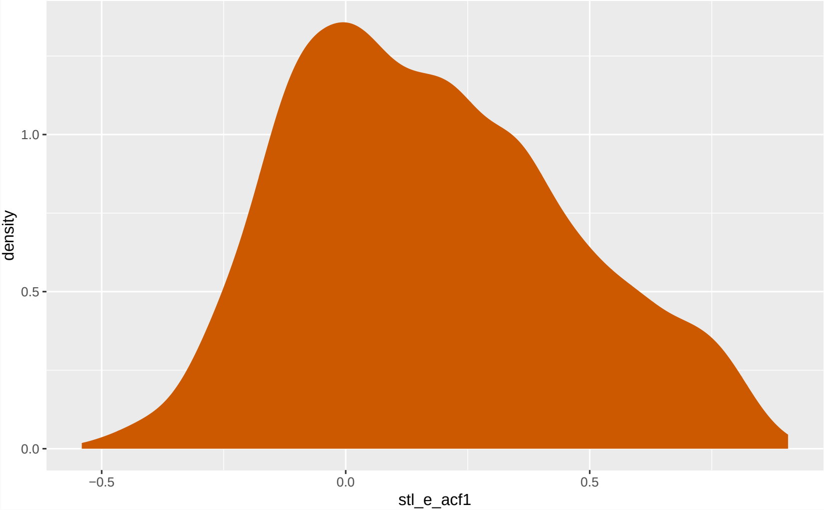
Distribution of Trend for M3



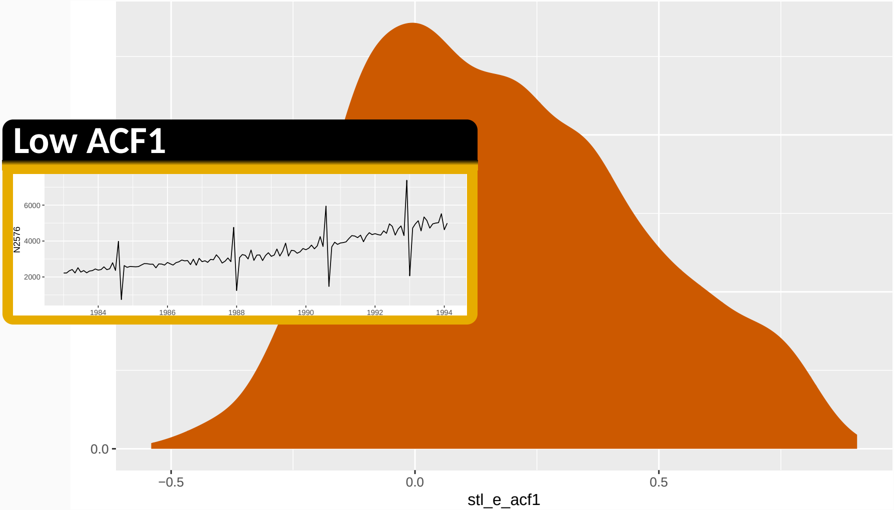
Distribution of Trend for M3



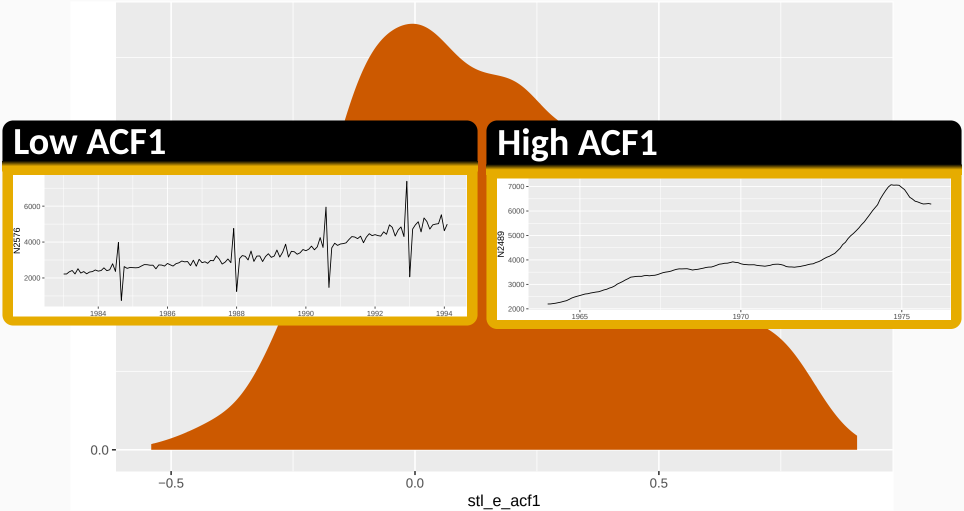
Distribution of Residual ACF1 for M3



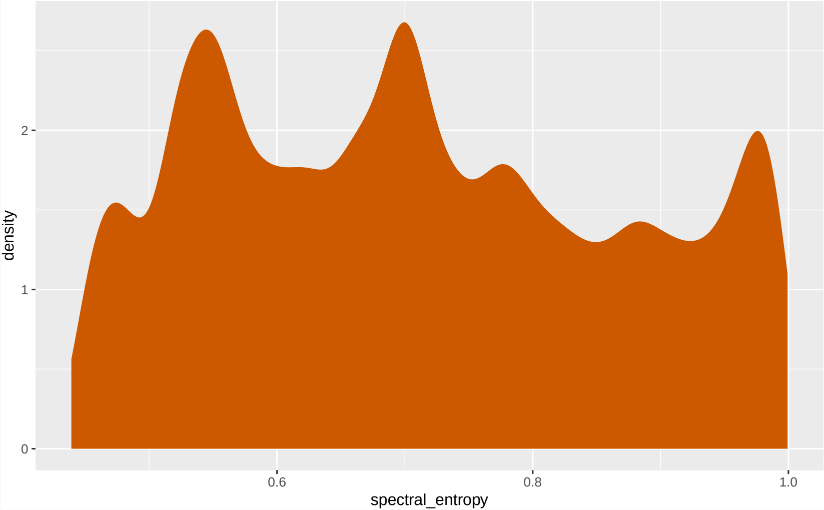
Distribution of Residual ACF1 for M3



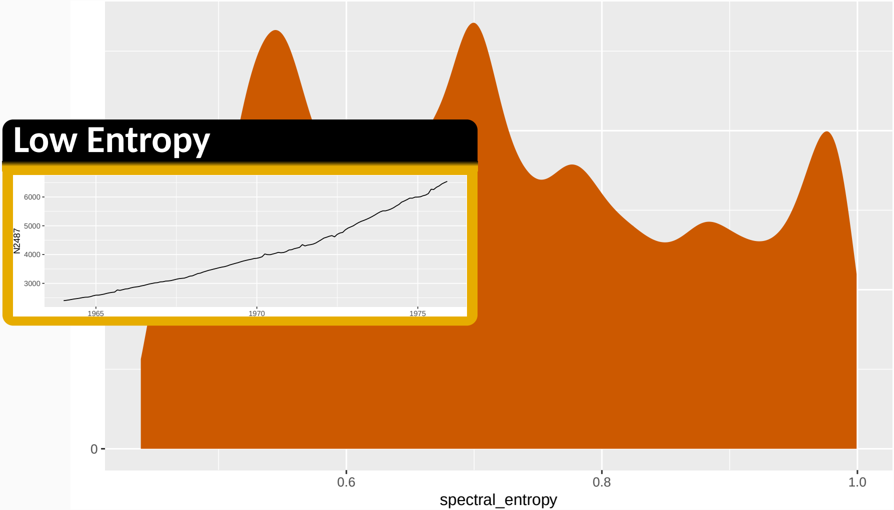
Distribution of Residual ACF1 for M3



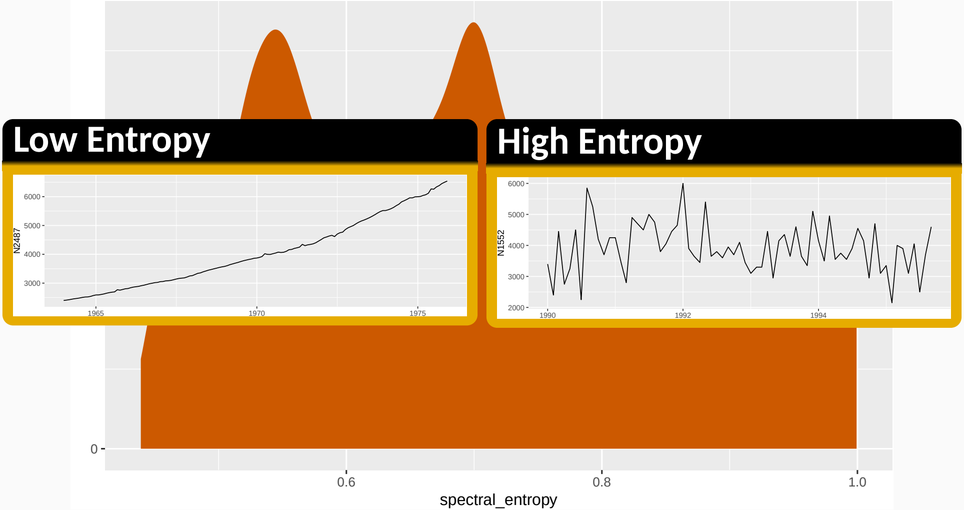
Distribution of Spectral Entropy for M3



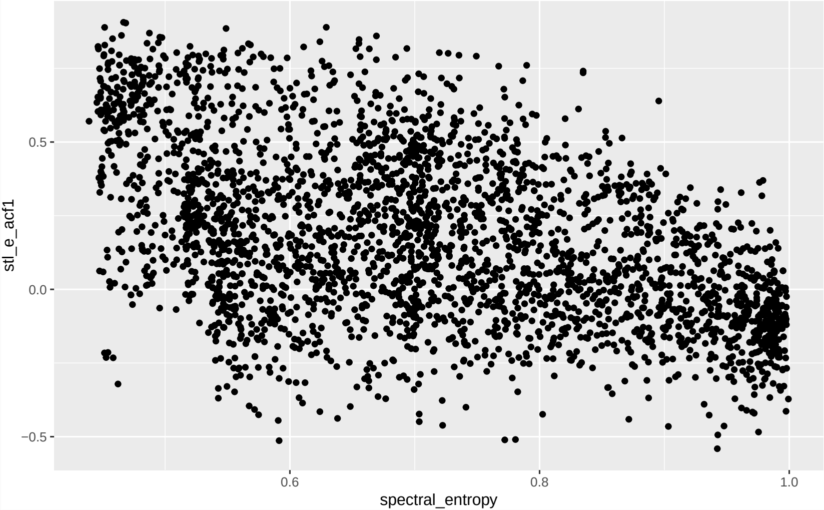
Distribution of Spectral Entropy for M3



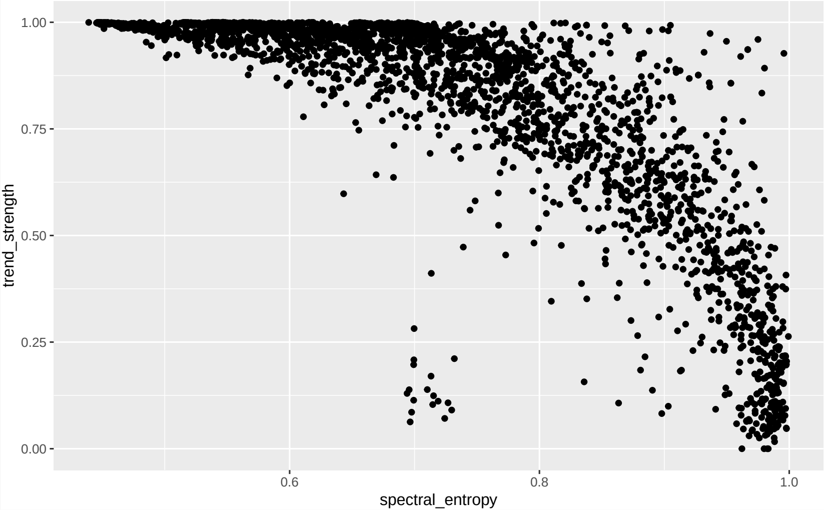
Distribution of Spectral Entropy for M3



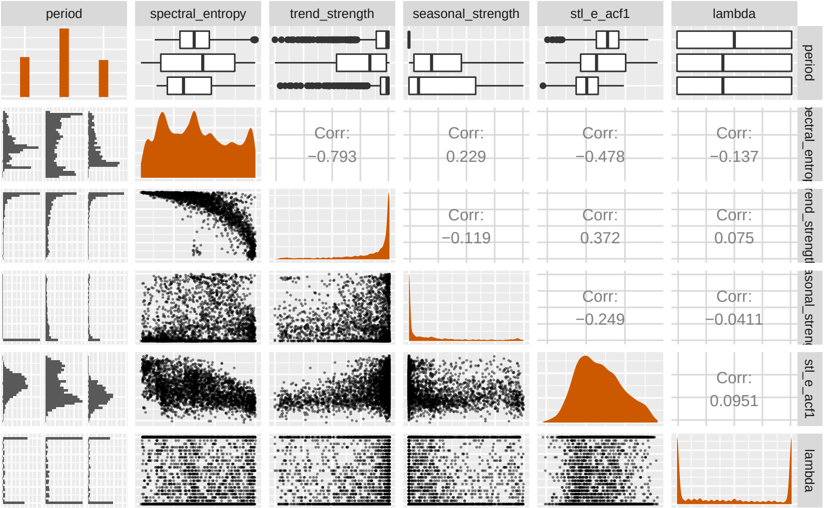
Feature distributions



