MONASH University

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BUSINESS
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Feature-based time series analysis

Rob J Hyndman

2/3 February 2022

Outline

1. Feature-based visualization
2. R packages
3. Feature-based anomaly detection
4. Feature-based forecasting

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2. R packages
3. Feature-based anomaly detection
4. Feature-based forecasting

M3 competition: 2000

ELSEVIER

International Journal of Forecasting 16 (2000) 451–476

international journal of forecasting

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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.

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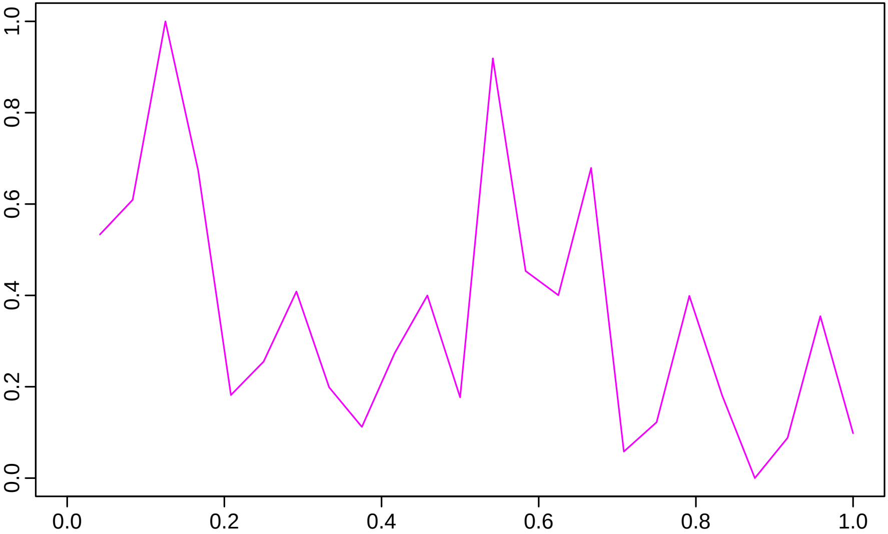
M3 competition: 2000

> "The M3-Competition is a final attempt by the authors to settle the accuracy issue of various time series methods… The extension involves the inclusion of more methods/ researchers (in particular in the areas of neural networks and expert systems) and more series."

- 3003 series
- All data from business, demography, finance and economics.
- Series length between 14 and 126.
- Either non-seasonal, monthly or quarterly.
- All time series positive.

How to plot lots of time series?



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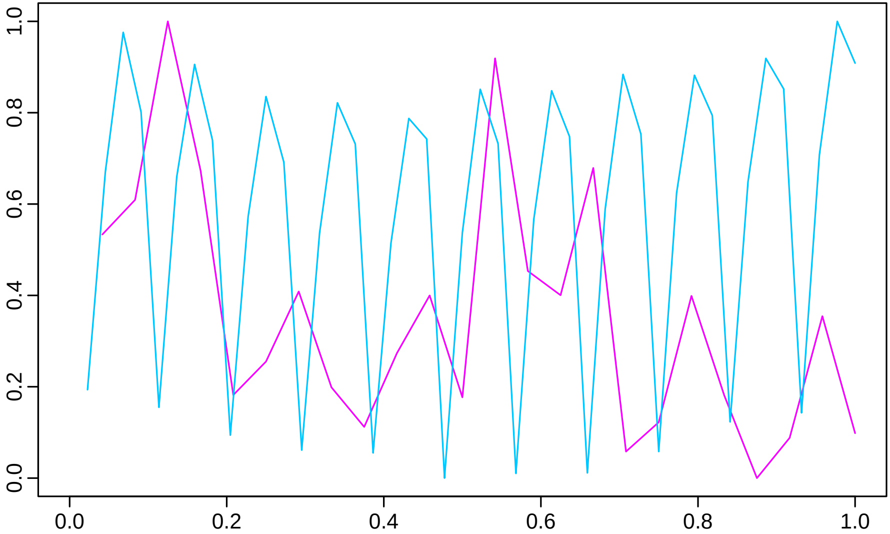

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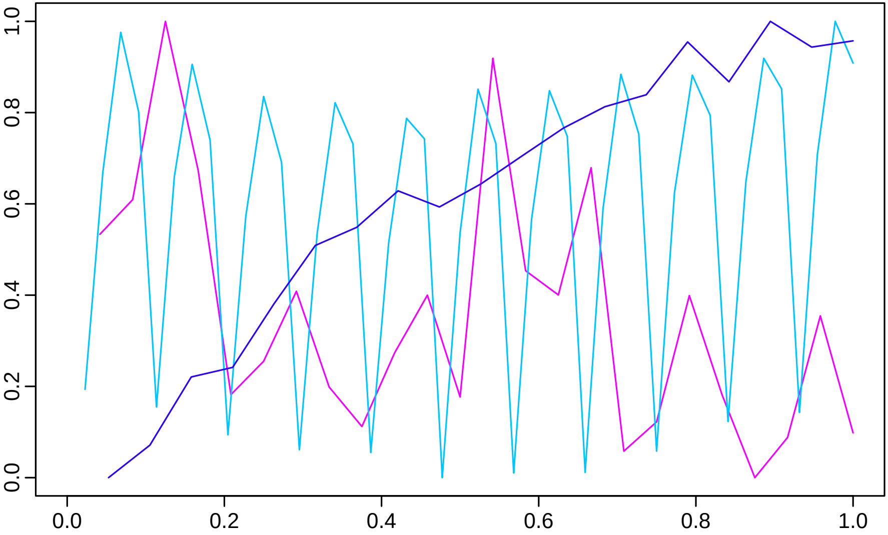

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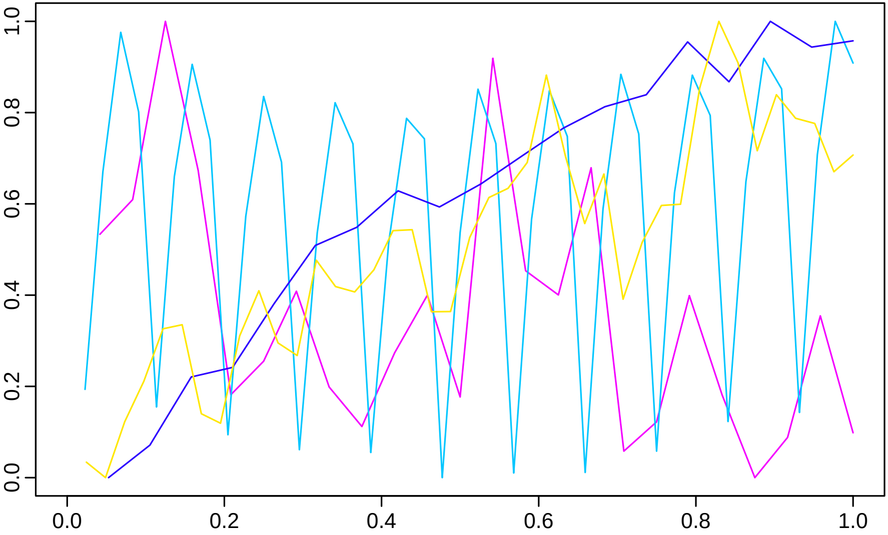

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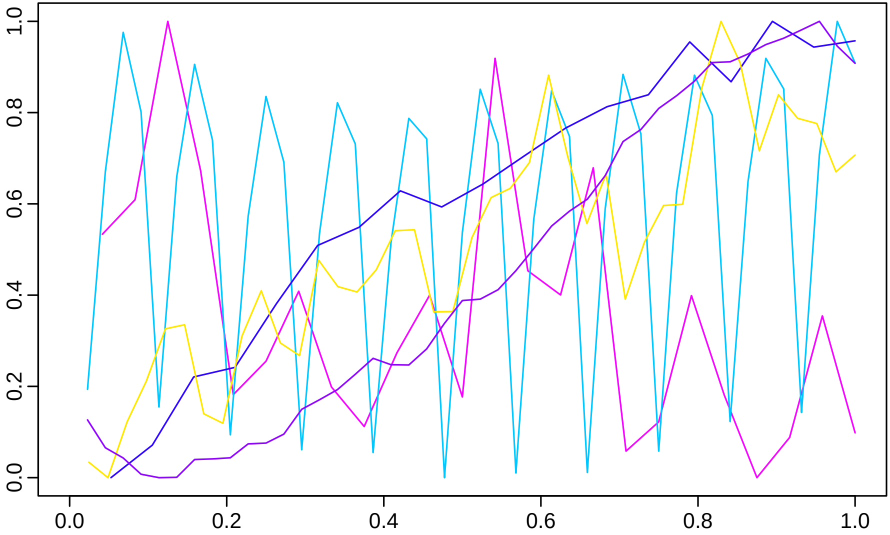

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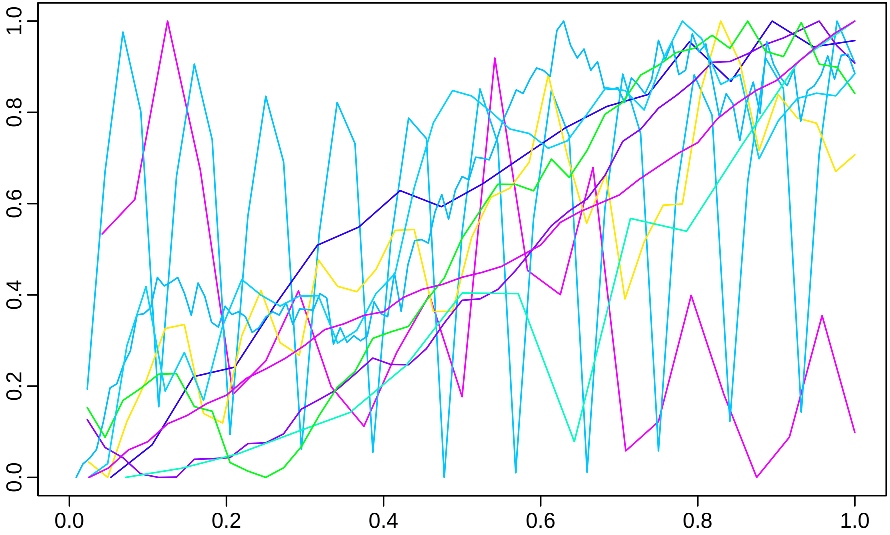

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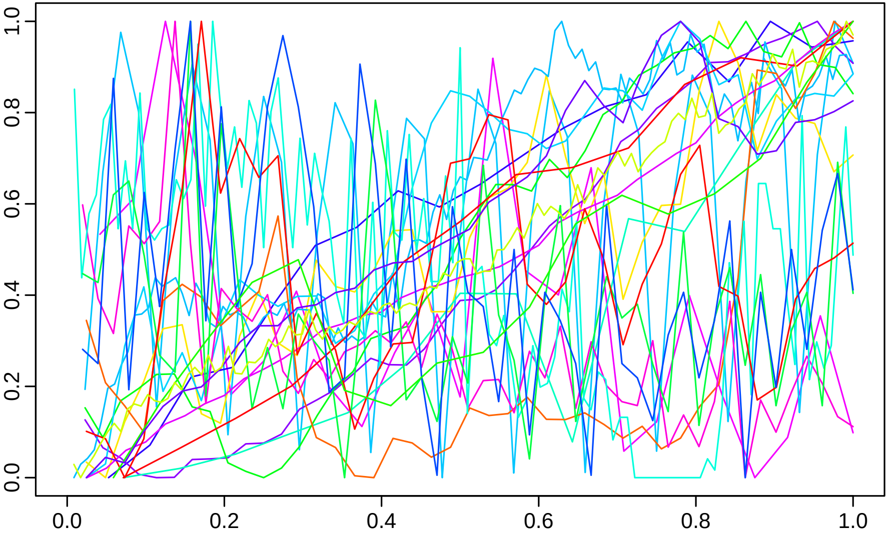

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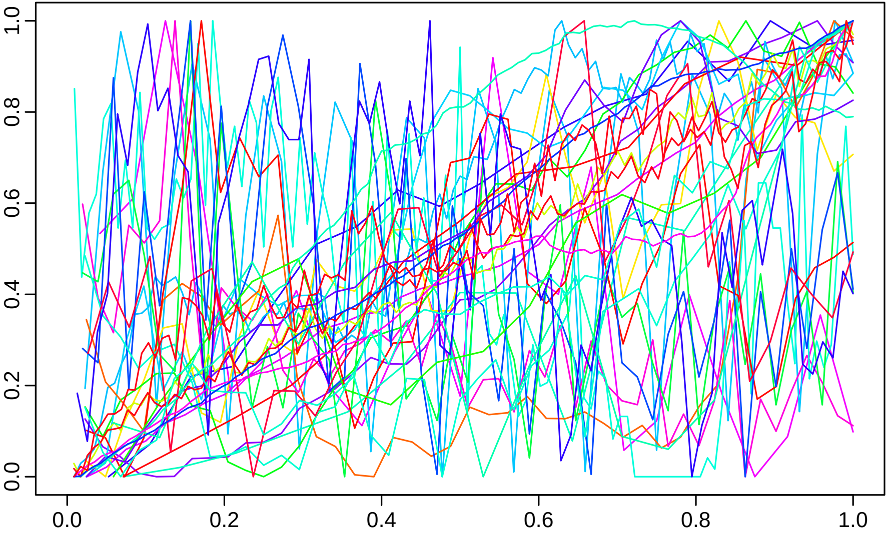

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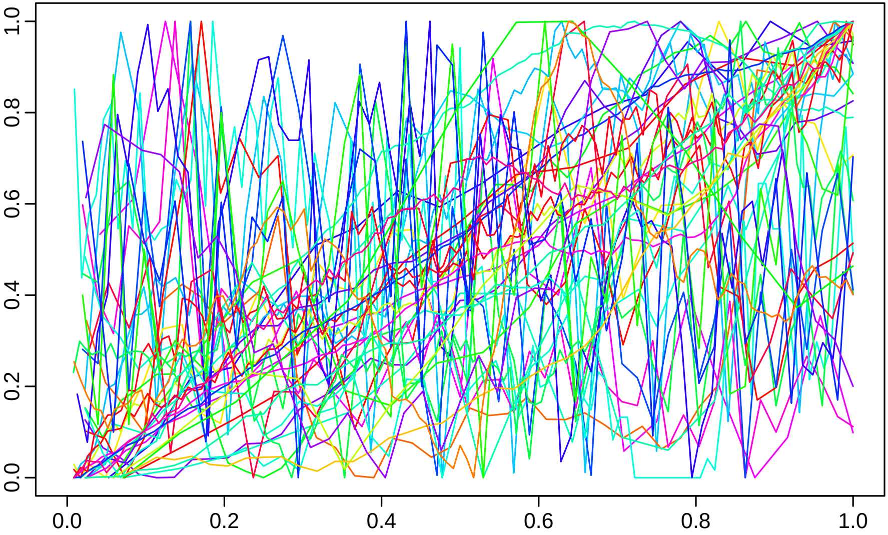

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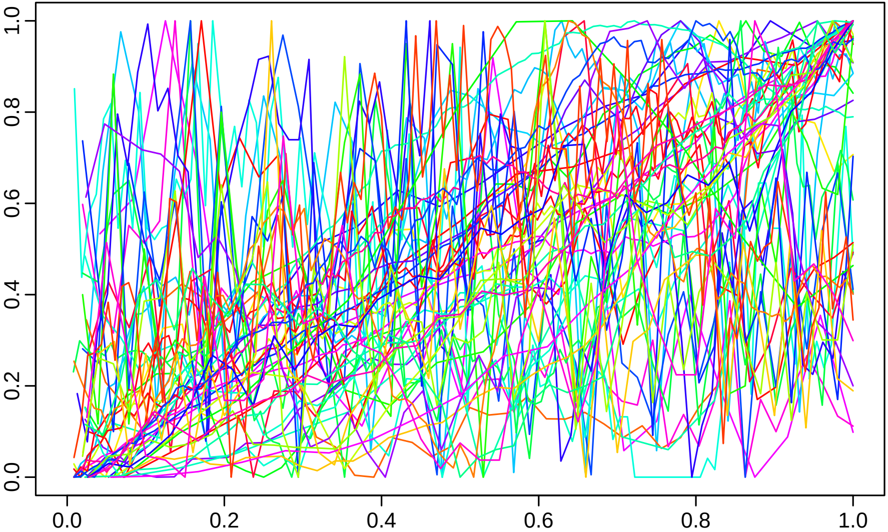