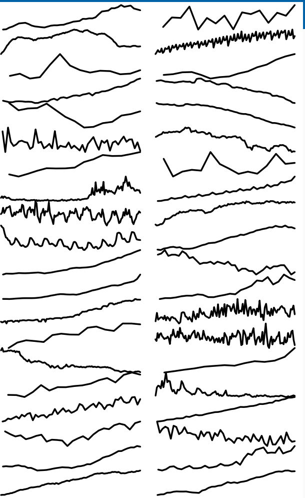
Feature distributions



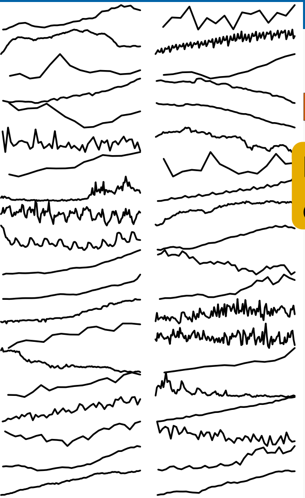
Feature distributions



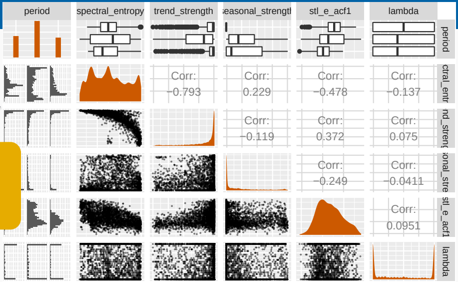
Dimension reduction for time series



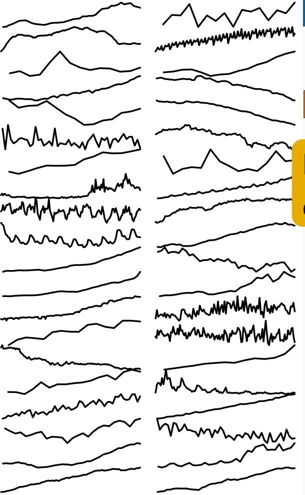
Dimension reduction for time series



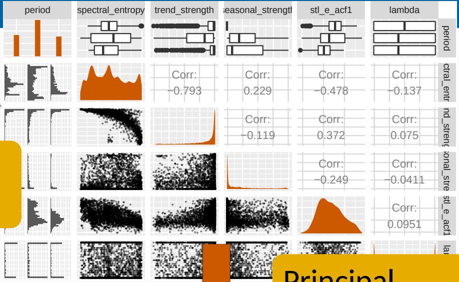
Feature calculation



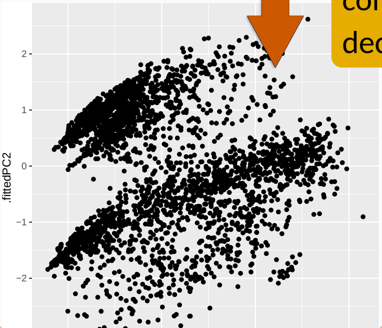
Dimension reduction for time series



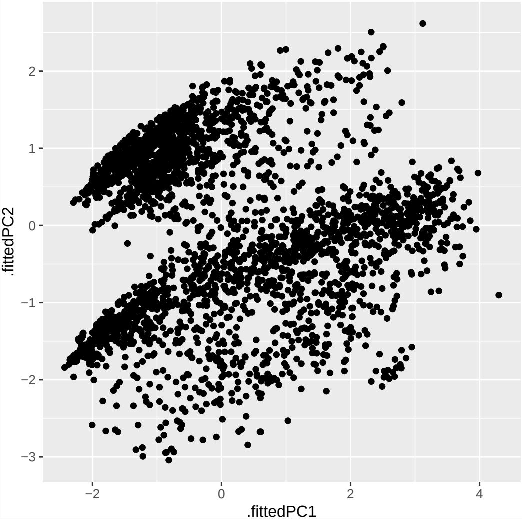
Feature calculation



Principal component decomposition

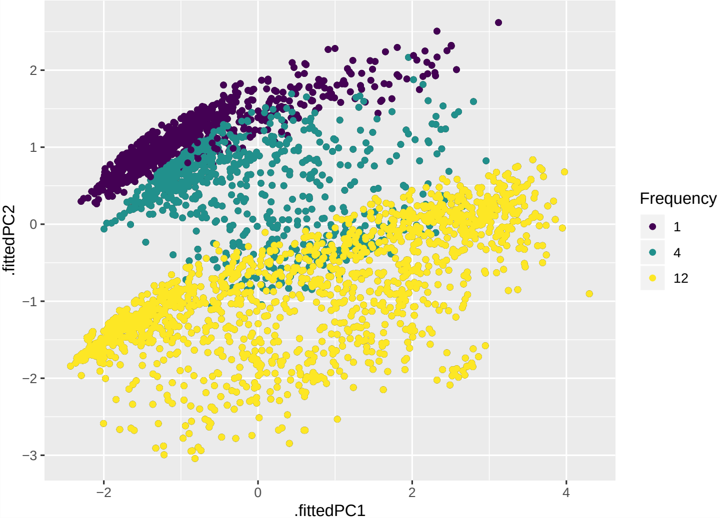


M3 feature space

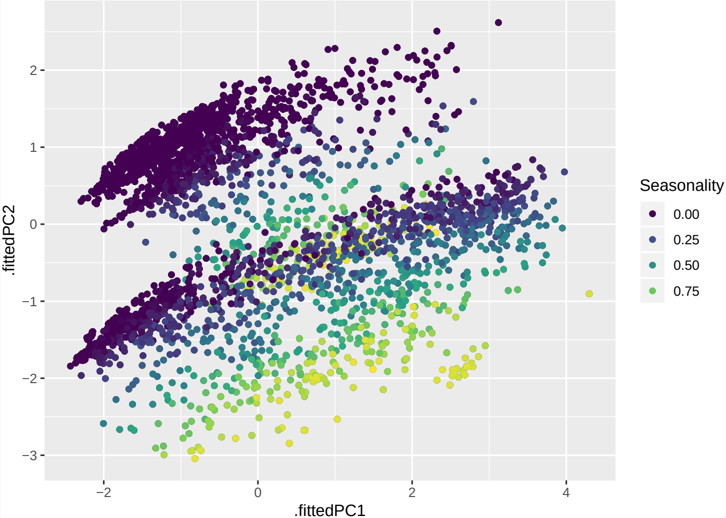


First two PCs explain 58.5% of the variance.