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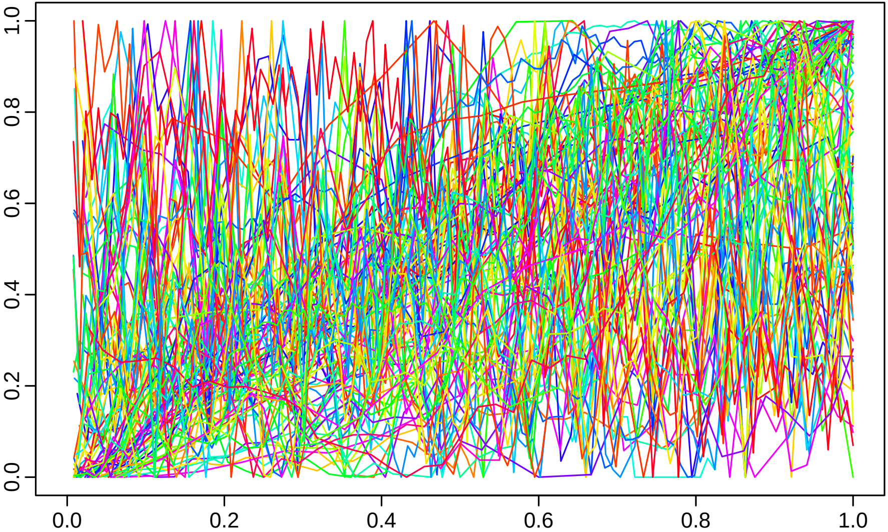

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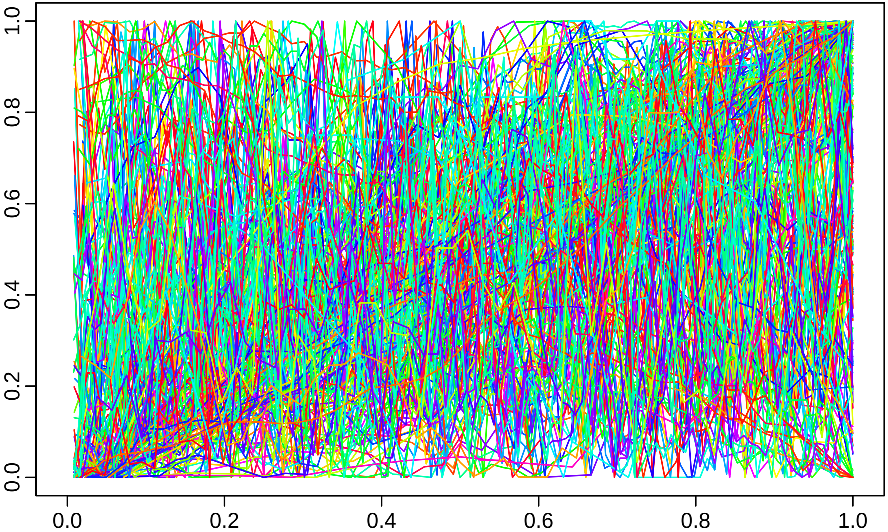

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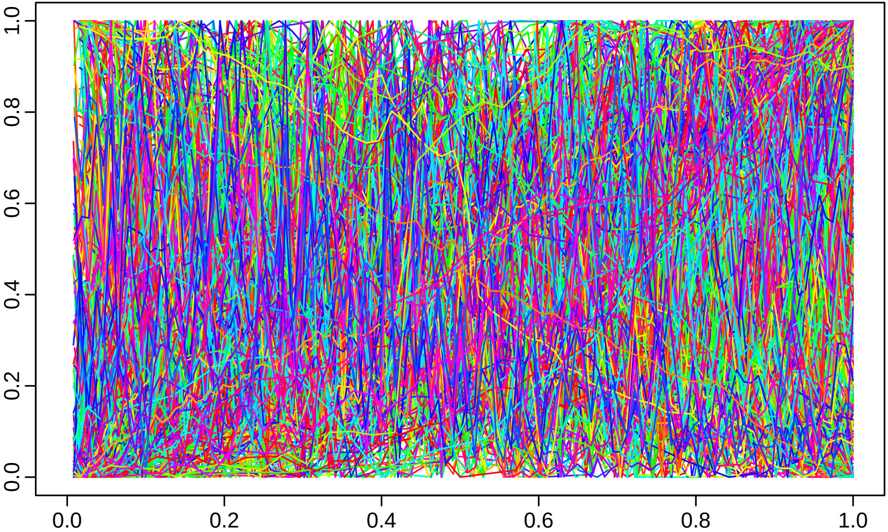

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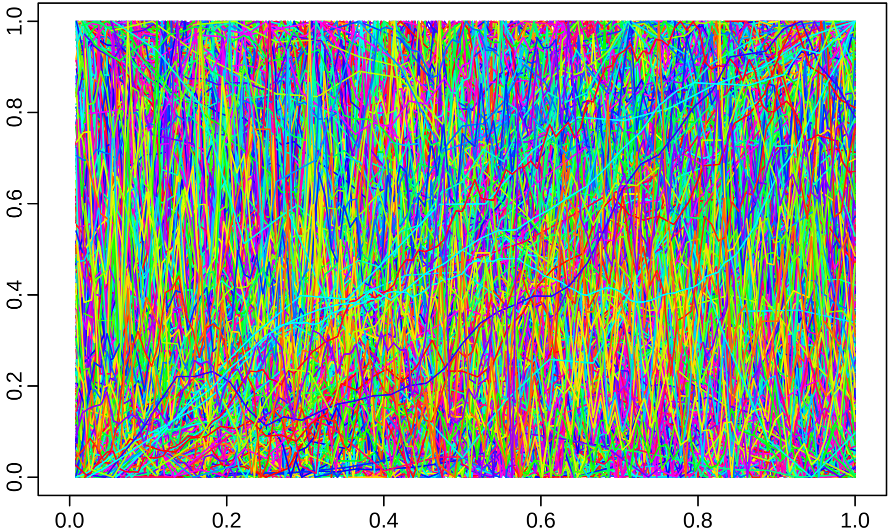
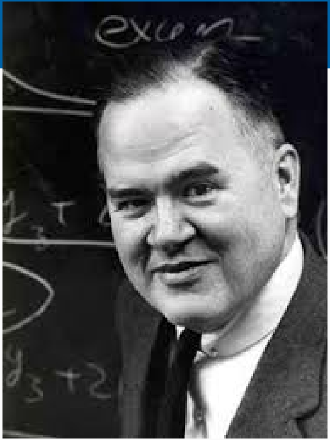


Key idea

Cognostics

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



John W Tukey

Key idea

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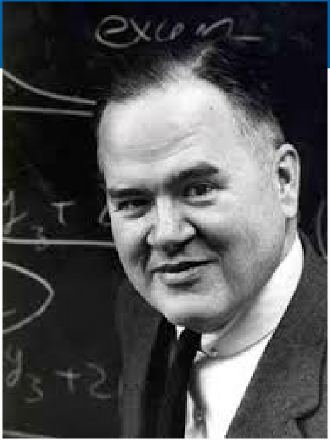
Computer-produced diagnostics
(Tukey and Tukey, 1985).

Examples for time series

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

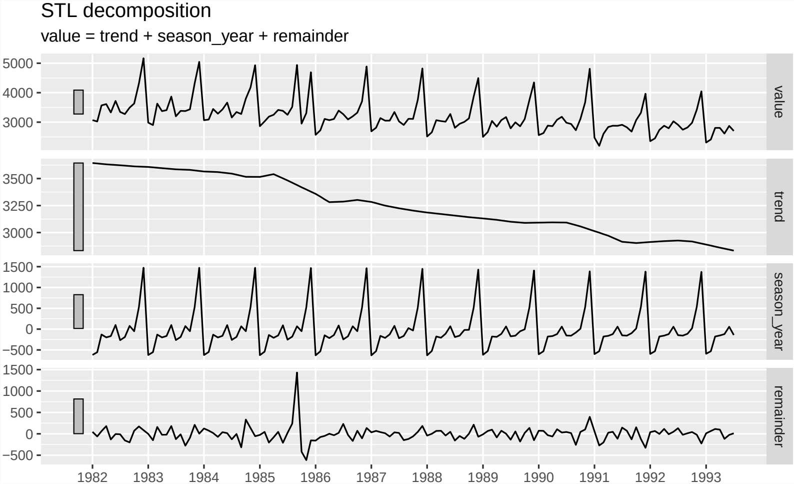


John W Tukey

Called “features” in the machine learning literature
and “statistics” in the statistics 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

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

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3. Strength of trend
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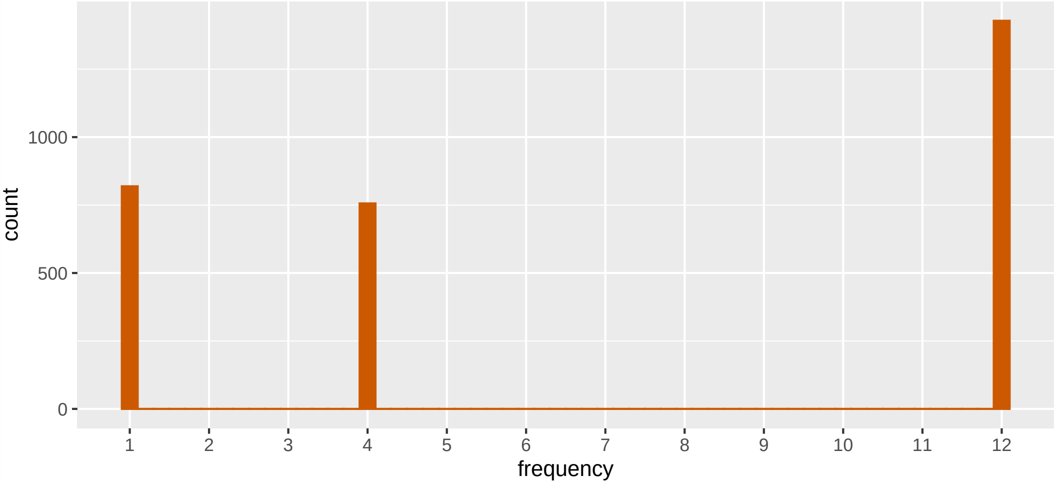
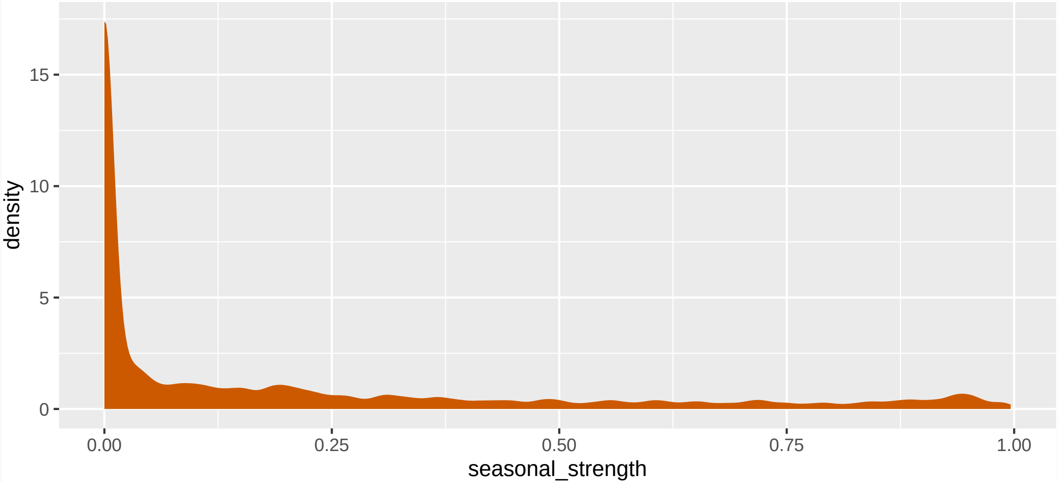
For other analyses, it may be appropriate to have different requirements.

Distribution of Period for M3



Distribution of Seasonality for M3



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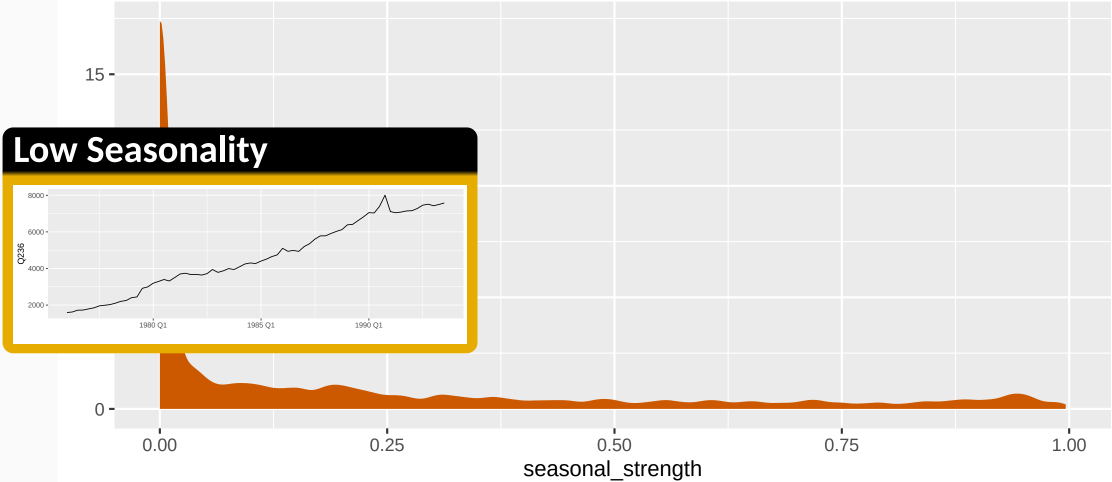
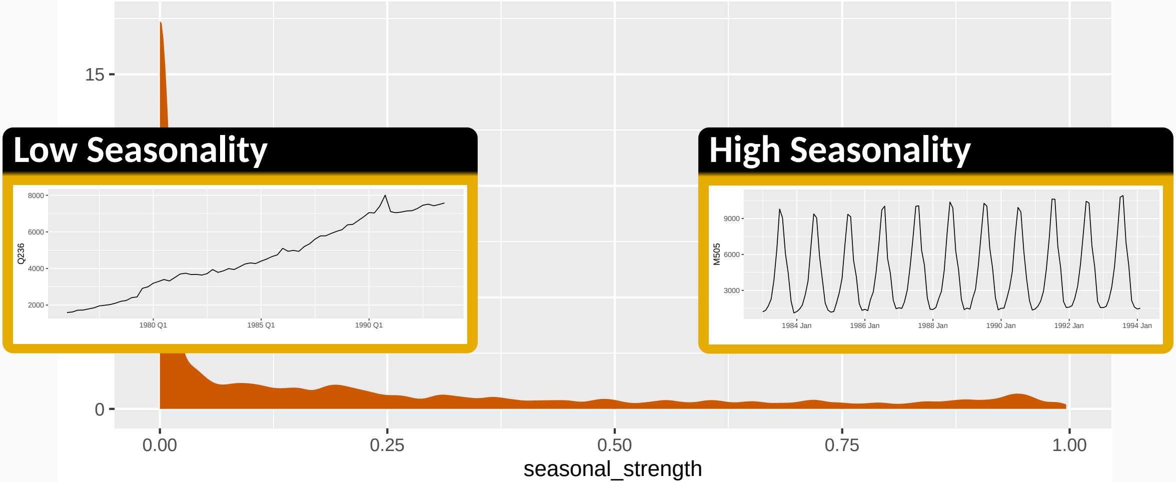
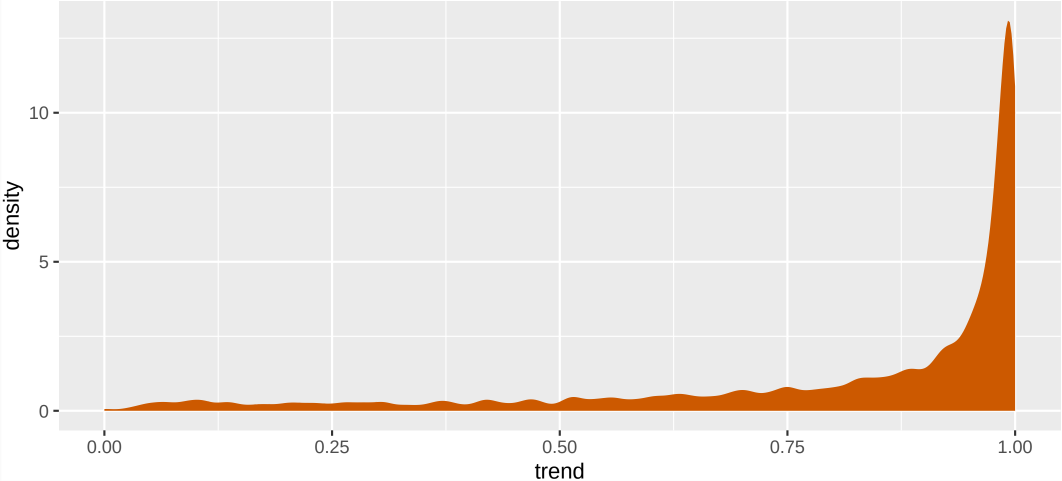