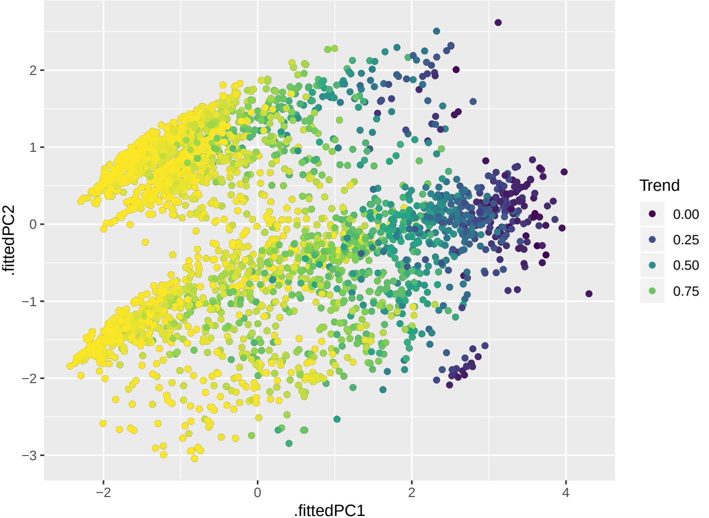
M3 feature space



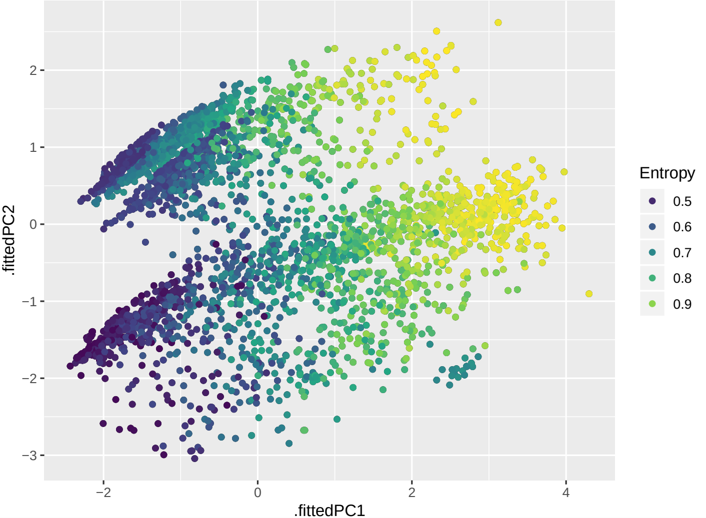
M3 feature space



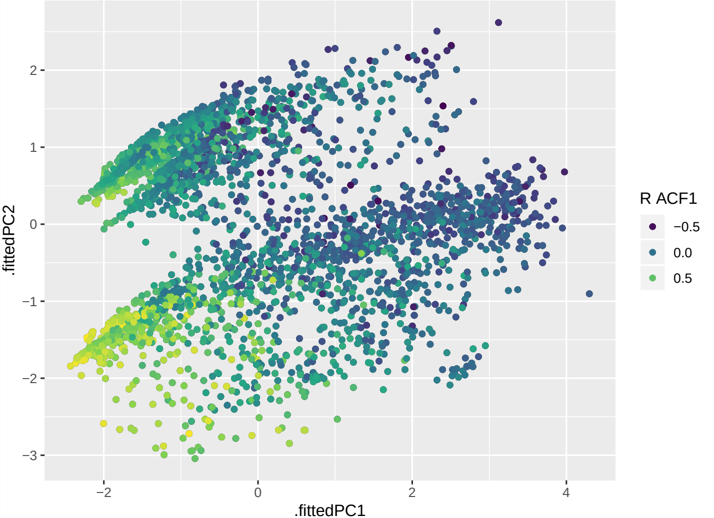
M3 feature space



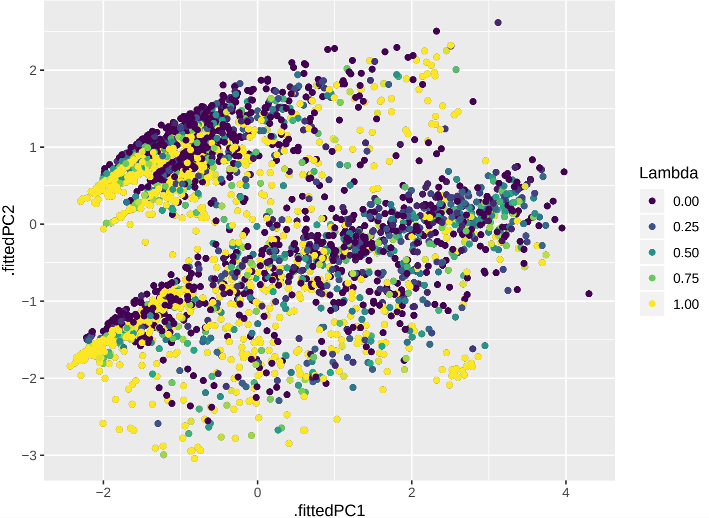
M3 feature space



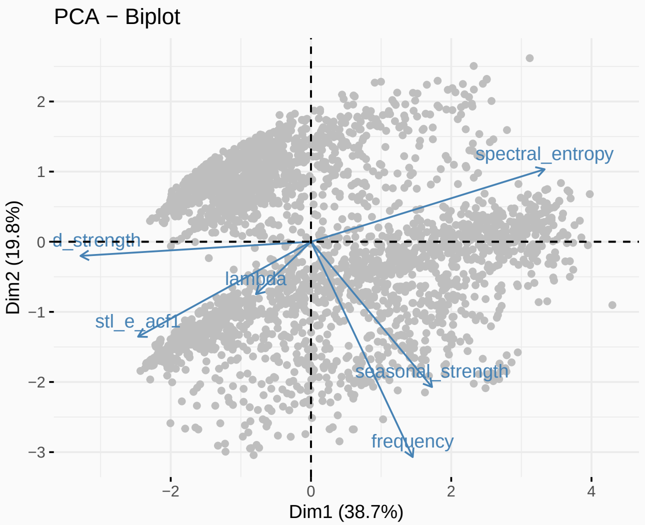
M3 feature space



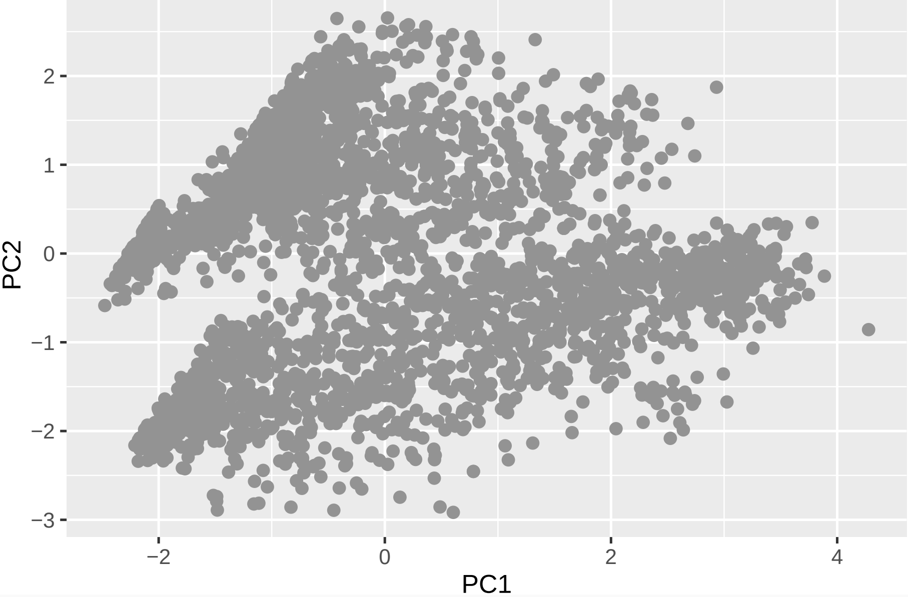
M3 feature space



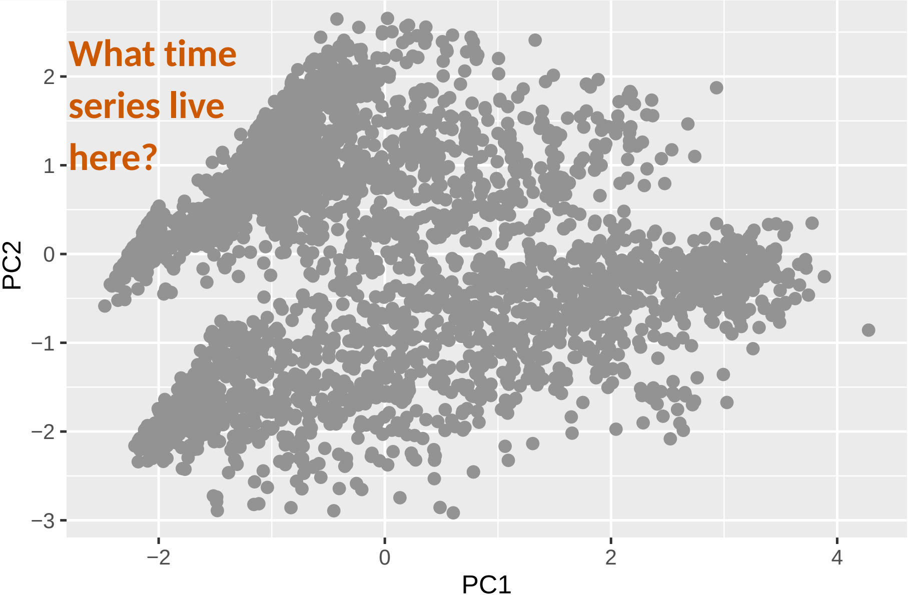
M3 feature space



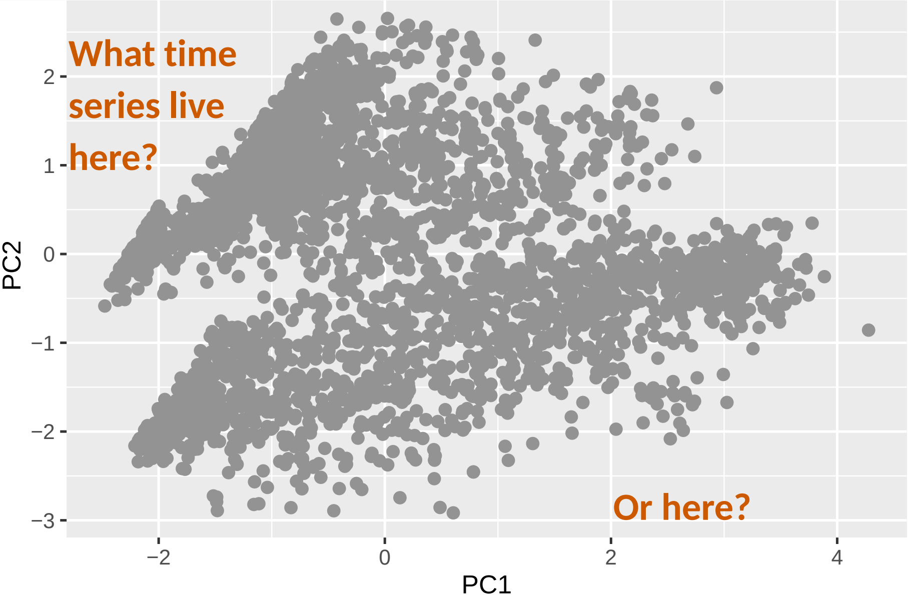
What about the holes?



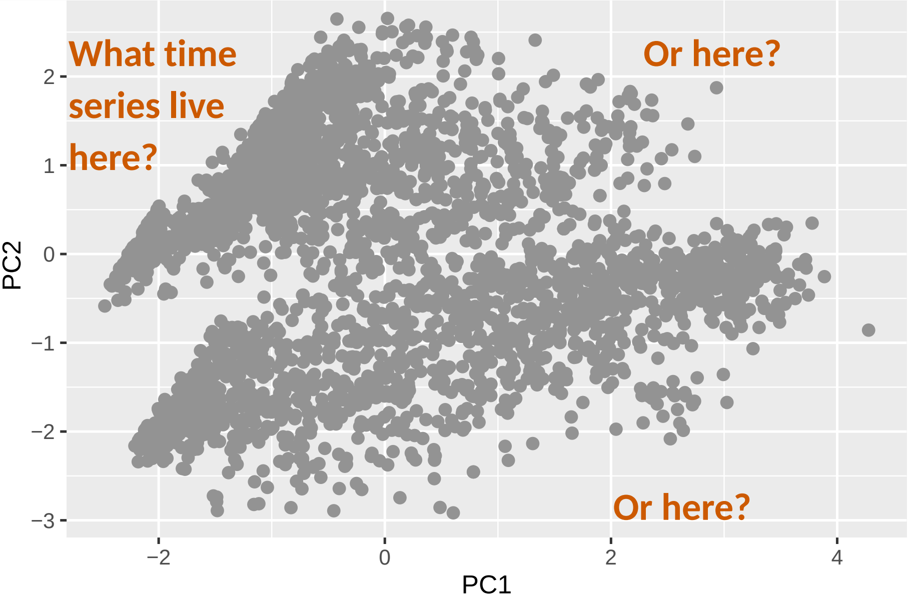
What about the holes?



What about the holes?



What about the holes?



Generating new time series

We can use the feature space to:

- Generate new time series with similar features to existing series
- Generate new time series where there are “holes” in the feature space.

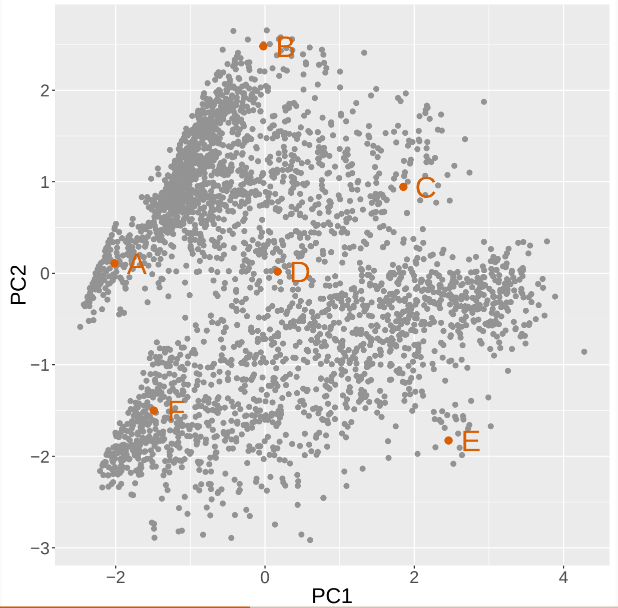
Generating new time series

We can use the feature space to:

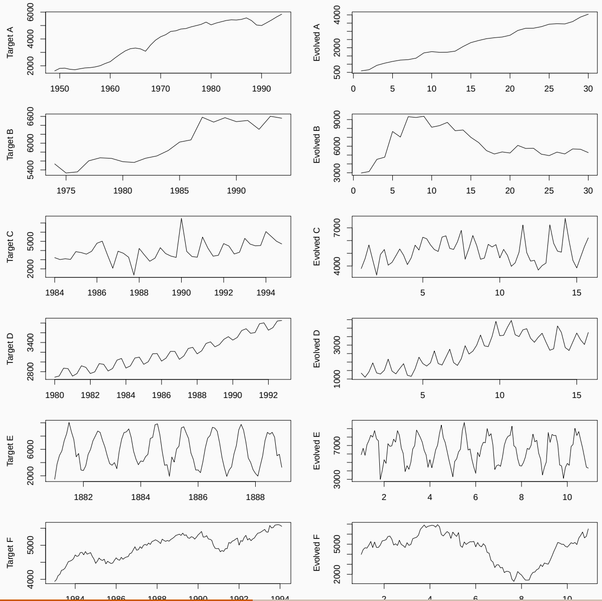
- Generate new time series with similar features to existing series
- Generate new time series where there are "holes" in the feature space.

- Let $\{\mathrm{PC}_1, \mathrm{PC}_2, \dots, \mathrm{PC}_n\}$ be a "population" of time series of specified length and period.
- Genetic algorithm uses a process of selection, crossover and mutation to evolve the population towards a target point T_i.
- Optimize: Fitness $(\mathrm{PC}_j) = -\sqrt{(|\mathrm{PC}_j - T_i|^2)}$.
- Initial population random with some series in neighbourhood of T_i.

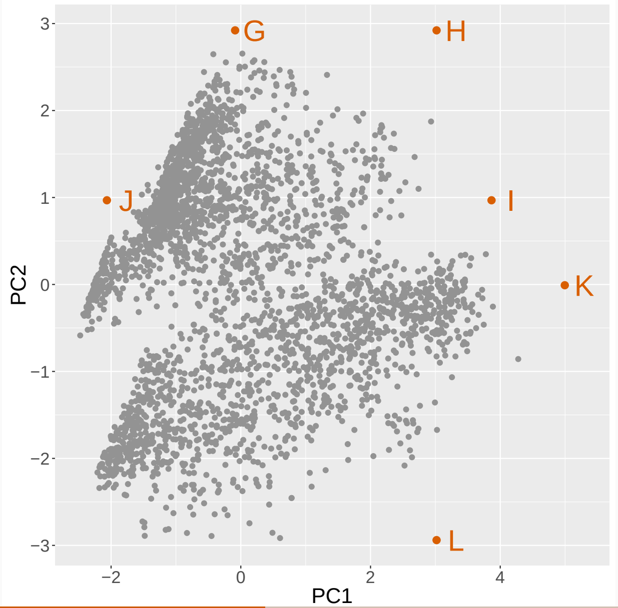
Evolving new time series



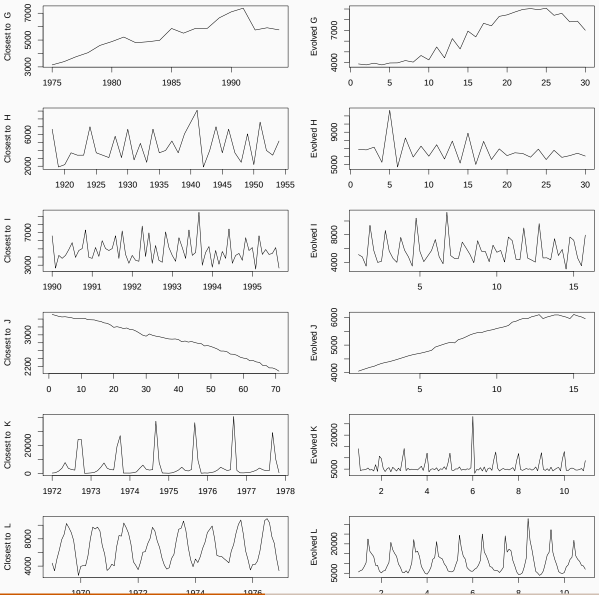
Evolving new time series



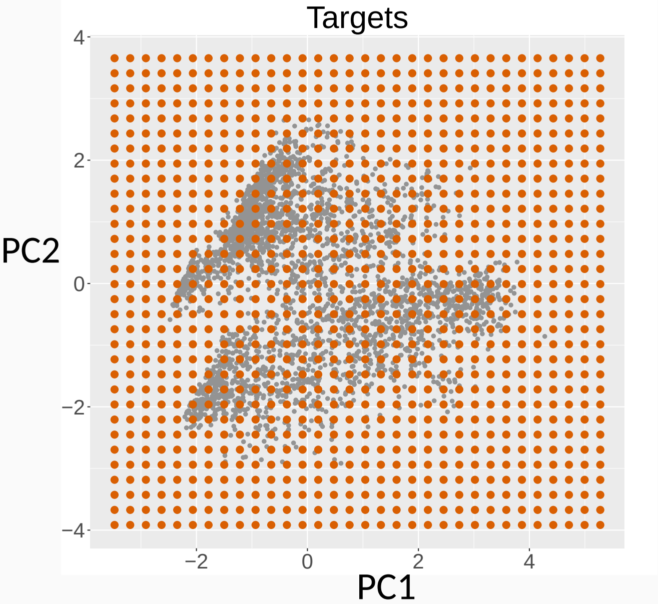
Evolving new time series



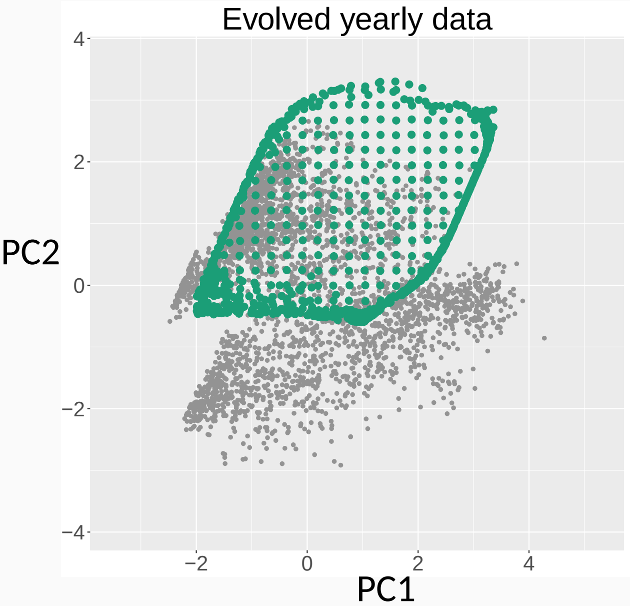
Evolving new time series



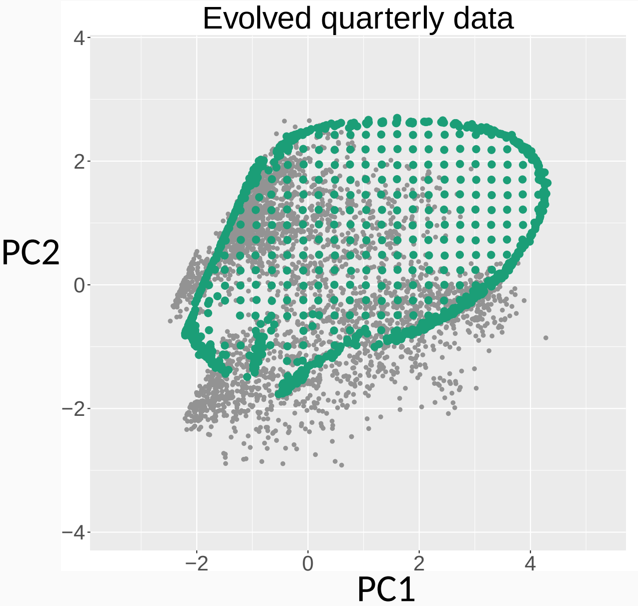
Evolving new time series



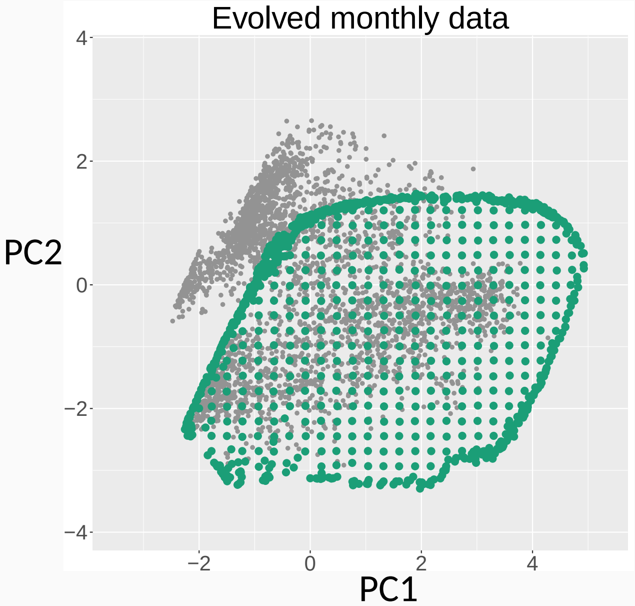
Evolving new time series



Evolving new time series



Evolving new time series



Outline

Tidyverts packages

tidyverts.org

tsibble

tsibbledata

feasts

fable

Overview

Feature Extraction And Statistics for Time Series

- works with tidy temporal data provided by the tsibble package.
- produces time series features, decompositions, statistical summaries and visualisations.