Distribution of Seasonality for M3



Distribution of Trend for M3



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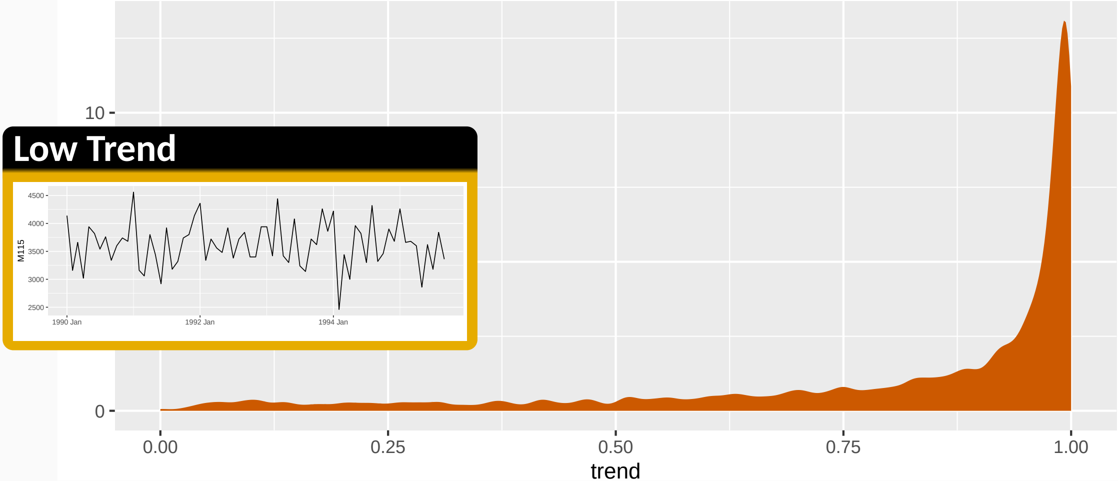

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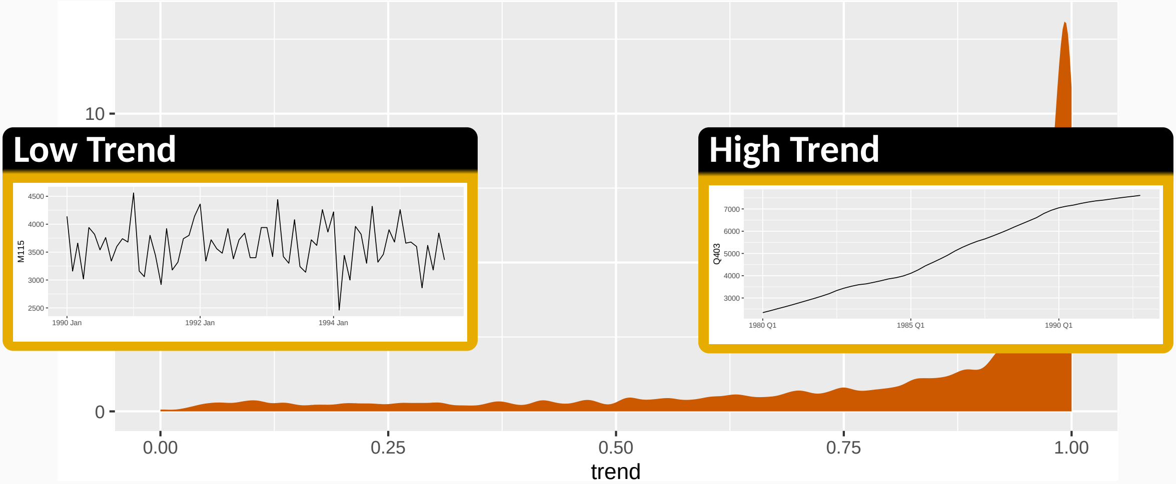
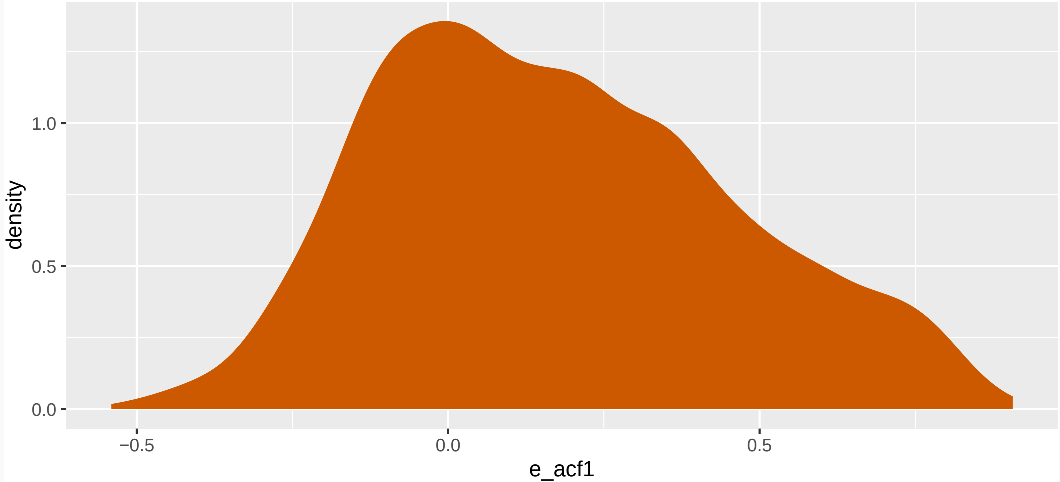


Distribution of Residual ACF1 for M3



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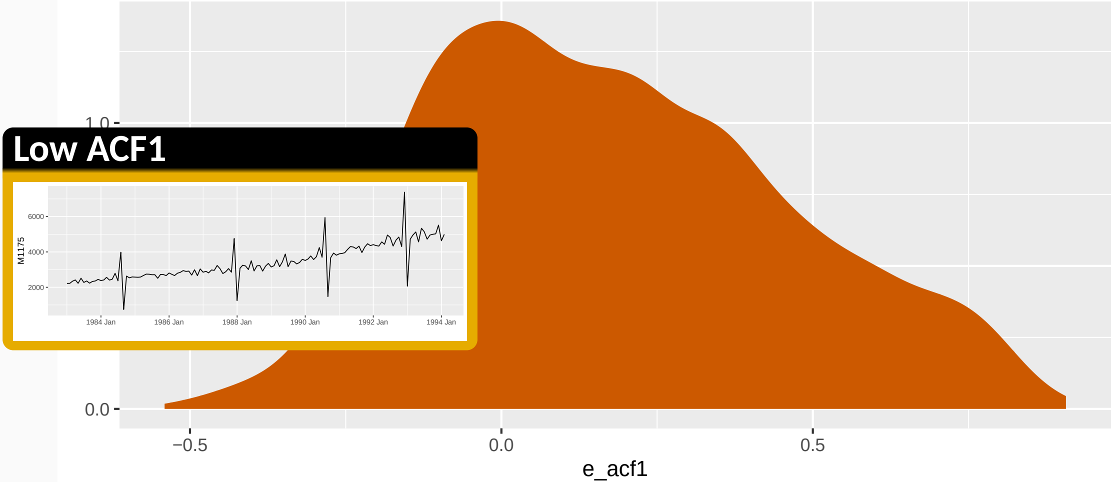

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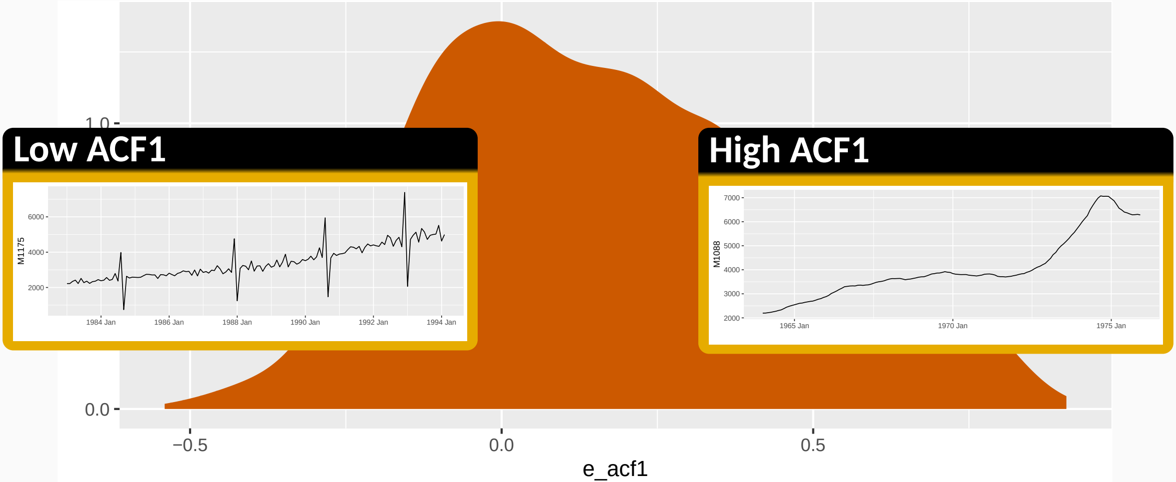
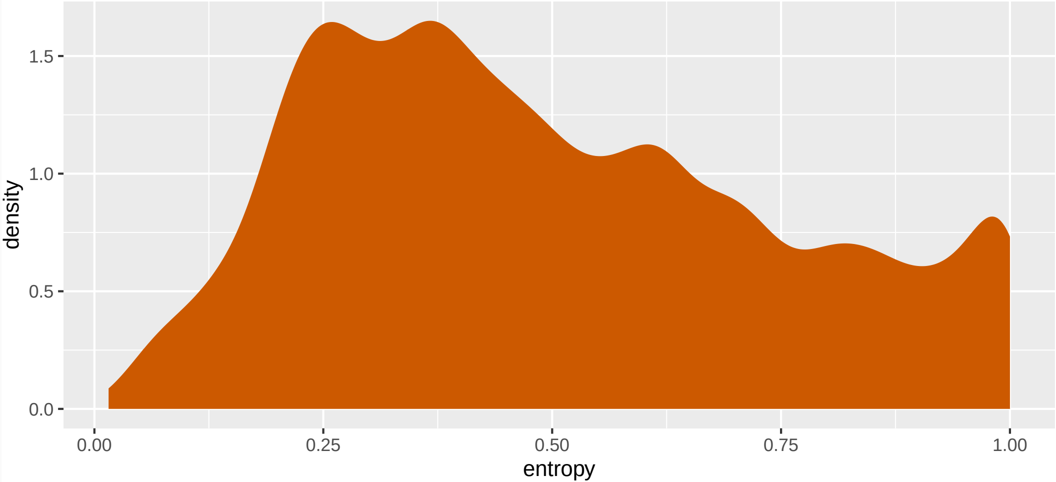


Distribution of Spectral Entropy for M3



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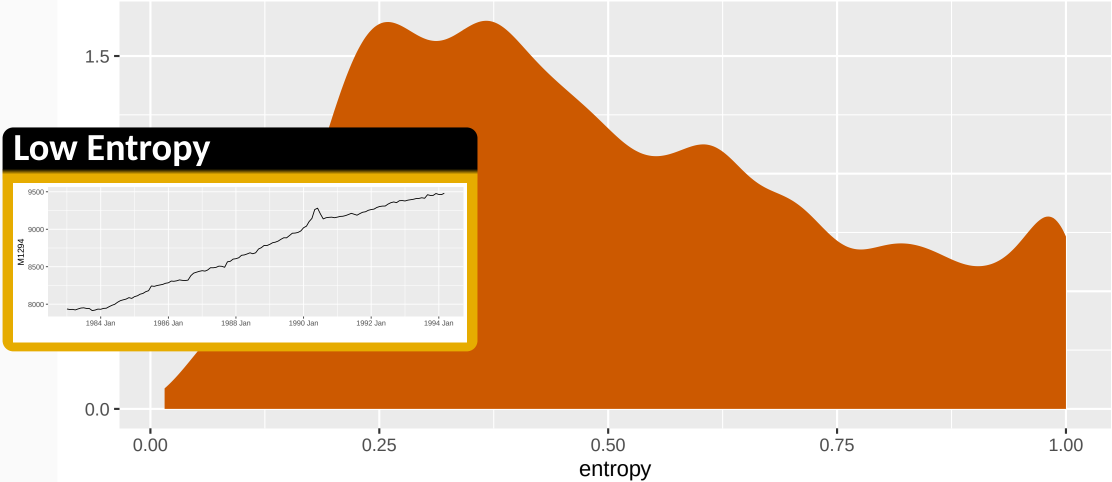
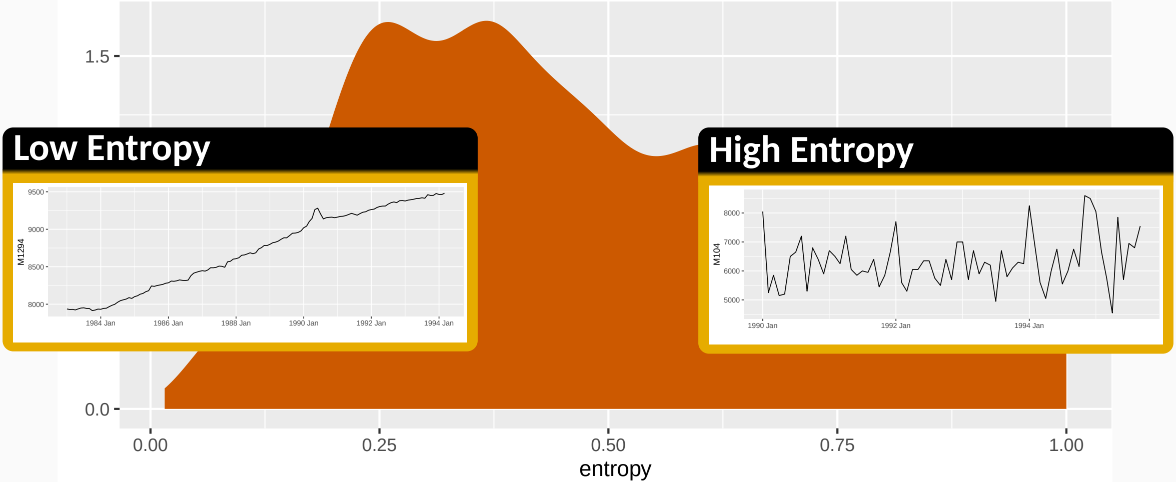
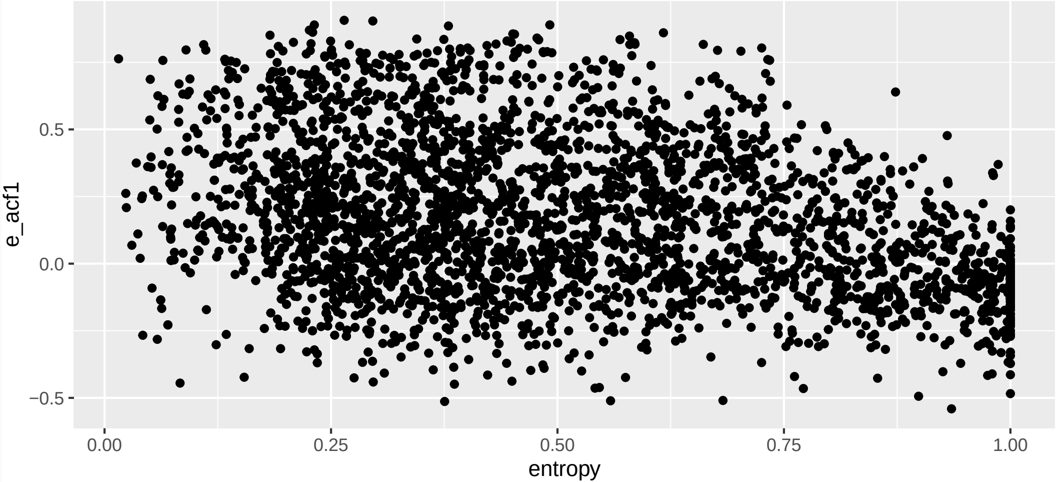