tsibble objects

```
tourism
```

```
## # A tsibble: 24,320 x 5 [1Q]
## # Key:       Region, State, Purpose [304]
##    Quarter Region   State Purpose  Trips
##      <qtr> <chr>    <chr> <chr>    <dbl>
##  1 1998 Q1 Adelaide SA    Business  135.
##  2 1998 Q2 Adelaide SA    Business  110.
##  3 1998 Q3 Adelaide SA    Business  166.
##  4 1998 Q4 Adelaide SA    Business  127.
##  5 1999 Q1 Adelaide SA    Business  137.
##  6 1999 Q2 Adelaide SA    Business  200.
##  7 1999 Q3 Adelaide SA    Business  169.
##  8 1999 Q4 Adelaide SA    Business  134.
##  9 2000 Q1 Adelaide SA    Business  154.
## 10 2000 Q2 Adelaide SA    Business  169.
## # ... with 24,310 more rows
```

tsibble objects

```
tourism
```

```
## # A tsibble: 24,320 x 5 [1Q]
## # Key:       Region, State, Purpose [304]
##    Quarter Region   State Purpose  Trips
##    Index   <chr>    <chr> <chr>    <dbl>
##  1 1998 Q1 Adelaide SA    Business  135.
##  2 1998 Q2 Adelaide SA    Business  110.
##  3 1998 Q3 Adelaide SA    Business  166.
##  4 1998 Q4 Adelaide SA    Business  127.
##  5 1999 Q1 Adelaide SA    Business  137.
##  6 1999 Q2 Adelaide SA    Business  200.
##  7 1999 Q3 Adelaide SA    Business  169.
##  8 1999 Q4 Adelaide SA    Business  134.
##  9 2000 Q1 Adelaide SA    Business  154.
## 10 2000 Q2 Adelaide SA    Business  169.
## # ... with 24,310 more rows
```

tsibble objects

```r
tourism
```

```
## # A tsibble: 24,320 x 5 [1Q]
## # Key:       Region, State, Purpose [304]
##    Quarter Region   State Purpose  Trips
##    Index   Keys                    <dbl>
##  1 1998 Q1 Adelaide SA    Business  135.
##  2 1998 Q2 Adelaide SA    Business  110.
##  3 1998 Q3 Adelaide SA    Business  166.
##  4 1998 Q4 Adelaide SA    Business  127.
##  5 1999 Q1 Adelaide SA    Business  137.
##  6 1999 Q2 Adelaide SA    Business  200.
##  7 1999 Q3 Adelaide SA    Business  169.
##  8 1999 Q4 Adelaide SA    Business  134.
##  9 2000 Q1 Adelaide SA    Business  154.
## 10 2000 Q2 Adelaide SA    Business  169.
## # ... with 24,310 more rows
```

tsibble objects

```
tourism
```

```
## # A tsibble: 24,320 x 5 [1Q]
## # Key:       Region, State, Purpose [304]
##    Quarter Region   State Purpose  Trips
##    Index   Keys                    Measure
##  1 1998 Q1 Adelaide SA    Business  135.
##  2 1998 Q2 Adelaide SA    Business  110.
##  3 1998 Q3 Adelaide SA    Business  166.
##  4 1998 Q4 Adelaide SA    Business  127.
##  5 1999 Q1 Adelaide SA    Business  137.
##  6 1999 Q2 Adelaide SA    Business  200.
##  7 1999 Q3 Adelaide SA    Business  169.
##  8 1999 Q4 Adelaide SA    Business  134.
##  9 2000 Q1 Adelaide SA    Business  154.
## 10 2000 Q2 Adelaide SA    Business  169.
## # ... with 24,310 more rows
```

tsibble objects

```
tourism
```

```
## # A tsibble: 24,320 x 5 [1Q]
## # Key:       Region, State, Purpose [304]
##    Quarter Region   State Purpose   Trips
##    
##  1 1998 Q1 Adelaide SA    Business  135.
##  2 1998 Q2 Adelaide SA    Business  110.
##  3 1998 Q3 Adelaide SA    Business  166.
##  4 1998 Q4 Adelaide SA    Business  127.
##  5 1999 Q1 Adelaide SA    Business  137.
##  6 1999 Q2 Adelaide SA    Business  200.
##  7 1999 Q3 Adelaide SA    Business  169.
##  8 1999 Q4 Adelaide SA    Business  134.
##  9 2000 Q1 Adelaide SA    Business  154.
## 10 2000 Q2 Adelaide SA    Business  169.
## # ... with 24,310 more rows
```

Index

Keys

Measure

Domestic visitor nights in thousands by state/region and purpose.

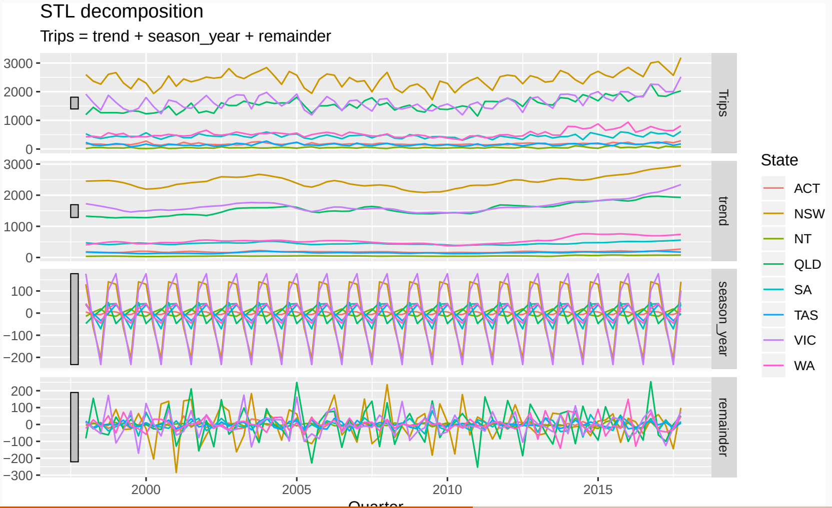
Holidays by state

```r
holidays <- tourism %>%
  filter(Purpose=="Holiday") %>%
  group_by(State) %>%
  summarise(Trips = sum(Trips))
```

```
## # A tsibble: 640 x 3 [1Q]
## # Key:       State [8]
##    Quarter State Trips
##      <qtr> <chr> <dbl>
##  1 1998 Q1 ACT    183.
##  2 1998 Q2 ACT    172.
##  3 1998 Q3 ACT    173.
##  4 1998 Q4 ACT    146.
##  5 1999 Q1 ACT    162.
##  6 1999 Q2 ACT    165.
##  7 1999 Q3 ACT    151.
##  8 1999 Q4 ACT    200.
##  9 2000 Q1 ACT    279.
## 10 2000 Q2 ACT    157.
```

Decompositions

```r
holidays %>% STL(Trips ~ season(window = "periodic")) %>%
  autoplot()
```



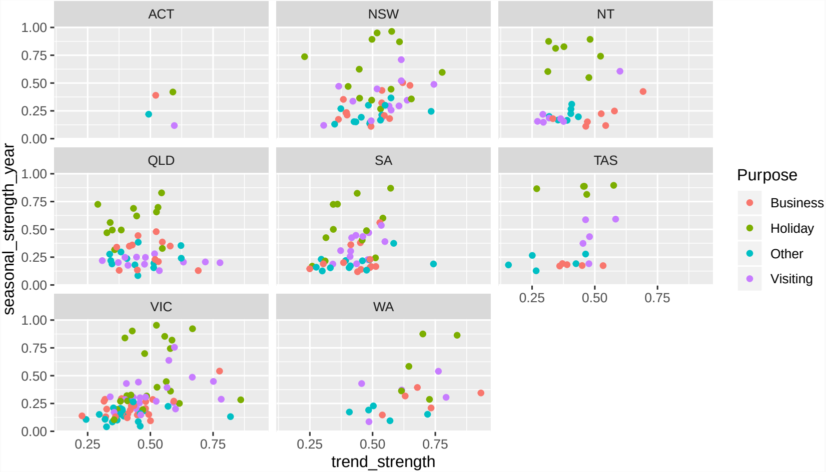
Feature extraction and statistics

```r
tourism %>% features(Trips, feature_set(tags="stl"))
```

```
## # A tibble: 304 x 12
##    Region State Purpose trend_strength seasonal_streng~
##    <chr>  <chr> <chr>            <dbl>            <dbl>
##  1 Adela~ SA    Busine~          0.451            0.380
##  2 Adela~ SA    Holiday          0.541            0.601
##  3 Adela~ SA    Other            0.743            0.189
##  4 Adela~ SA    Visiti~          0.433            0.446
##  5 Adela~ SA    Busine~          0.453            0.140
##  6 Adela~ SA    Holiday          0.512            0.244
##  7 Adela~ SA    Other            0.584            0.374
##  8 Adela~ SA    Visiti~          0.481            0.228
##  9 Alice~ NT    Busine~          0.526            0.224
## 10 Alice~ NT    Holiday          0.377            0.827
## # ... with 294 more rows, and 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>
```

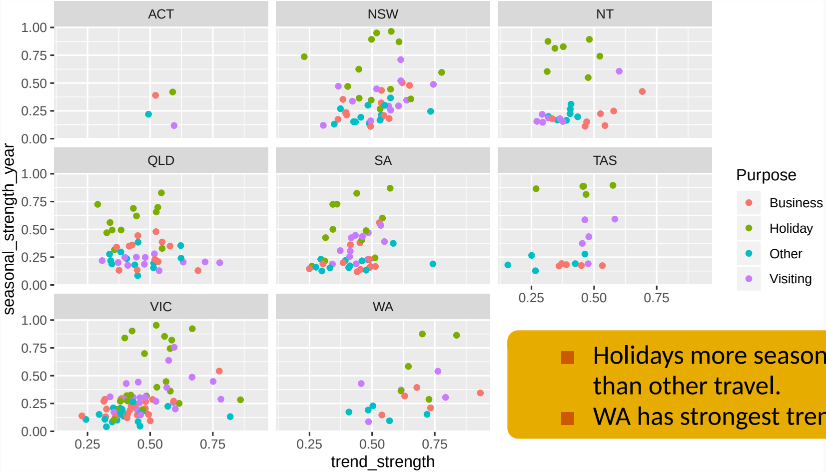
Feature extraction and statistics

```
tourism %>% features(Trips, feature_set(tags="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, feature_set(tags="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:

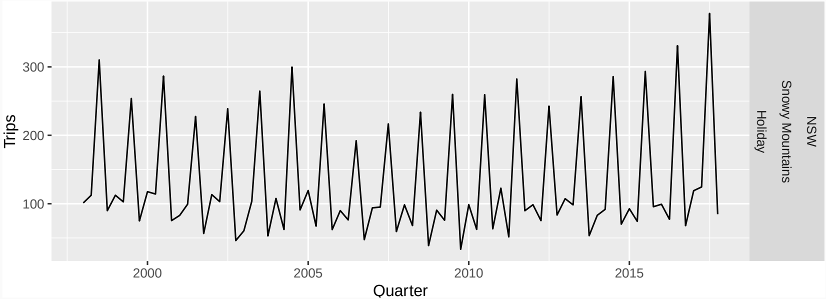
```
most_seasonal <- tourism %>%
  features(Trips, feature_set(tags="stl")) %>%
  filter(seasonal_strength_year == max(seasonal_strength_year))
```

Feature extraction and statistics

Find the most seasonal time series:

```
most_seasonal <- tourism %>%
  features(Trips, feature_set(tags="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

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

All features from the feasts package

```
## # A tibble: 304 x 47
##    Region State Purpose trend_strength seasonal_streng~
##    <chr>  <chr> <chr>            <dbl>            <dbl>
##  1 Adela~ SA    Busine~          0.451            0.380
##  2 Adela~ SA    Holiday          0.541            0.601
##  3 Adela~ SA    Other            0.743            0.189
##  4 Adela~ SA    Visiti~          0.433            0.446
##  5 Adela~ SA    Busine~          0.453            0.140
##  6 Adela~ SA    Holiday          0.512            0.244
##  7 Adela~ SA    Other            0.584            0.374
##  8 Adela~ SA    Visiti~          0.481            0.228
##  9 Alice~ NT    Busine~          0.526            0.224
## 10 Alice~ NT    Holiday          0.377            0.827
## # ... with 294 more rows, and 42 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>,
```

Feature extraction and statistics

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

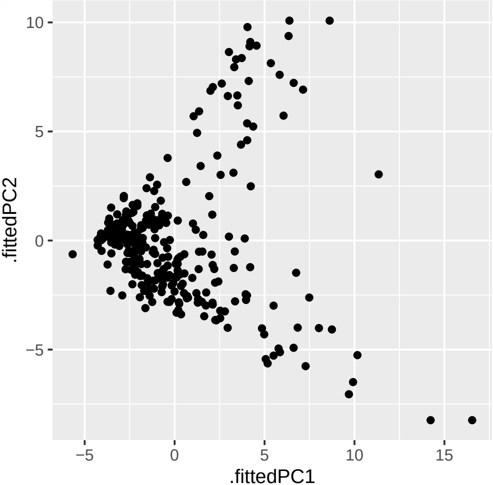
```
## # A tibble: 304 x 92
##    .rownames Region State Purpose trend_strength
##    <fct>     <chr>  <chr> <chr>            <dbl>
##  1 1         Adela~ SA    Busine~          0.451
##  2 2         Adela~ SA    Holiday          0.541
##  3 3         Adela~ SA    Other            0.743
##  4 4         Adela~ SA    Visiti~          0.433
##  5 5         Adela~ SA    Busine~          0.453
##  6 6         Adela~ SA    Holiday          0.512
##  7 7         Adela~ SA    Other            0.584
##  8 8         Adela~ SA    Visiti~          0.481
##  9 9         Alice~ NT    Busine~          0.526
## 10 10        Alice~ NT    Holiday          0.377
## # ... with 294 more rows, and 87 more variables:
## #   seasonal_strength_year <dbl>, 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>,
```

Principal components based on all features from the feasts package

Feature extraction and statistics

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

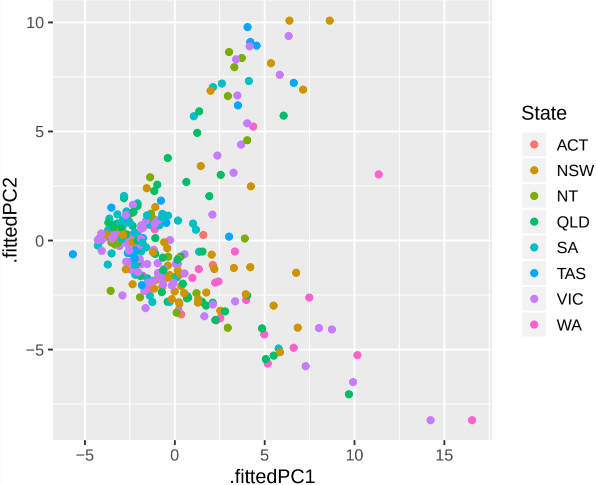
Principal components based on all features from the feasts package



Feature extraction and statistics

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

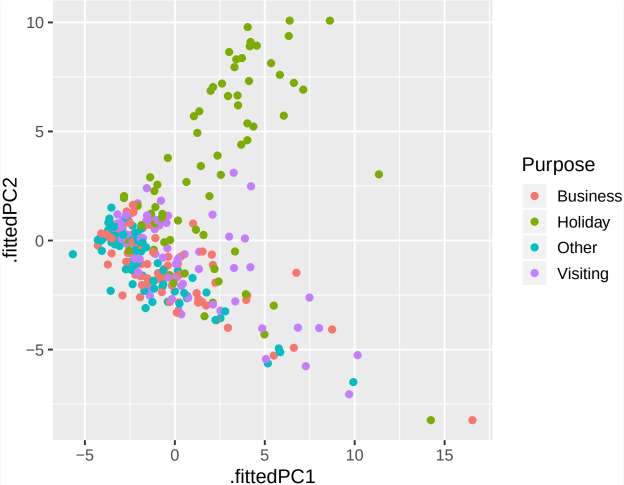
Principal components based on all features from the feasts package



Feature extraction and statistics

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

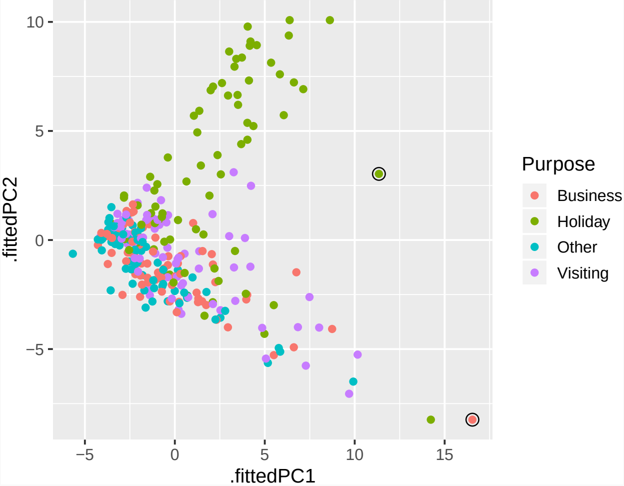
Principal components based on all features from the feasts package



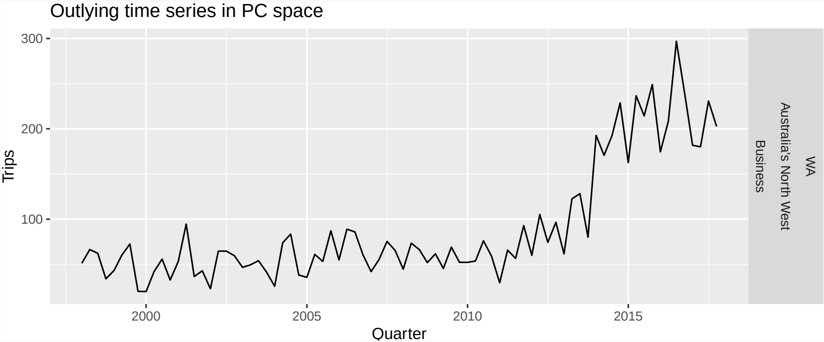
Feature extraction and statistics

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

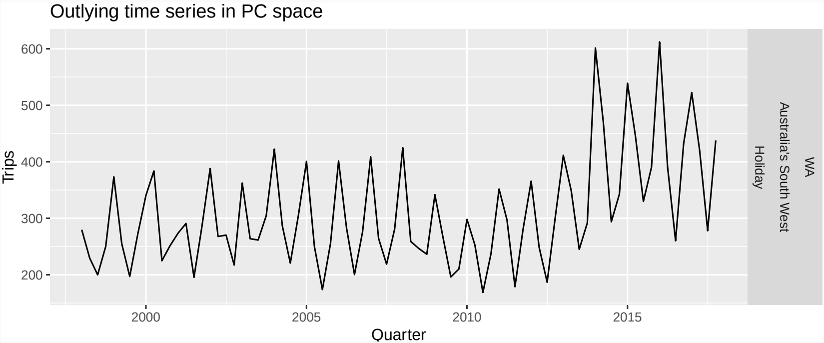
Principal components based on all features from the feasts package



Feature extraction and statistics



Feature extraction and statistics

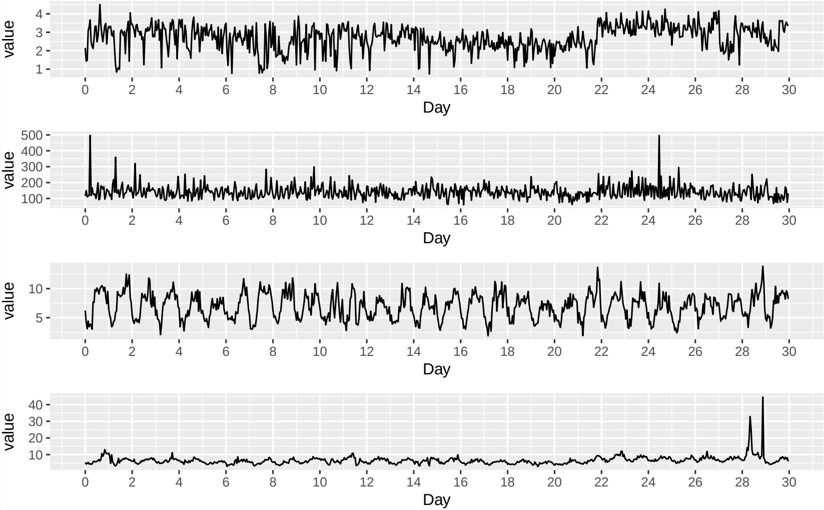


Outline

Yahoo server metrics

- Tens of thousands of time series collected at one-hour intervals over 1–2 months.
- Consisting of several server metrics (e.g. CPU usage and paging views) from many server farms globally.
- Aim: find unusual (anomalous) time series.