Distribution of Spectral Entropy for M3



Feature distributions



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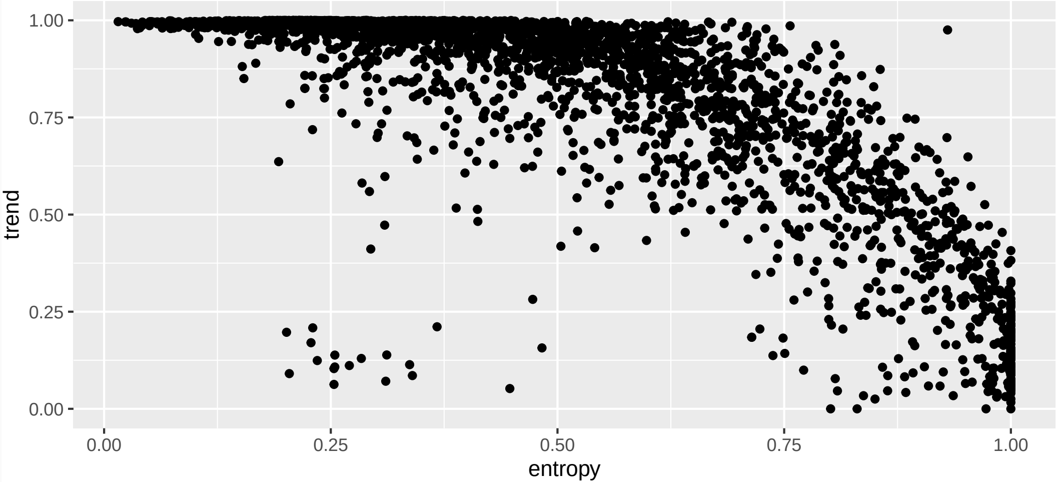

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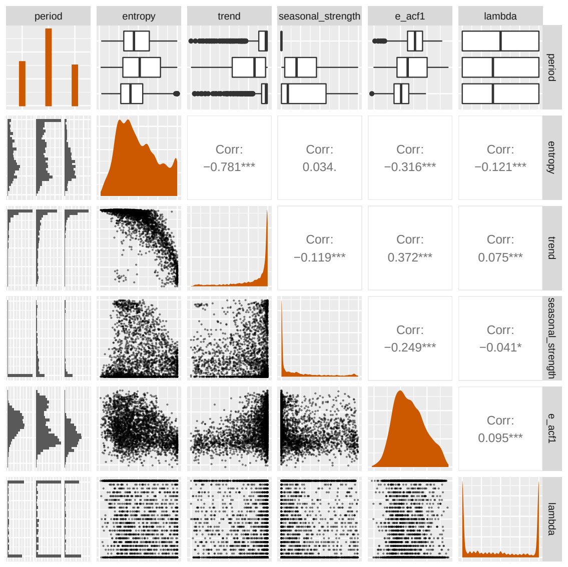
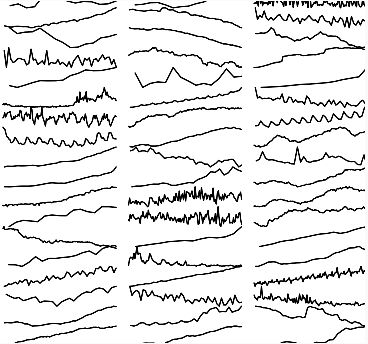


Dimension reduction for time series



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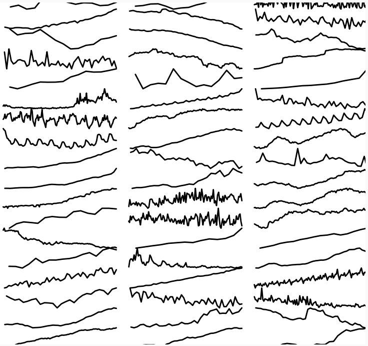
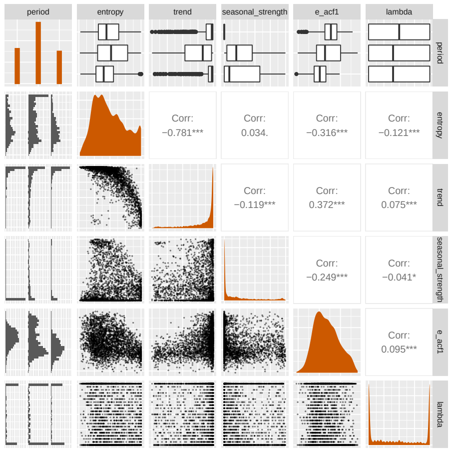


Feature calculation



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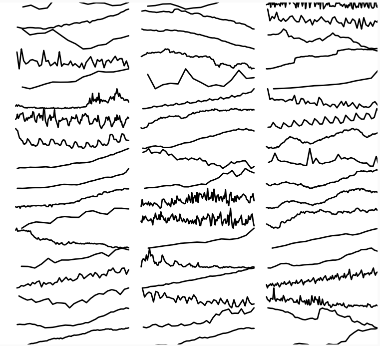

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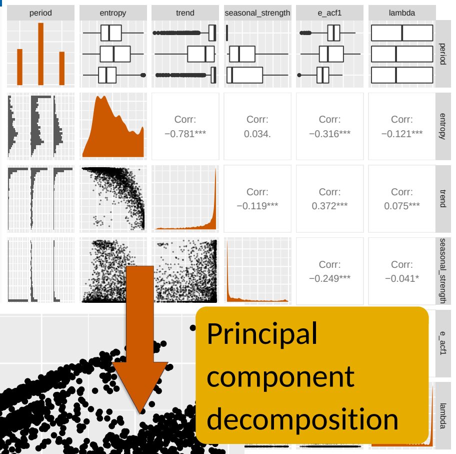
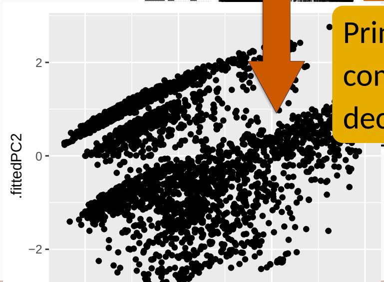
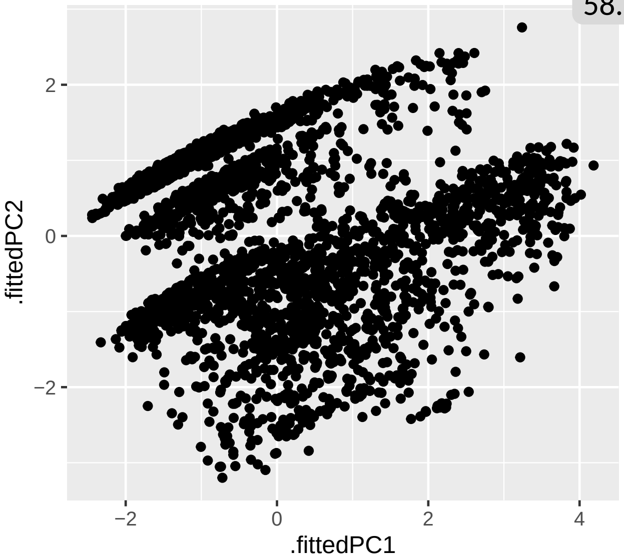


Principal component decomposition



M3 feature space

First two PCs explain 58.5% of the variance.



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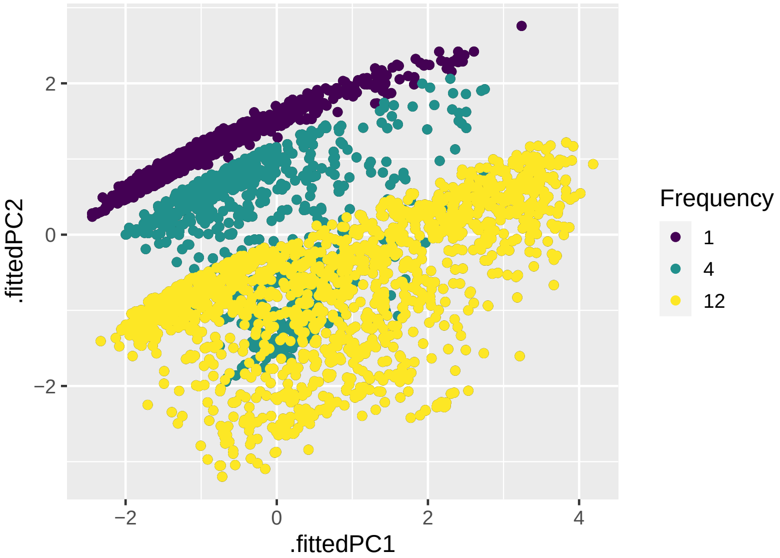

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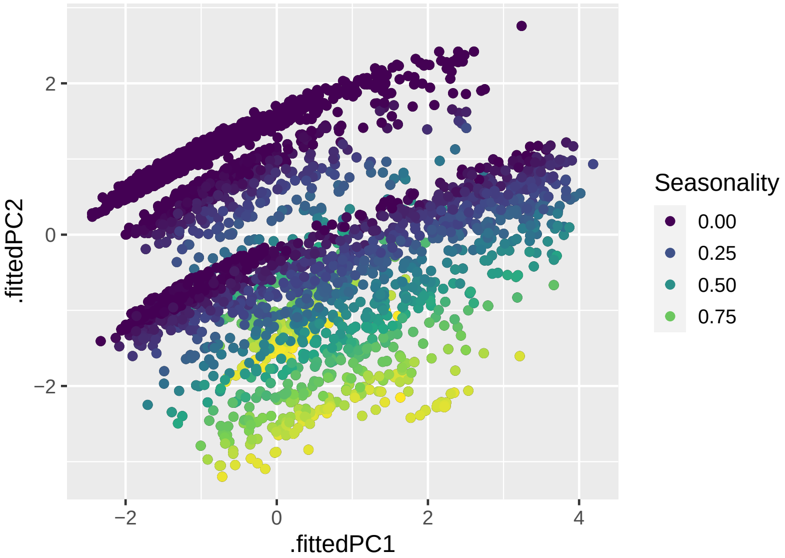

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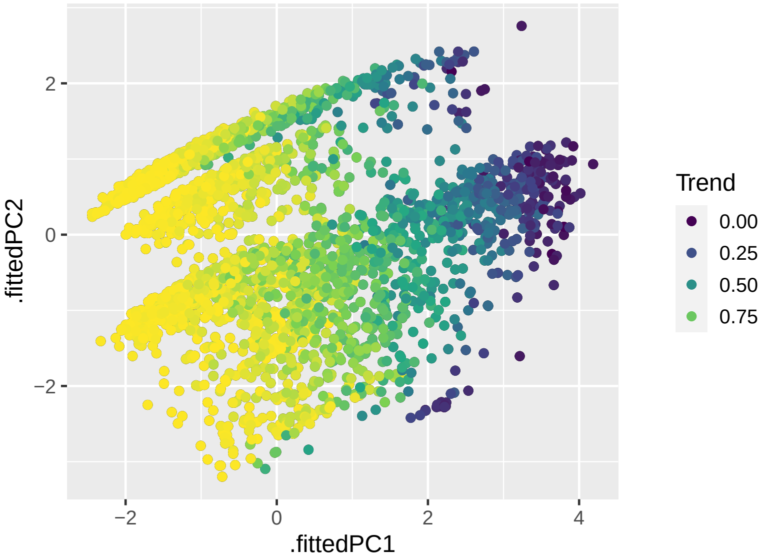

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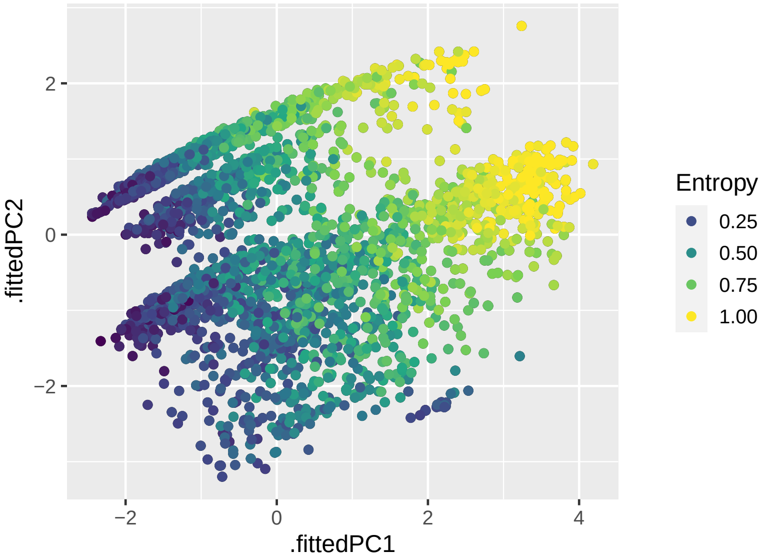

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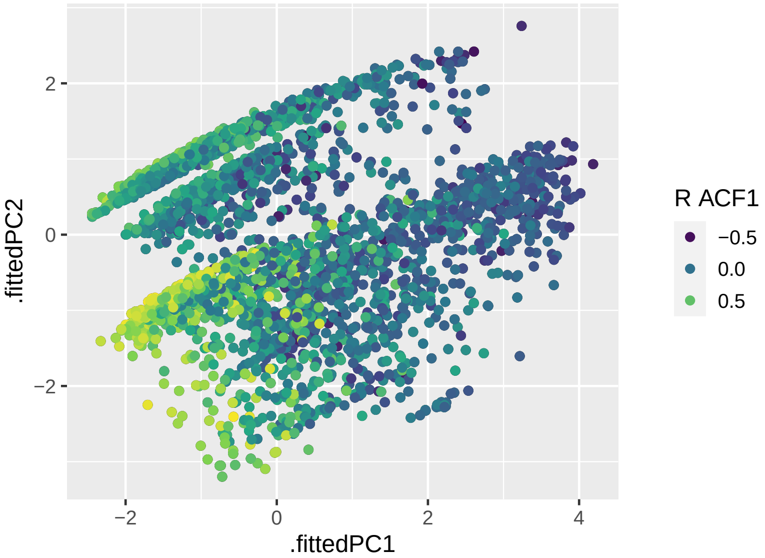

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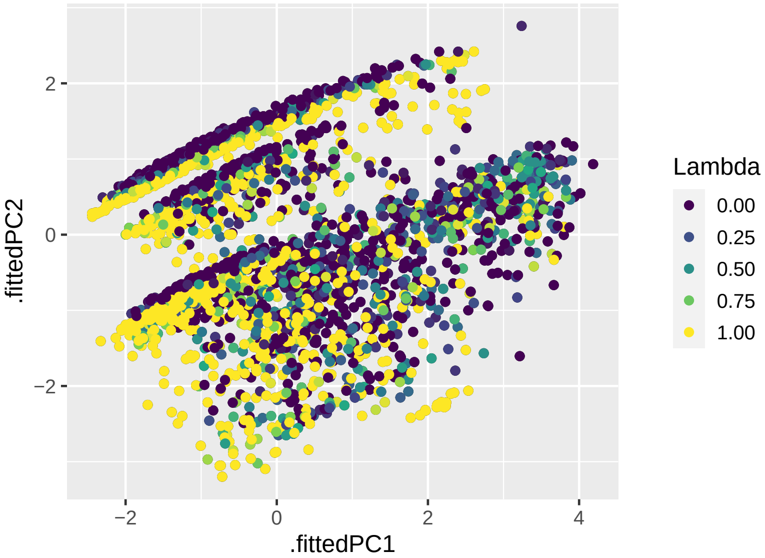

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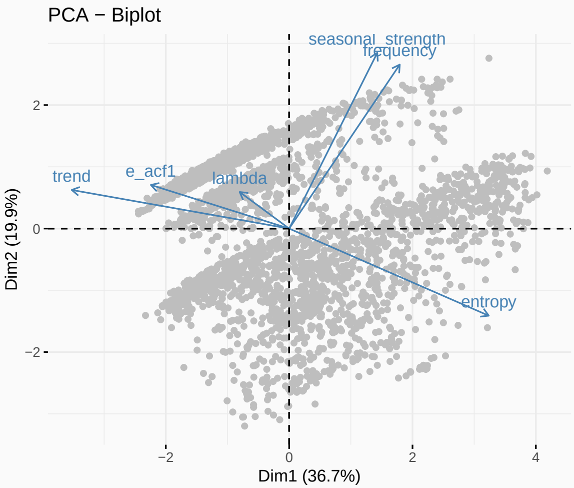
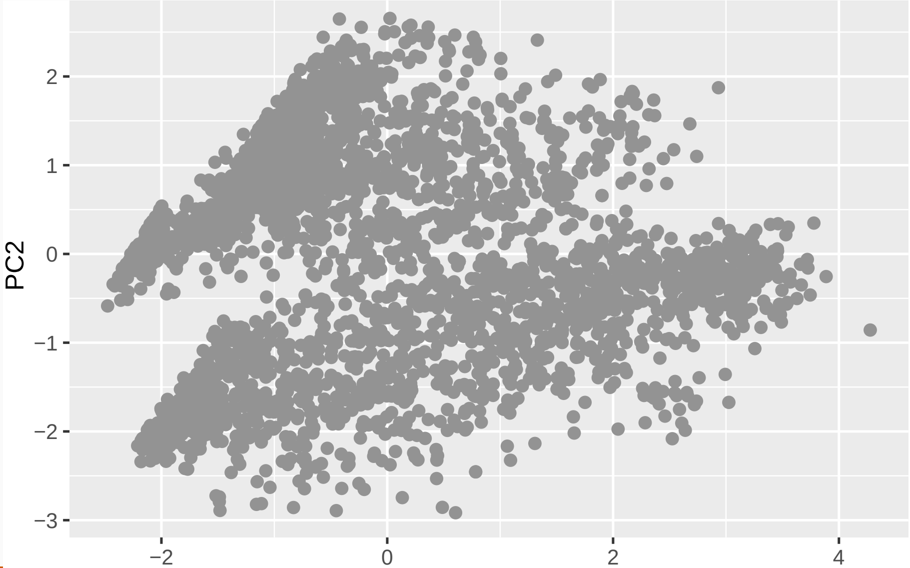


What about the holes?



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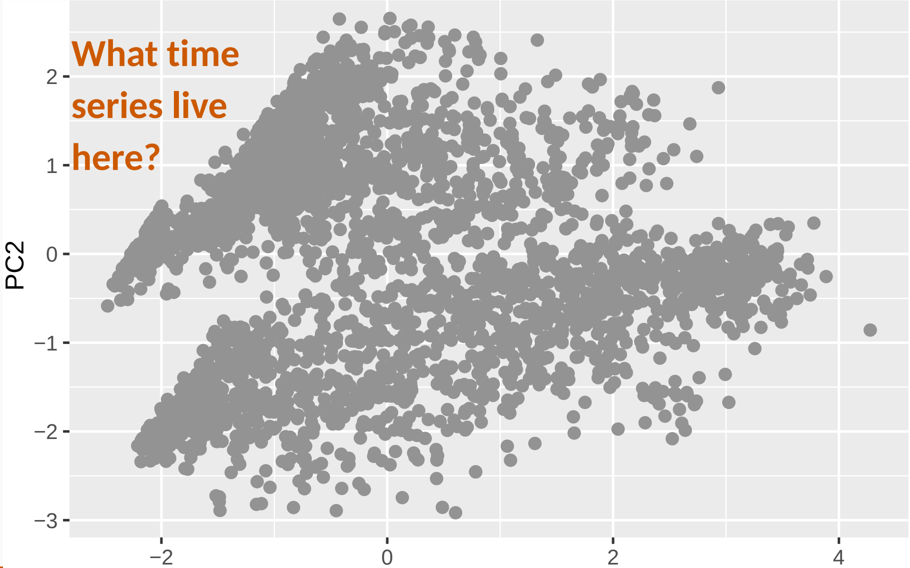

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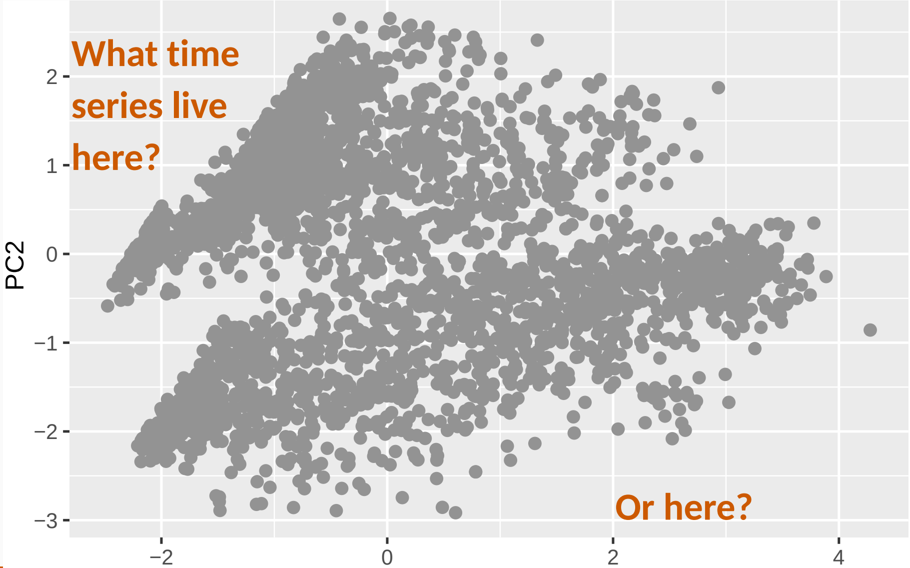

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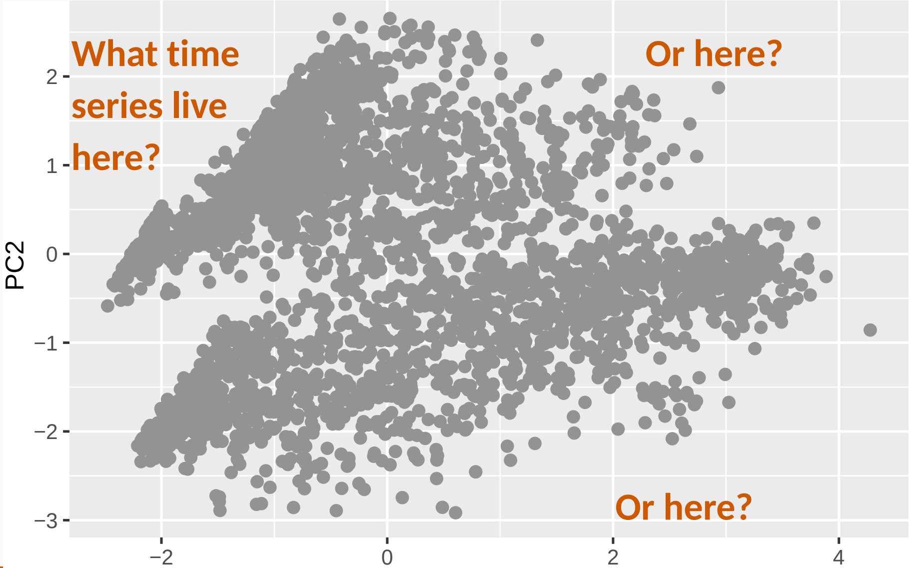

Generating new time series

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.

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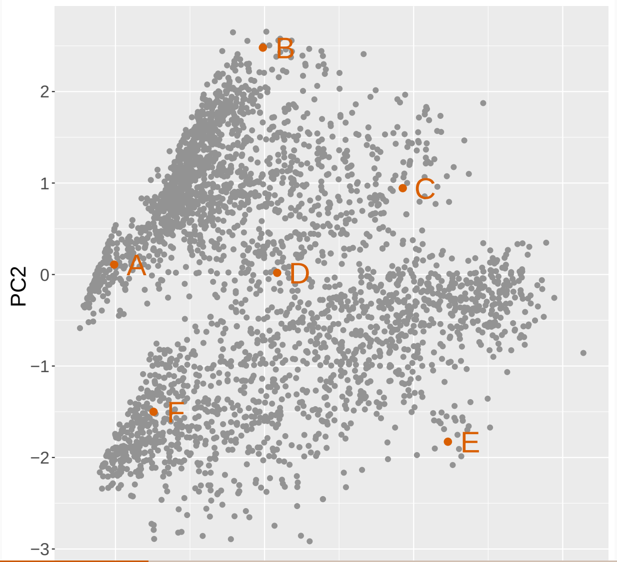
- Let $\{\mathrm{PC}_1, \mathrm{PC}_2, \dots, \mathrm{PC}_n\}$ be a "population" of time series of specified length and period.
- Genetic algorithm uses a process of selection, crossover and mutation to evolve the population towards a target point T_i.
- Optimize: Fitness $(\mathrm{PC}_j) = -\sqrt{(|\mathrm{PC}_j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

Evolving new time series



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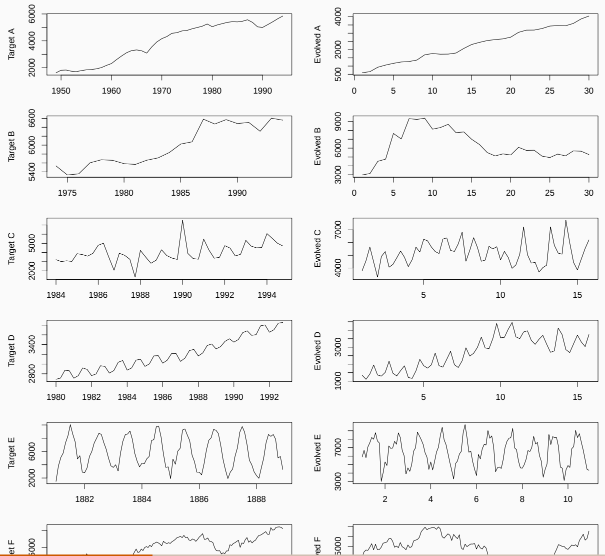

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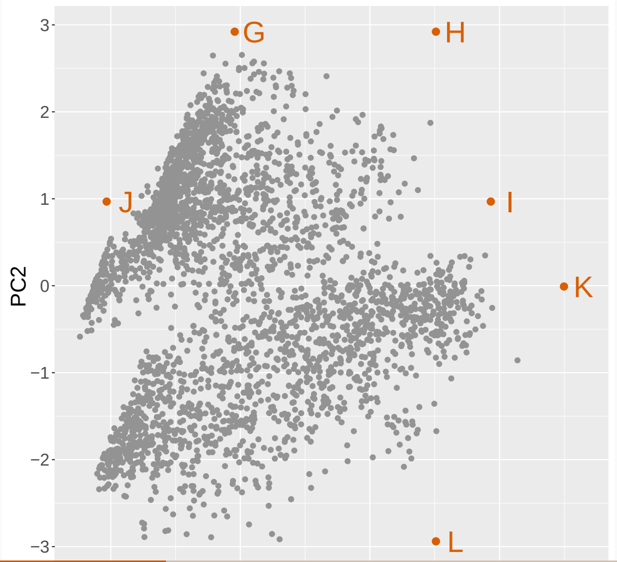

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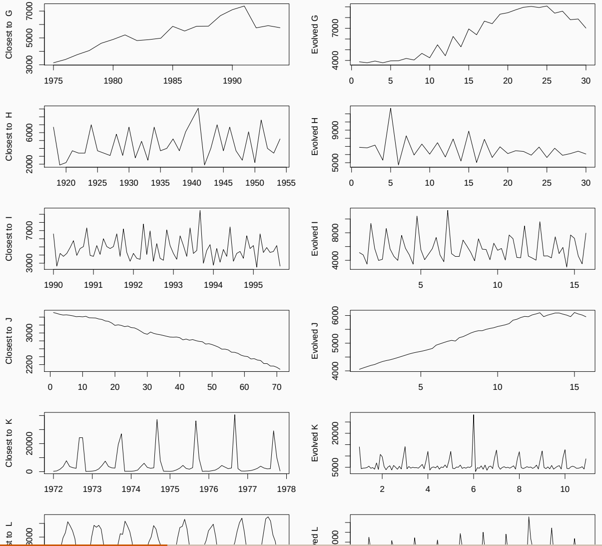

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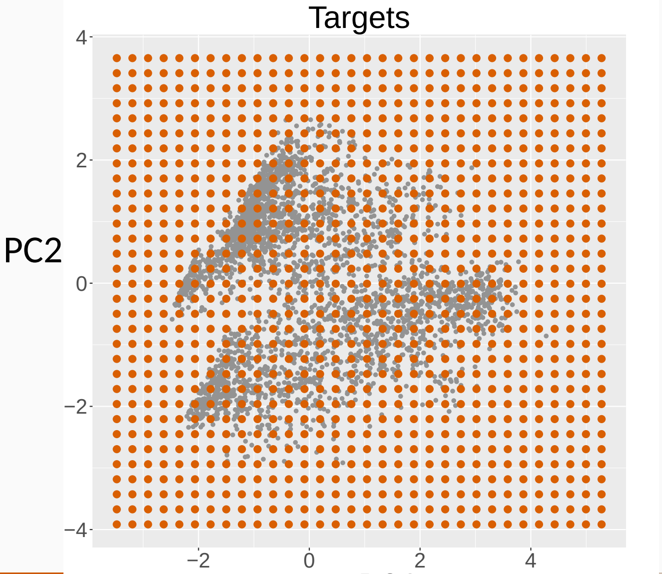

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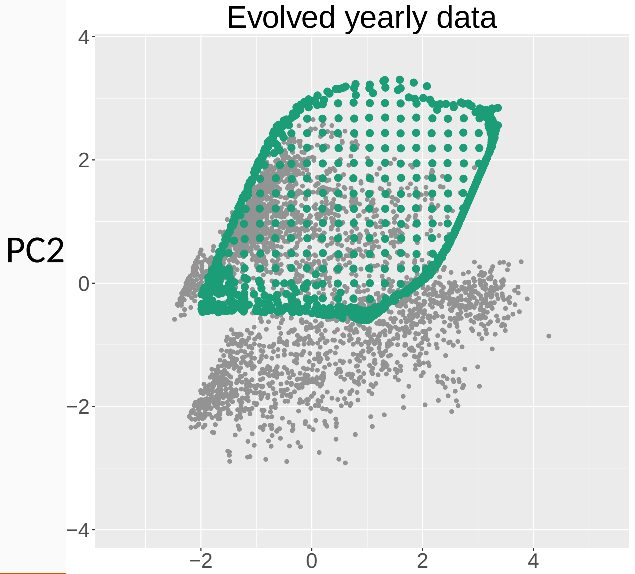

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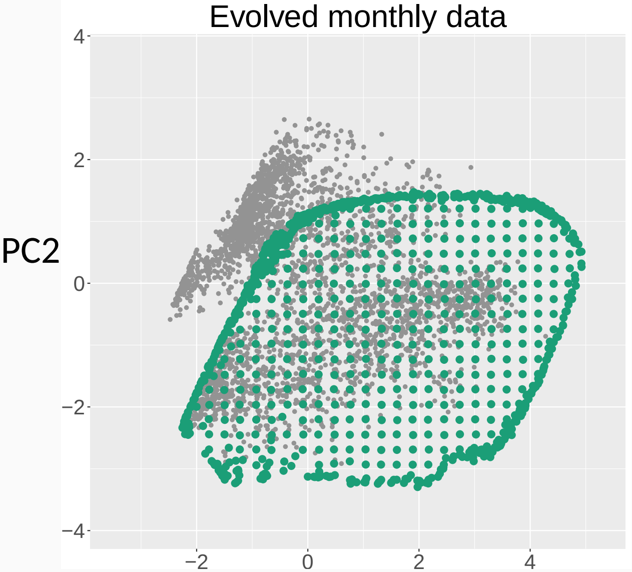

Outline

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2. R packages
3. Feature-based anomaly detection
4. Feature-based forecasting

Tidyverts packages

tidyverts.org

tsibble

tsibbledata

feasts

fable

tsibble objects

```r
library(tidyverse)
library(tsibble)
library(feasts)
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.
```

tsibble objects

```
library(tidyverse)
library(tsibble)
library(feasts)
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.
```

tsibble objects

```
library(tidyverse)
library(tsibble)
library(feasts)
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.
```

tsibble objects

```r
library(tidyverse)
library(tsibble)
library(feasts)
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.
```

`tsibble` objects

```
library(tidyverse)
library(tsibble)
library(feasts)
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.
```

Index

Keys

Measure

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

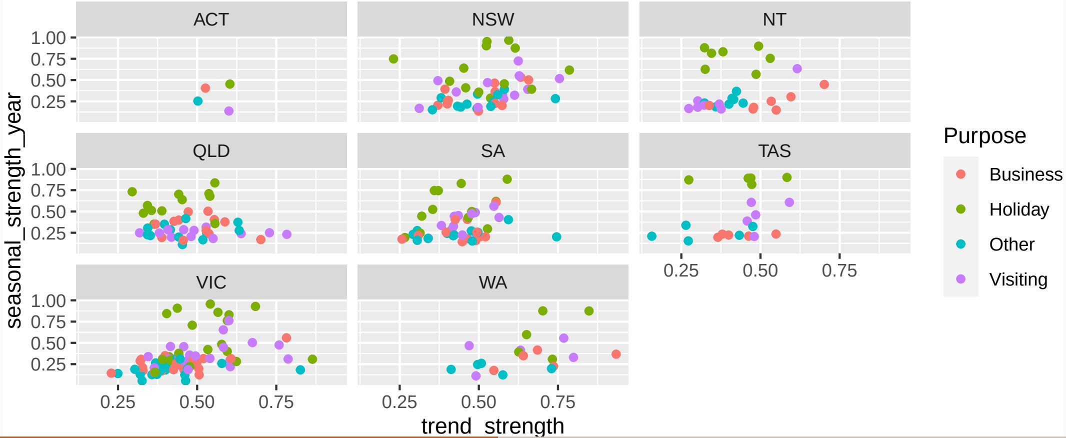
Feature extraction and statistics

```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 Adelaide       SA    Busine~          0.464            0.407
##  2 Adelaide       SA    Holiday          0.554            0.619
##  3 Adelaide       SA    Other            0.746            0.202
##  4 Adelaide       SA    Visiti~          0.435            0.452
##  5 Adelaide Hills SA    Busine~          0.464            0.179
##  6 Adelaide Hills SA    Holiday          0.528            0.296
##  7 Adelaide Hills SA    Other            0.593            0.404
##  8 Adelaide Hills SA    Visiti~          0.488            0.254
##  9 Alice Springs  NT    Busine~          0.534            0.251
## 10 Alice Springs  NT    Holiday          0.381            0.832
## # ... with 294 more rows, and 7 more variables:
## #   seasonal_peak_year <dbl>, seasonal_trough_year <dbl>,
## #   spikiness <dbl>, linearity <dbl>, curvature <dbl>,
```