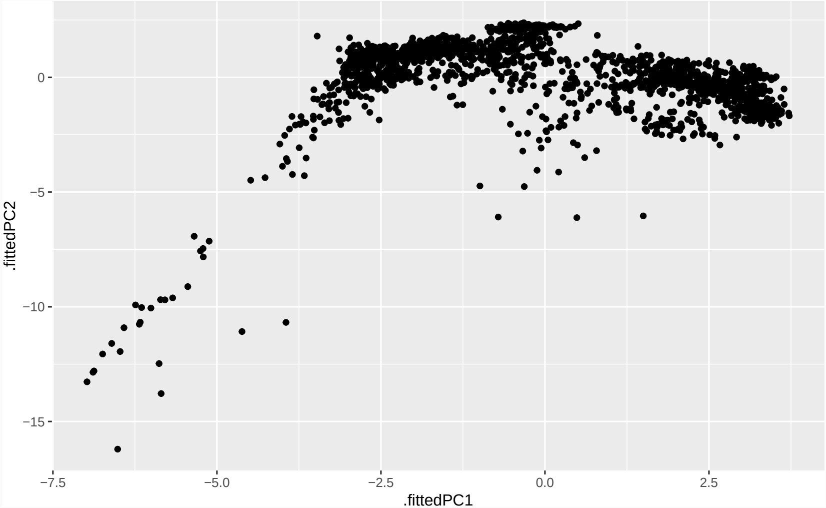
Yahoo server metrics



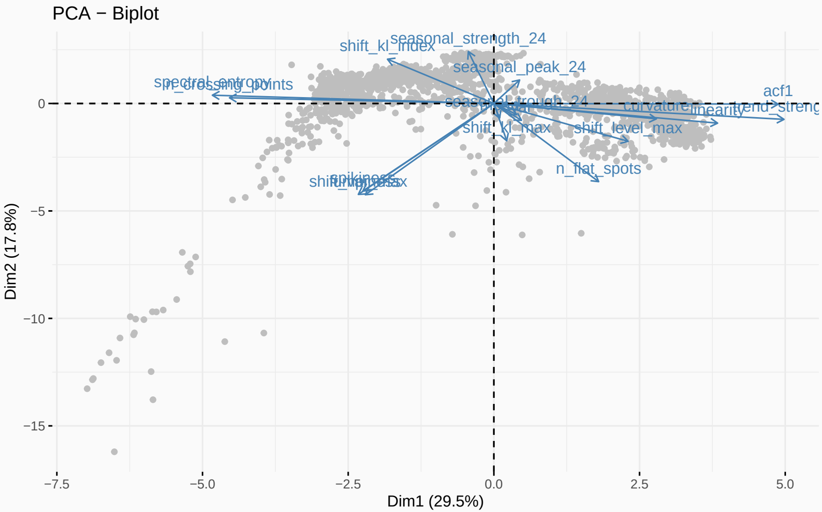
Yahoo server metrics

- **ACF1**: first order autocorrelation = $\text{Corr}(Y_t, Y_{t-1})$
- Strength of **trend** and **seasonality** based on STL
- Size of seasonal **peak** and **trough**
- Spectral **entropy**
- **Lumpiness**: variance of block variances (block size 24).
- **Spikiness**: variances of leave-one-out variances of STL remainders.
- **Level shift**: Maximum difference in trimmed means of consecutive moving windows of size 24.
- **Variance change**: Max difference in variances of consecutive moving windows of size 24.
- **Flat spots**: Discretize sample space into 10 equal-sized intervals. Find max run length in any interval.
- Number of **crossing points** of mean line.
- **Kullback-Leibler score**: Maximum of $D_{KL}(P\|Q) = \int P(x)\ln P(x)/Q(x)dx$ where P and Q are estimated by kernel density estimators applied to consecutive windows

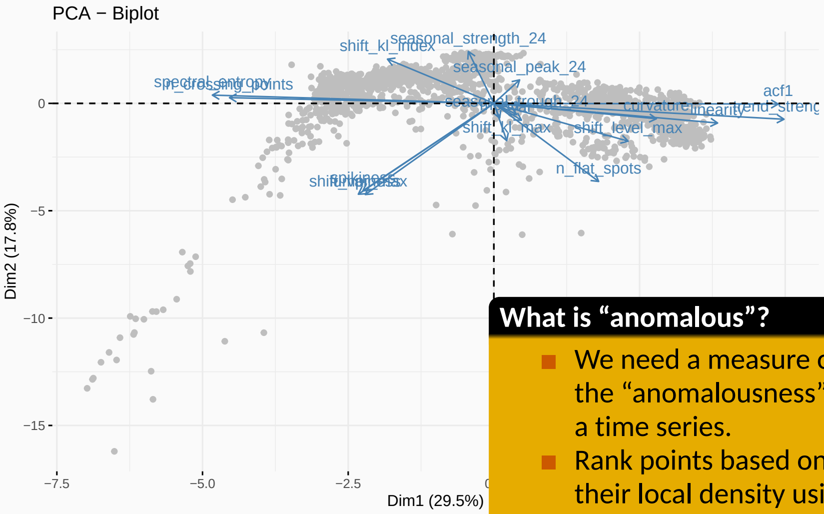
Feature space



Feature space



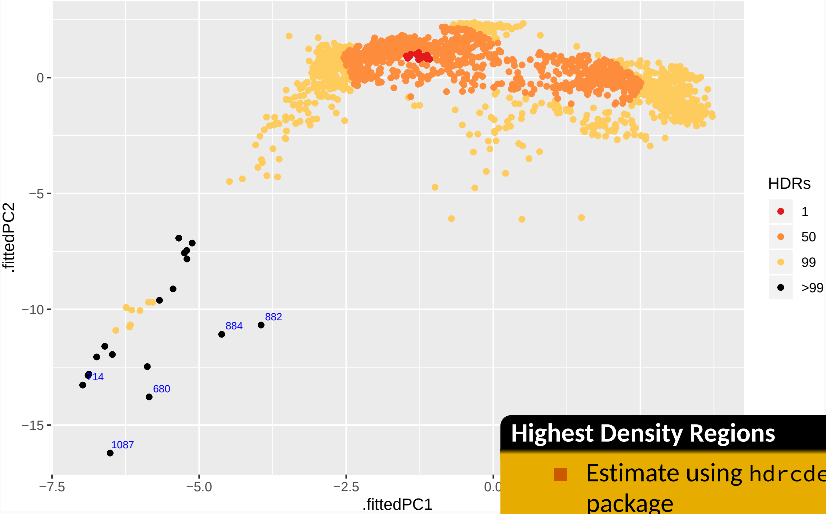
Feature space



What is "anomalous"?

- We need a measure of the "anomalousness" of a time series.
- Rank points based on their local density using a bivariate kernel density estimate.

Finding weird time series



Highest Density Regions

- Estimate using `hdrcde` package
- Highlight outlying points as those with lowest density.

Outline

Forecast model selection

Features used to select a forecasting model

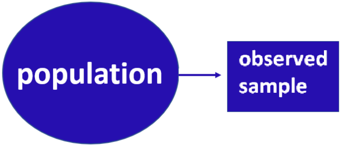
- length
- strength of seasonality
- strength of trend
- linearity
- curvature
- spikiness
- stability
- lumpiness
- first ACF value of remainder series
- parameter estimates of Holt's linear trend method
- spectral entropy
- Hurst exponent
- nonlinearity
- parameter estimates of Holt-Winters' additive method
- unit root test statistics
- first ACF value of residual series of linear trend model
- ACF and PACF based features

- calculated on both the raw and differenced series

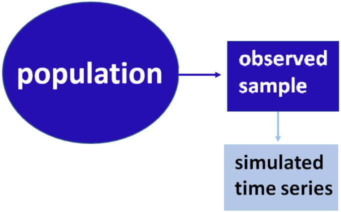
FFORMS: Feature-based FORecast Model Selection

population

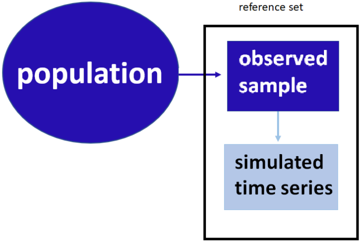
FFORMS: Feature-based FORecast Model Selection



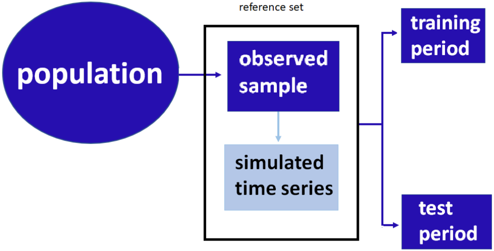
FFORMS: Feature-based FORecast Model Selection



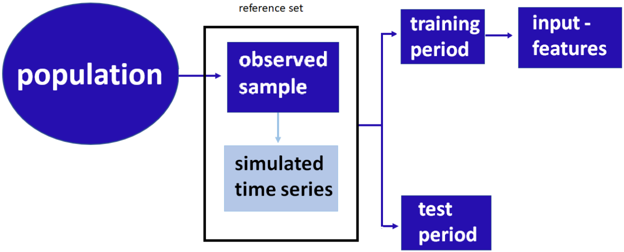
FFORMS: Feature-based FORecast Model Selection



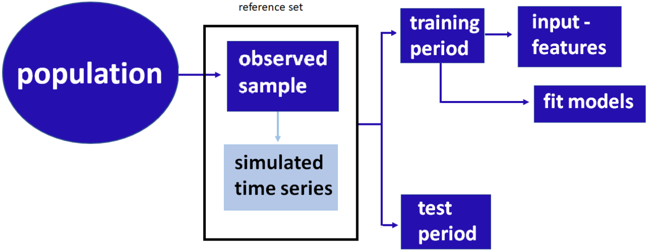
FFORMS: Feature-based FORecast Model Selection



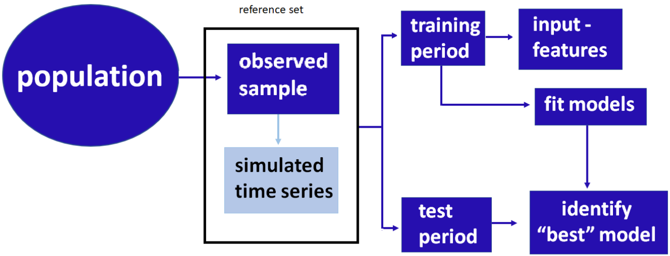
FFORMS: Feature-based FORecast Model Selection



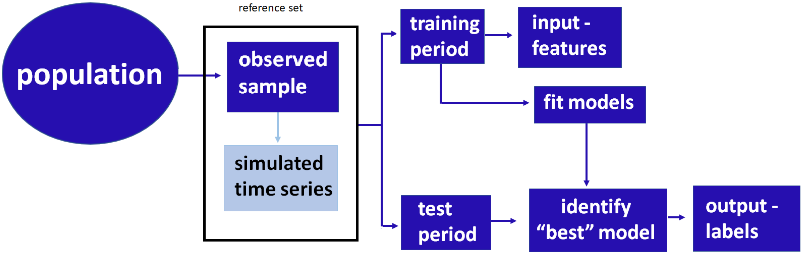
FFORMS: Feature-based FORecast Model Selection



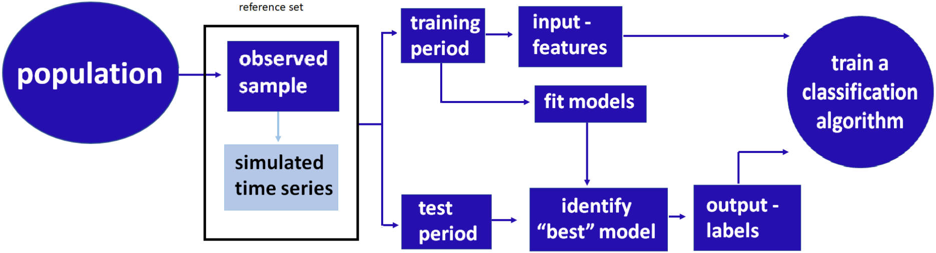
FFORMS: Feature-based FORecast Model Selection



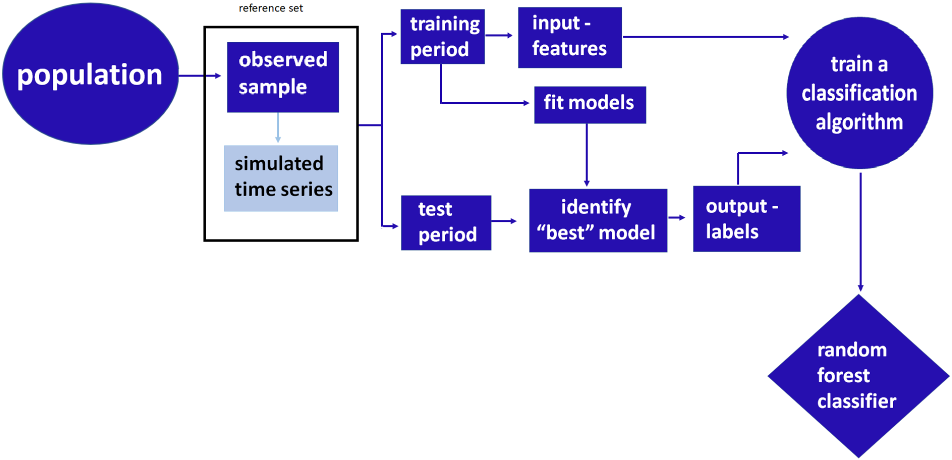
FFORMS: Feature-based FORecast Model Selection