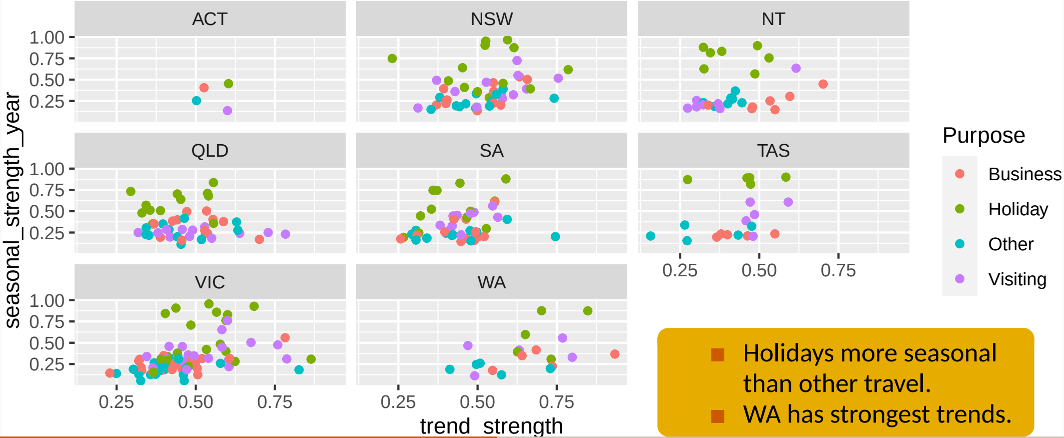
Feature extraction and statistics

```
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

```r
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:

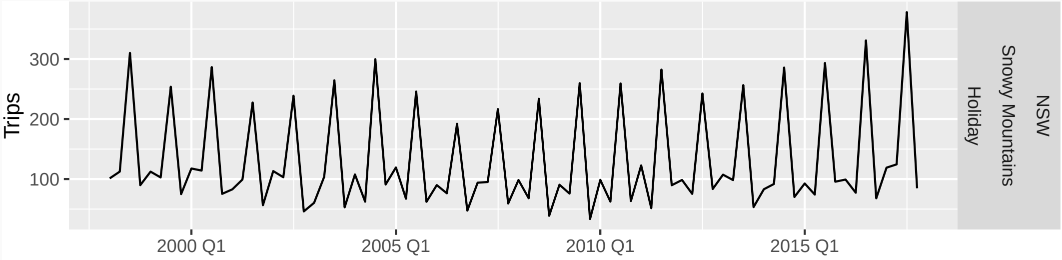
```
most_seasonal <- tourism %>%
  features(Trips, feature_set(tags="stl")) %>%
  filter(seasonal_strength_year == max(seasonal_strength_year))
```

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 51
##    Region         State Purpose trend_strength seasonal_streng~
##    <chr>          <chr> <chr>            <dbl>            <dbl>
##  1 Adelaide       SA    Busine~          0.464            0.407
##  2 Adelaide       SA    Holiday          0.554            0.619
##  3 Adelaide       SA    Other            0.746            0.202
##  4 Adelaide       SA    Visiti~          0.435            0.452
##  5 Adelaide Hills SA    Busine~          0.464            0.179
##  6 Adelaide Hills SA    Holiday          0.528            0.296
##  7 Adelaide Hills SA    Other            0.593            0.404
##  8 Adelaide Hills SA    Visiti~          0.488            0.254
##  9 Alice Springs  NT    Busine~          0.534            0.251
## 10 Alice Springs  NT    Holiday          0.381            0.832
## # ... with 294 more rows, and 46 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>,
```

Feature extraction and statistics

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

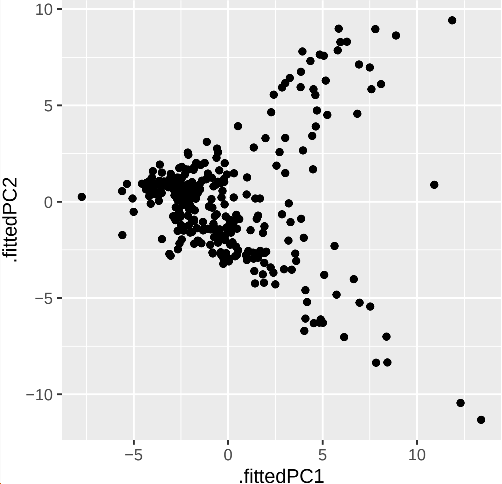
```
## # A tibble: 304 x 100
##    .rownames Region         State Purpose  trend_s
##    <chr>     <chr>          <chr> <chr>
##  1 1         Adelaide       SA    Business
##  2 2         Adelaide       SA    Holiday
##  3 3         Adelaide       SA    Other
##  4 4         Adelaide       SA    Visiting
##  5 5         Adelaide Hills SA    Business
##  6 6         Adelaide Hills SA    Holiday            0.528
##  7 7         Adelaide Hills SA    Other              0.593
##  8 8         Adelaide Hills SA    Visiting           0.488
##  9 9         Alice Springs  NT    Business           0.534
## 10 10        Alice Springs  NT    Holiday            0.381
## # ... with 294 more rows, and 95 more variables:
## #   seasonal_strength_year <dbl>, seasonal_peak_year <dbl>,
## #   seasonal_trough_year <dbl>, spikiness <dbl>,
## #   linearity <dbl>, curvature <dbl>, stl_e_acf1 <dbl>,
```

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)
```

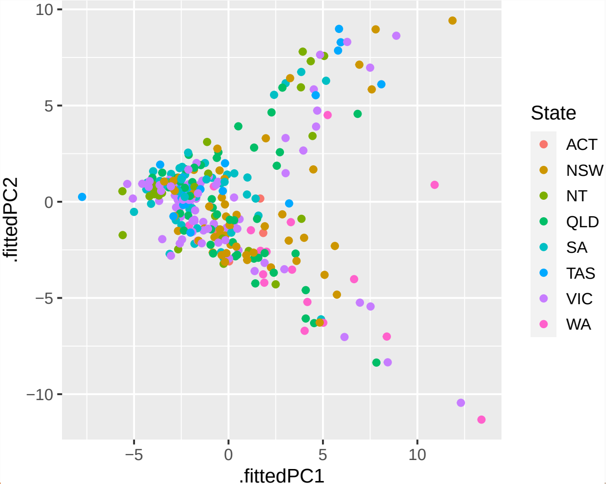
Principal components based on all features from the feasts package



Feature extraction and statistics

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

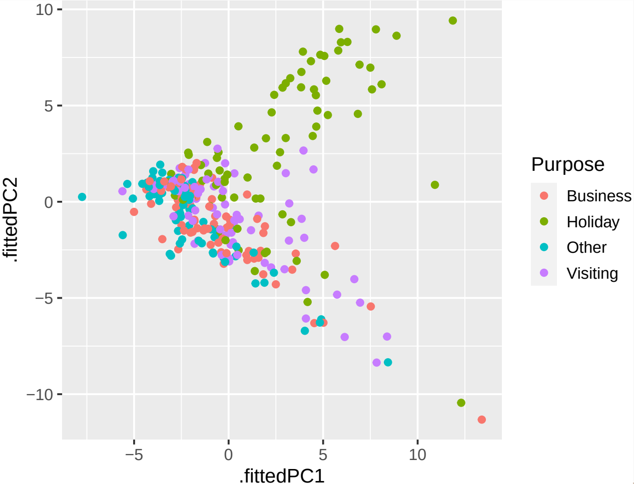
Principal components based on all features from the feasts package



Feature extraction and statistics

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

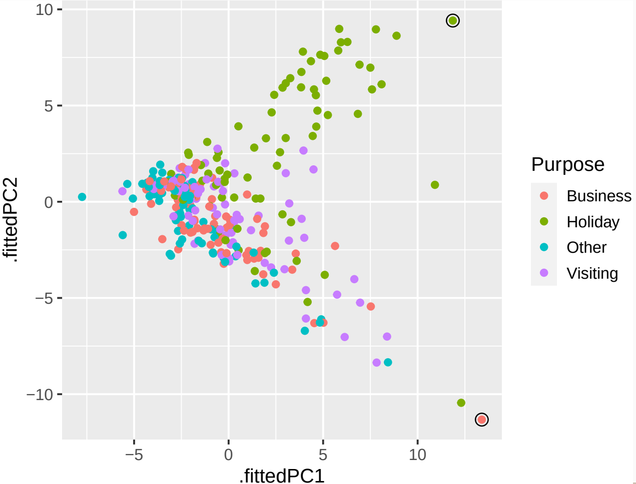
Principal components based on all features from the feasts package



Feature extraction and statistics

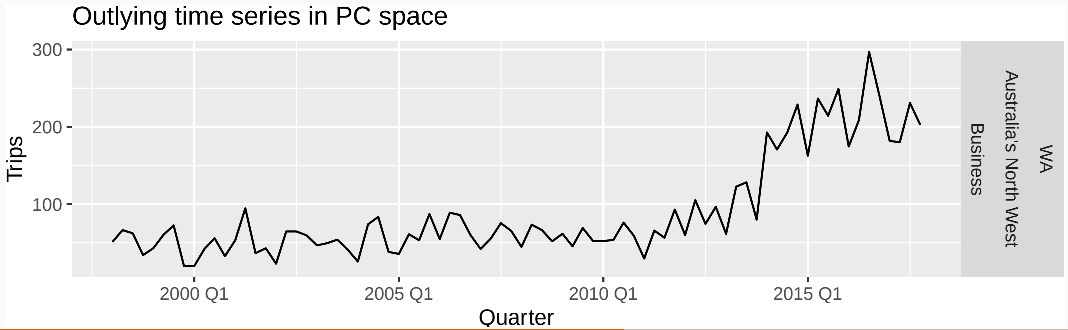
```
pcs %>% ggplot(aes(x=.fittedPC1, y=.fittedPC2, col=Purpose)) +
  geom_point() + theme(aspect.ratio=1)
```

Principal components based on all features from the feasts package



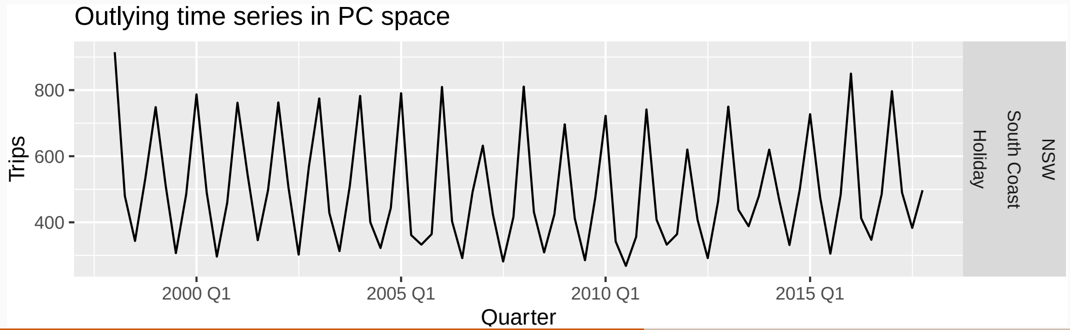
Feature extraction and statistics

```
pcs %>% filter(.fittedPC1 == max(.fittedPC1)) %>%
  left_join(tourism, by = c("State", "Region", "Purpose")) %>%
  ggplot(aes(x = Quarter, y = Trips)) +
    geom_line() +
    facet_grid(vars(State,Region,Purpose)) +
    ggtitle("Outlying time series in PC space") +
    theme(legend.position = "none")
```



Feature extraction and statistics

```
pcs %>% filter(.fittedPC1 > 10 & .fittedPC2 > 2.5) %>%
  left_join(tourism, by = c("State", "Region", "Purpose")) %>%
  ggplot(aes(x = Quarter, y = Trips)) +
    geom_line() +
    facet_grid(vars(State,Region,Purpose)) +
    ggtitle("Outlying time series in PC space") +
    theme(legend.position = "none")
```



Outline

1 Feature-based visualization

2 R packages

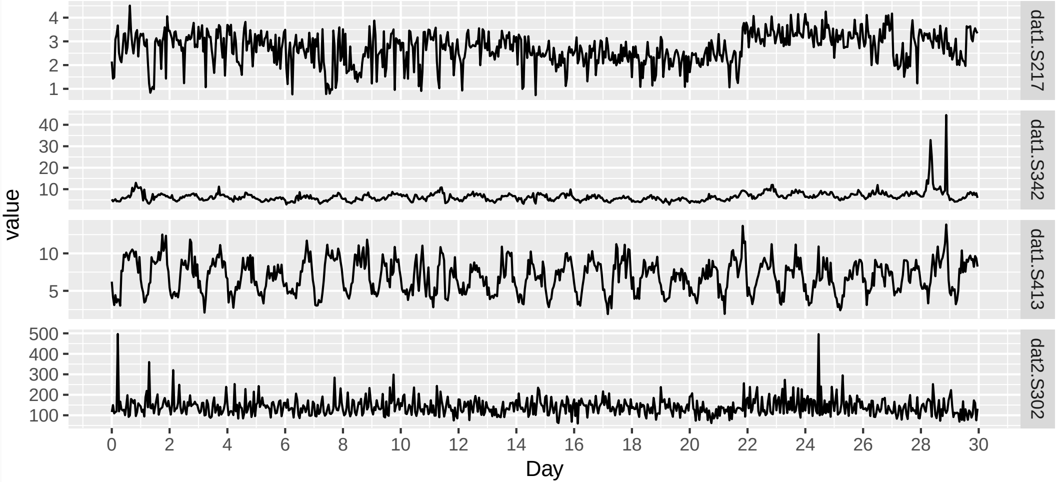
3 Feature-based anomaly detection

4 Feature-based forecasting

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.

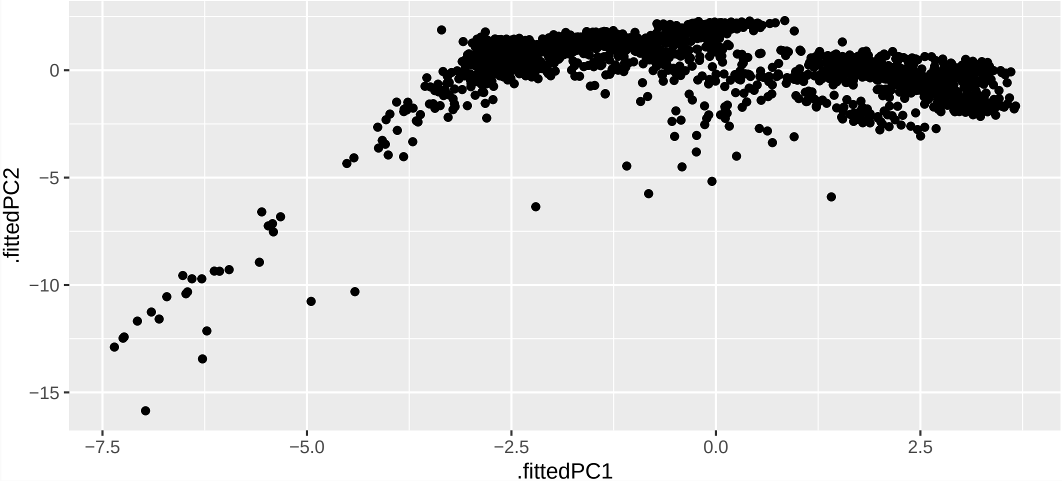
Yahoo server metrics



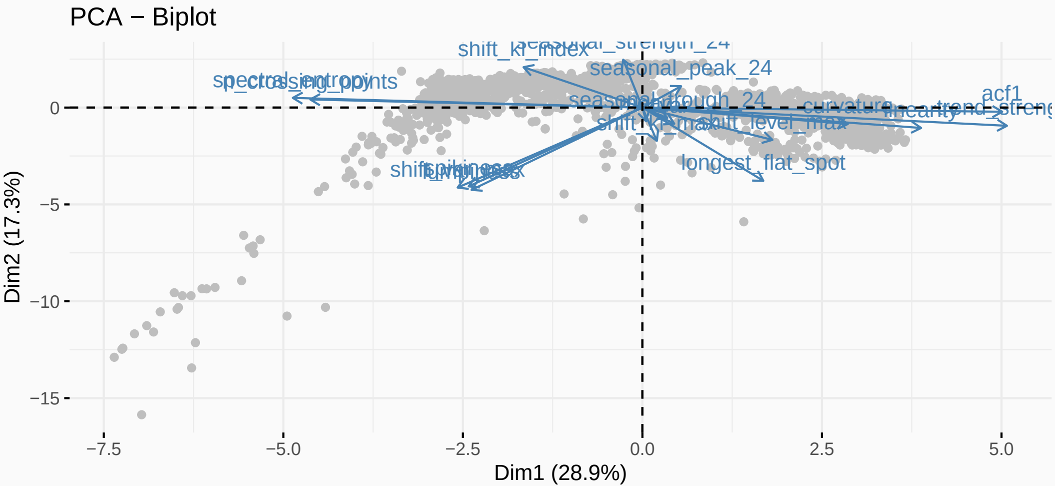
Yahoo server metrics

- **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 of size 48.
- **Change index**: Time of maximum KL score

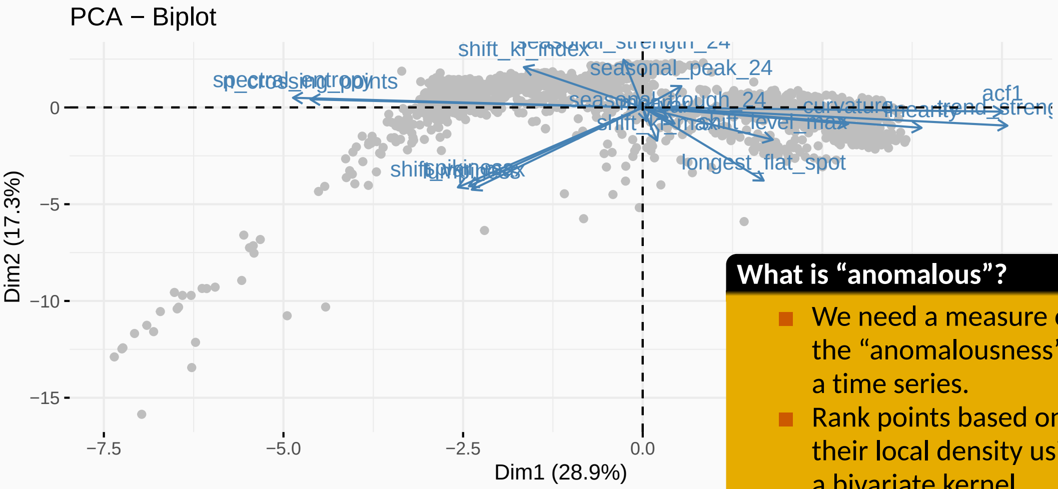
Feature space



Feature space



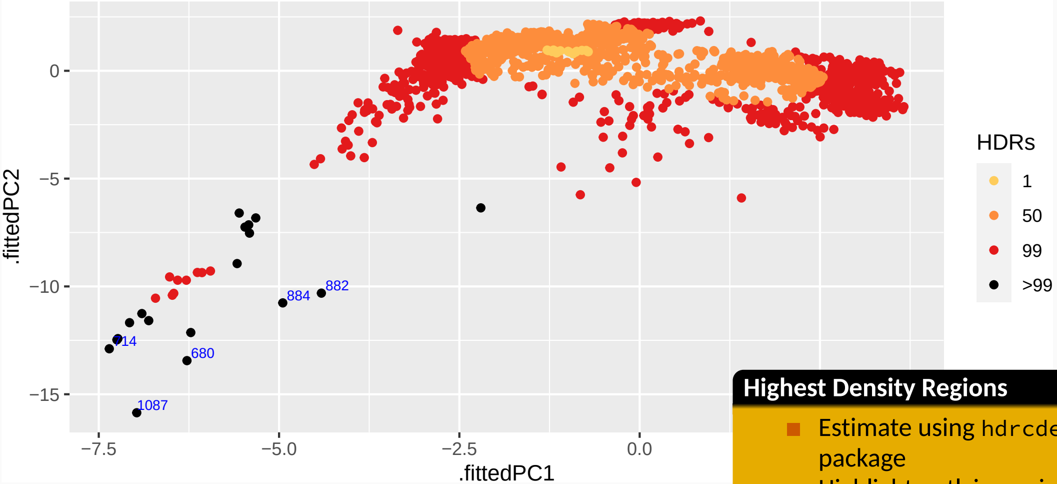
Feature space



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

1 Feature-based visualization

2 R packages

3 Feature-based anomaly detection

4 Feature-based forecasting

M competition: 1982

Journal of Forecasting, Vol. 1, 111–153 (1982)

The Accuracy of Extrapolation (Time Series) Methods: Results of a Forecasting Competition

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ABSTRACT

In the last few decades many methods have become available for forecasting. As always, when alternatives exist, choices need to be made so that an appropriate forecasting method can be selected and used for the specific situation being considered. This paper reports the results of a forecasting competition that provides information to facilitate such choice. Seven experts in each of the 24 methods forecasted up to 1001 series for six up to eighteen time horizons. The results of the competition are presented in this paper

M-competition

- 1001 series from demography, industry, economics.
- Annual, quarterly, monthly data.
- Anyone could submit forecasts.
- Multiple forecast measures used.

M3 competition: 2000

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.

M4 competition: 2018

International Journal of Forecasting 34 (2018) 802–808

Contents lists available at ScienceDirect

International Journal of Forecasting

journal homepage: www.elsevier.com/locate/ijforecast

ELSEVIER

The M4 Competition: Results, findings, conclusion and way forward

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[b] *Institute For the Future (IFF), Nicosia, Cyprus*
[c] *Forecasting and Strategy Unit, School of Electrical and Computer Engineering, National Technical University of Athens, Zografou, Greece*

Check for updates

ARTICLE INFO

Keywords:
Forecasting competitions
M Competitions

ABSTRACT

The M4 competition is the continuation of three previous competitions started more than 45 years ago whose purpose was to learn how to improve forecasting accuracy, and

M4 competition: 2018

- January – May 2018
- 100,000 time series: yearly, quarterly, monthly, weekly, daily, hourly.
- Point forecast and prediction intervals assessed.
- Code must be public
- 248 registrations, 50 submissions.

M4 competition: 2018

- January – May 2018
- 100,000 time series: yearly, quarterly, monthly, weekly, daily, hourly.
- Point forecast and prediction intervals assessed.
- Code must be public
- 248 registrations, 50 submissions.

Winning methods

1. Hybrid of Recurrent Neural Network and Exponential Smoothing models
2. FFORMA: Feature-based forecast combinations using xgboost to find weights

Features used to select a forecasting model

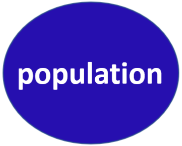
- length
- strength of seasonality
- strength of trend
- linearity
- curvature
- spikiness
- stability
- lumpiness
- parameter estimates of Holt’s linear trend method
- spectral entropy
- Hurst exponent
- nonlinearity
- parameter estimates of Holt-Winters’ additive method
- unit root test statistics
- crossing points, flat spots
- peaks, troughs
- ACF and PACF based features - calculated on raw, differenced, and remainder series.
- ARCH/GARCH statistics and ACF of squared series and residuals.

Features used to select a forecasting model

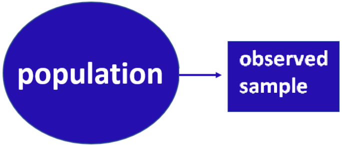
Why these features?

- Hyndman, Wang and Laptev. "Large scale unusual time series detection" (ICDM 2015).
- Kang, Hyndman & Smith-Miles. "Visualising forecasting algorithm performance using time series instance spaces" (IJF 2017).
- Talagala, Hyndman and Athanasopoulos. "Meta-learning how to forecast time series" (2018).
- Implemented in the **feasts** R package

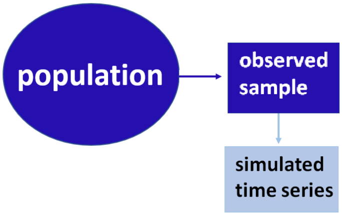
FFORMS: Feature-based FORecast Model Selection



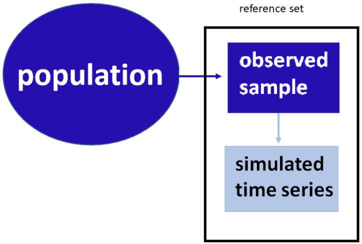
FFORMS: Feature-based FORecast Model Selection



FFORMS: Feature-based FORecast Model Selection



FFORMS: Feature-based FORecast Model Selection



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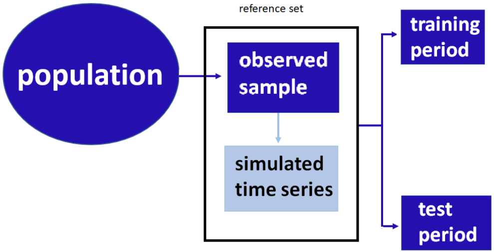
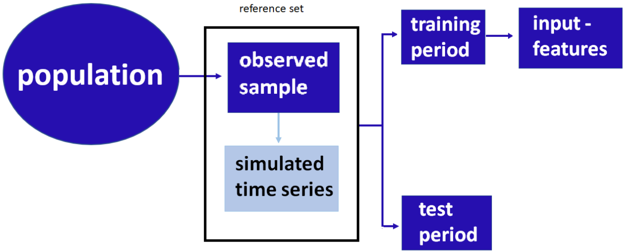


FFORMS: Feature-based FORecast Model Selection



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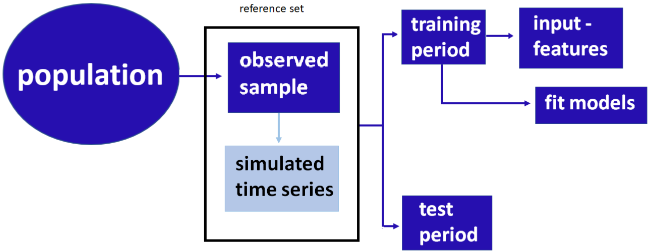
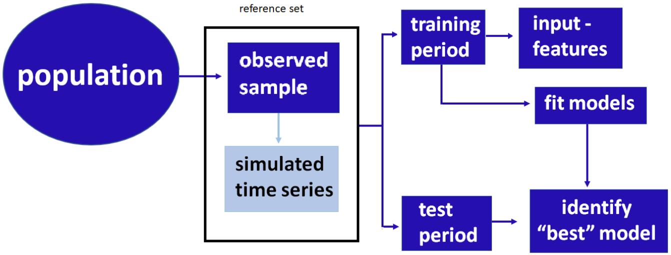
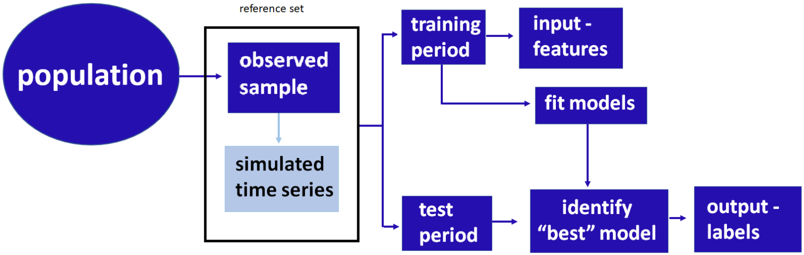


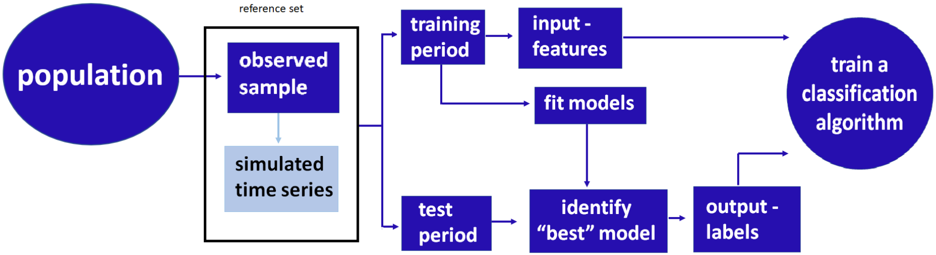
FFORMS: Feature-based FORecast Model Selection



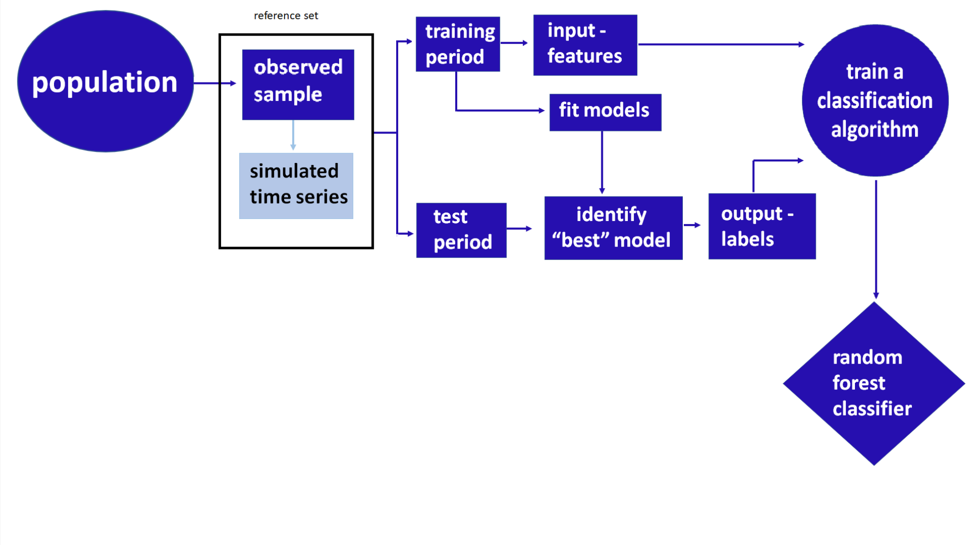
FFORMS: Feature-based FORecast Model Selection



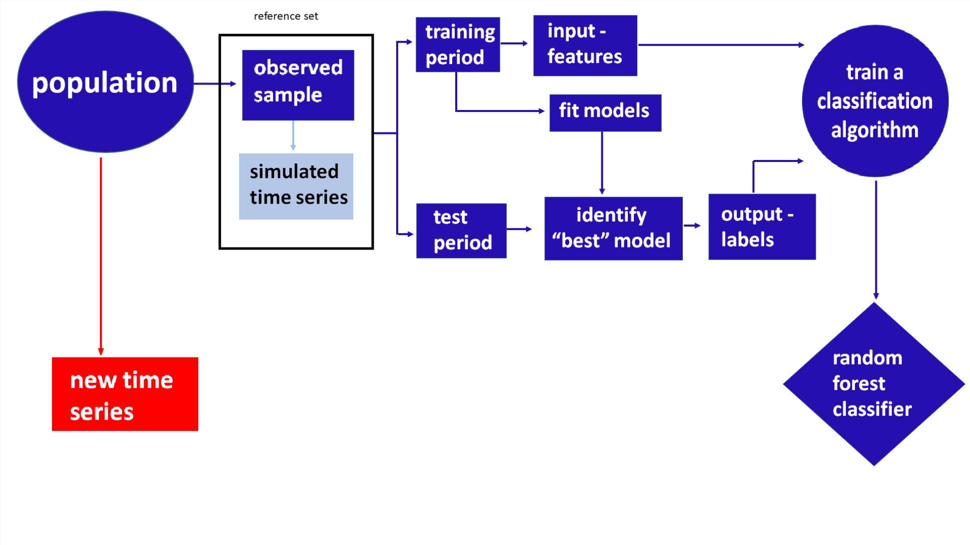
FFORMS: Feature-based FORecast Model Selection



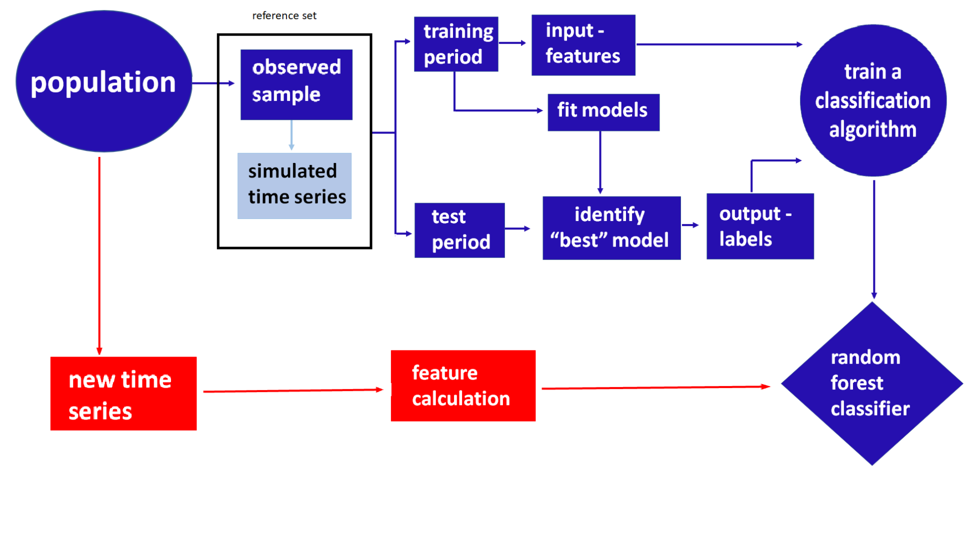
FFORMS: Feature-based FORecast Model Selection