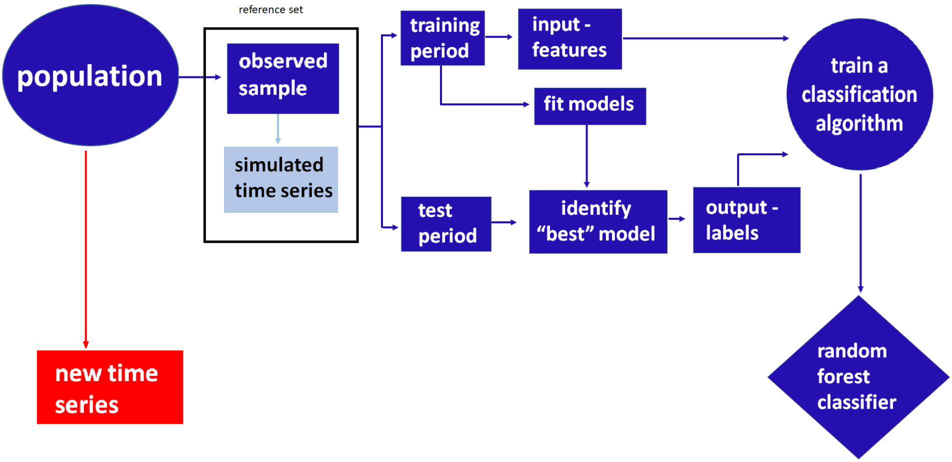
FFORMS: Feature-based FORecast Model Selection



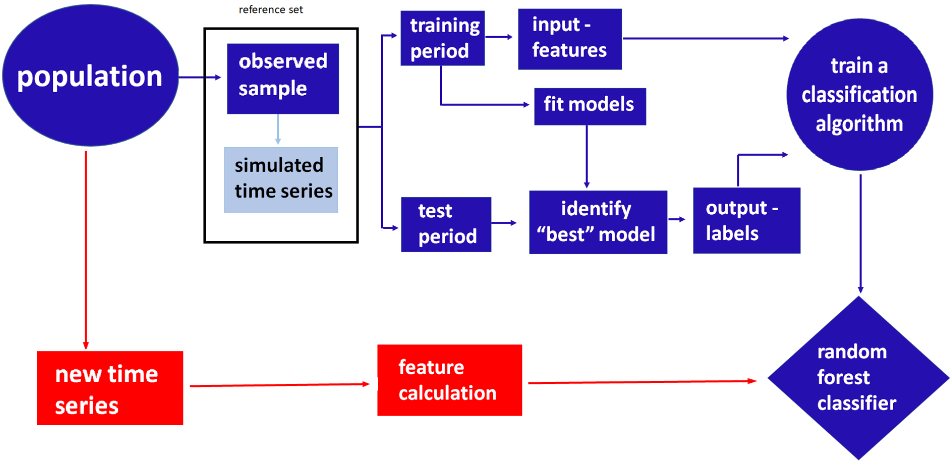
FFORMS: Feature-based FORecast Model Selection



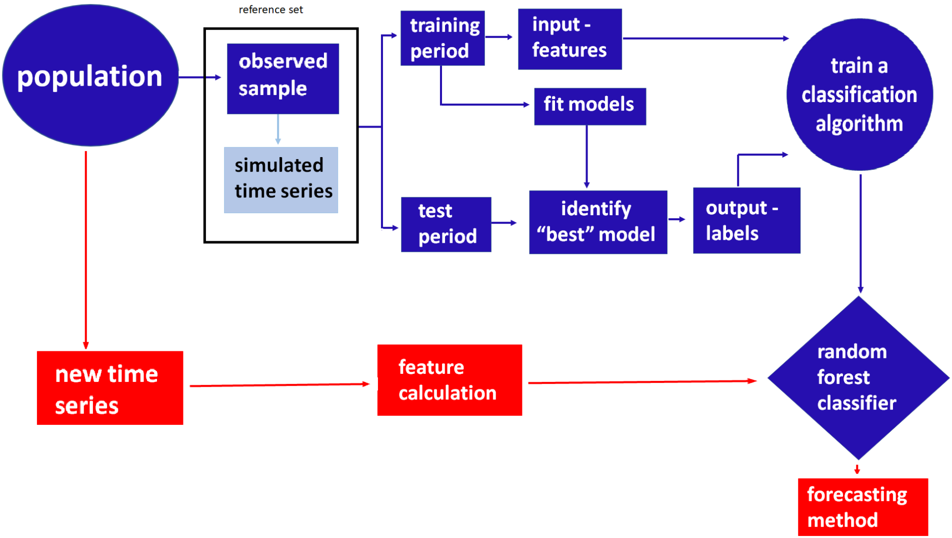
FFORMS: Feature-based FORecast Model Selection



FFORMS: Feature-based FORecast Model Selection



FFORMS: Feature-based FORecast Model Selection



Application to M competition data

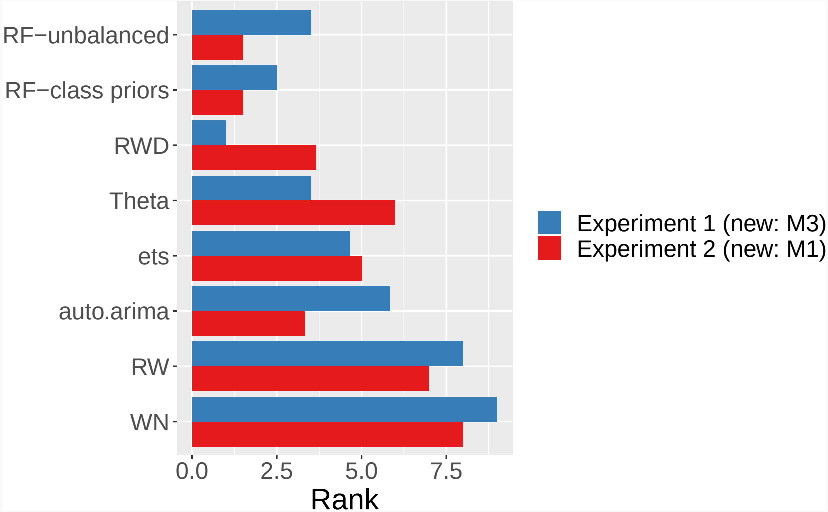
Experiment 1

	Source	Y	Q	M
Observed series	M1	181	203	617
Simulated series		362000	406000	123400
New series	M3	645	756	1428

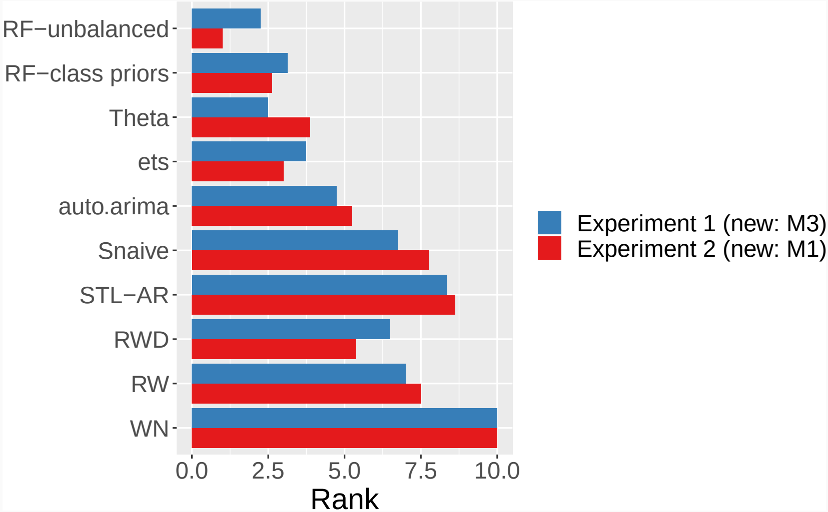
Experiment 2

	Source	Y	Q	M
Observed series	M3	645	756	1428
Simulated series		1290000	1512000	285600
New series	M1	181	203	617

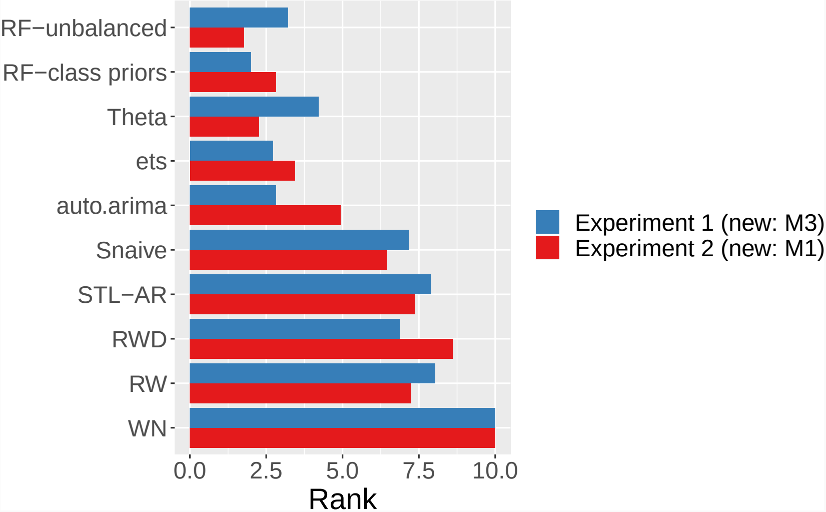
Results: Yearly



Results: Quarterly



Results: Monthly



Outline

FFORMA: Feature-based FORecast Model Averaging

- Like FFORMS but we use gradient boosted trees rather than a random forest.
- The optimization criterion is forecast accuracy not classification accuracy.
- The probability of each model being best is used to construct a model weight.
- A combination forecast is produced using these weights.
- **Came second in the M4 forecasting competition**

FFORMA: Feature-based FORecast Model Averaging

Models included

1. Naive
2. Seasonal naive
3. Random walk with drift
4. Theta method
5. ARIMA
6. ETS
7. TBATS
8. STLM-AR
9. NNAR

R Packages

- **seer**: FFORMS — selecting forecasting model using features.
  `github.com/thiyangt/seer`

- **M4metalearning**: FFORMA – forecast combinations using features to choose weights.
  `github.com/robjhyndman/M4metalearning`

Acknowledgments

Dilini Talagala

Kate Smith-Miles

George Athanasopoulos

Earo Wang

Thiyanga Talagala

Pablo Montero-Manso

Mitchell O’Hara-Wild

Yanfei Kang

Shanika Wickramasuriya