FFORMS: Feature-based FORecast Model Selection



FFORMS: Feature-based FORecast Model Selection



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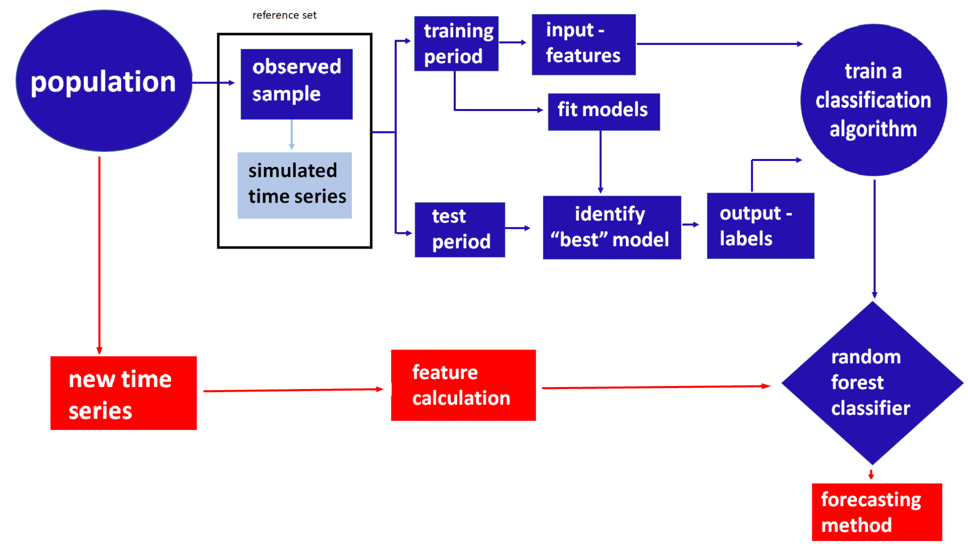


Application to M competition data

Experiment 1

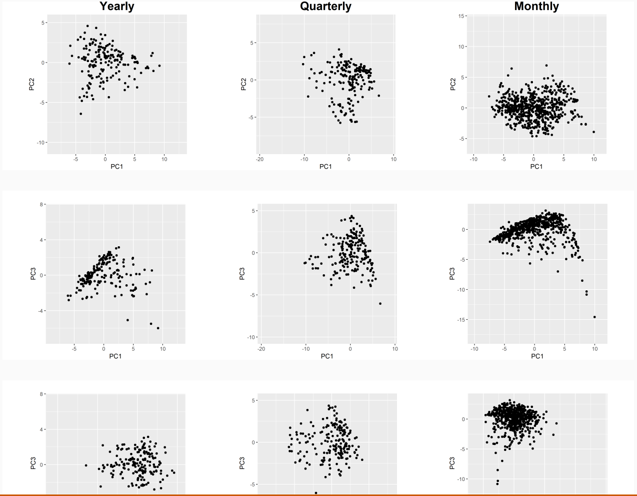
	Source	Y	Q	M
Observed series	M1	181	203	617
Simulated series		362000	406000	123400
New series	M3	645	756	1428

Experiment 2

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

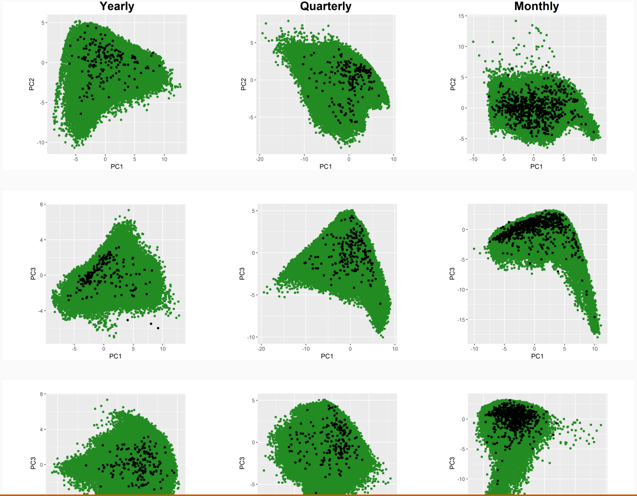
Experiment 1: Distribution of time series in PCA space

observed - M1



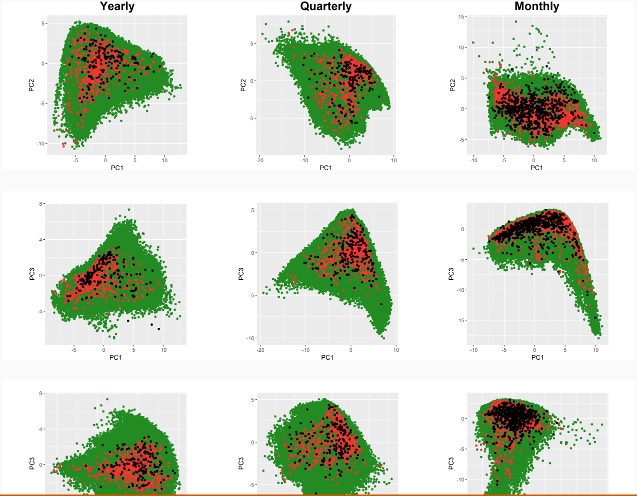
Experiment 1: Distribution of time series in PCA space

observed - M1 simulated



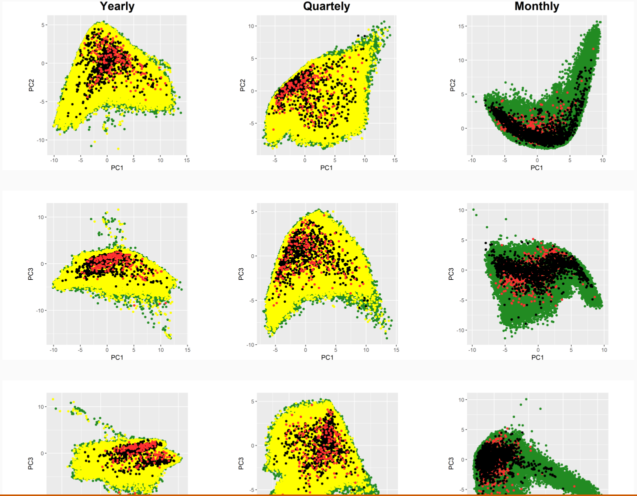
Experiment 1: Distribution of time series in PCA space

observed - M1 simulated new - M3

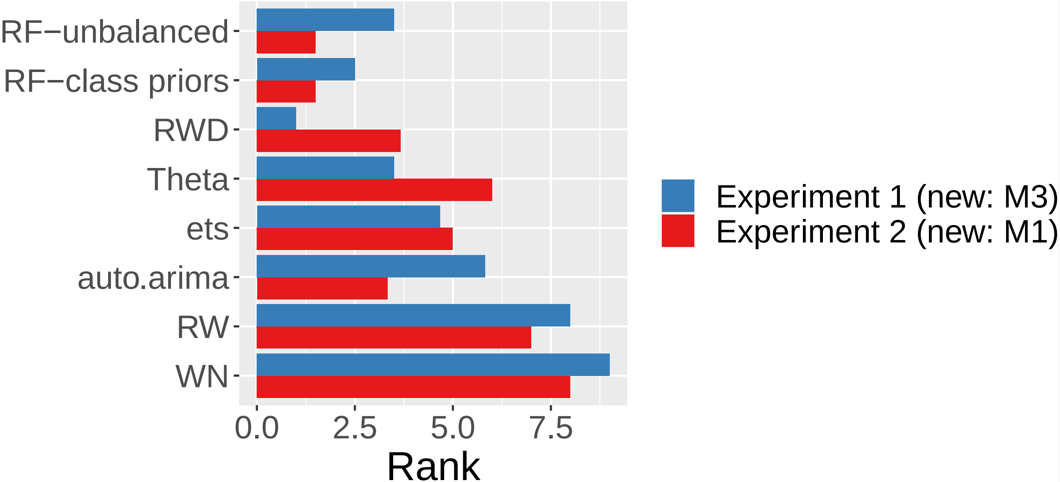


Experiment 2: Distribution of time series in PCA space

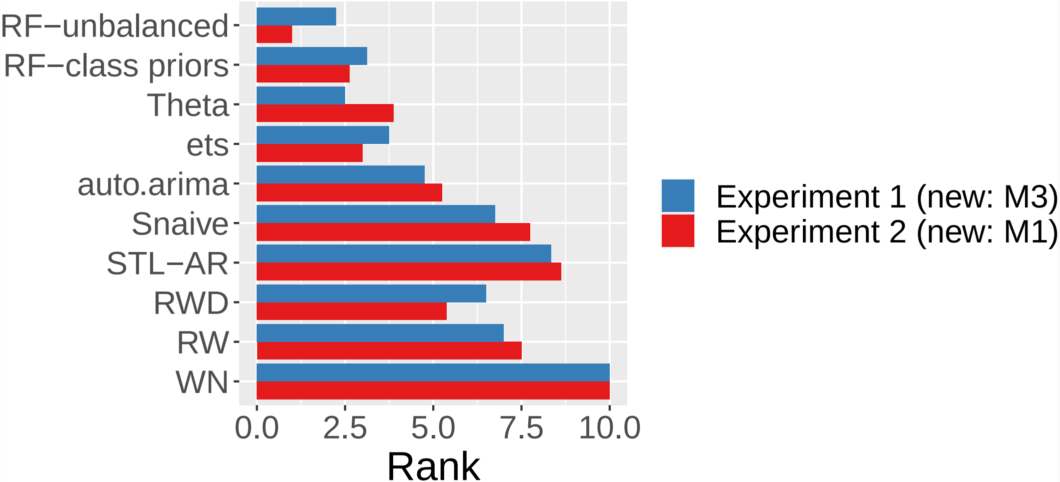
observed - M3 | simulated | subset | new - M1



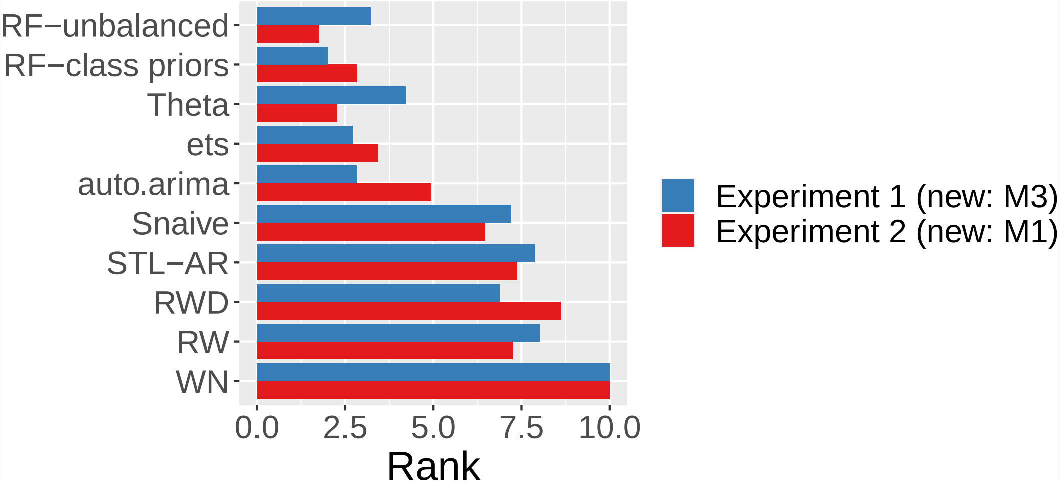
Results: Yearly



Results: Quarterly



Results: Monthly



FFORMA: Feature-based FORecast Model Averaging

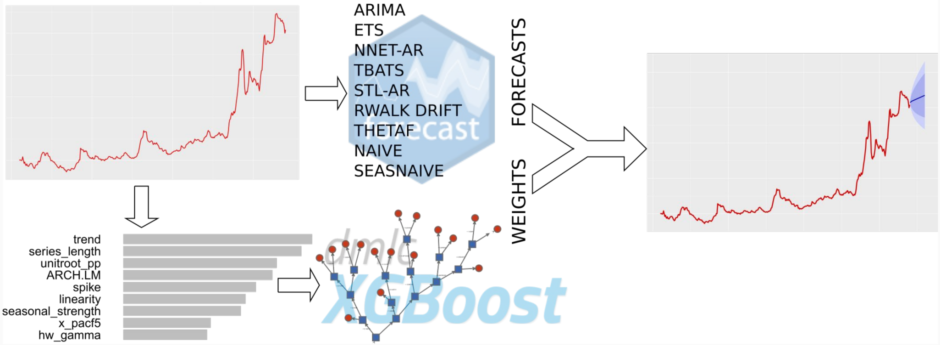
- Like FFORMS but using gradient boosted trees (xgboost) rather than random forest.
- Trained on temporal holdout version of M4 dataset, where size of test sets equal to required forecast horizons
- Optimization criterion: forecast accuracy not classification accuracy.
- Probability of each model being best is used to construct model weights for combination forecast.
- 5 days computing time.

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. STL decomposition with AR for seasonally adjusted series
9. Neural network autoregression

FFORMA: Feature-based FORecast Model Averaging

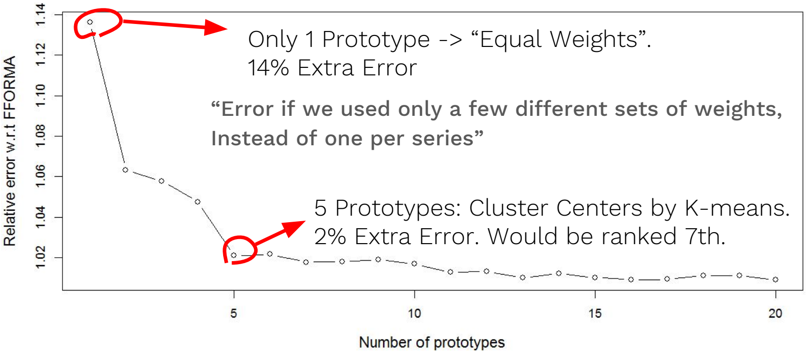


M4 competition results (based on average OWA)

1st	0.821	
2nd	0.838	(FFORMA)

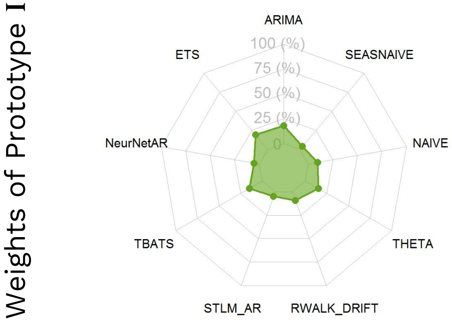
FFORMA: Feature-based FORecast Model Averaging

Looking for Prototypes in the weights

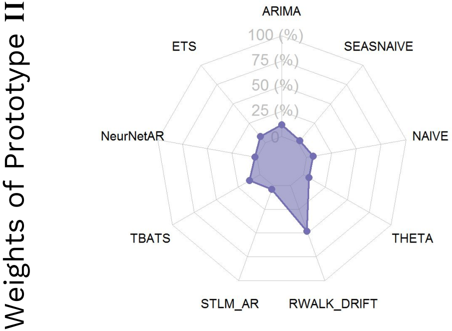


FFORMA: Feature-based FORecast Model Averaging

“Roughly Equal Weights”. 40000 Series in M4

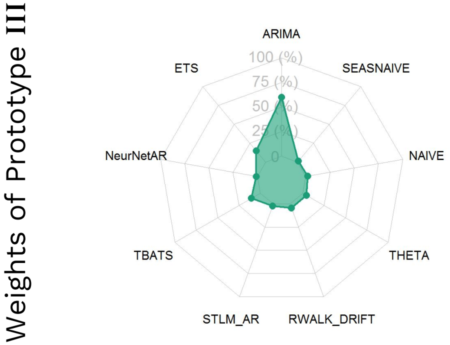


“Mostly RandomWalk Drift”. 20000 Series in M4



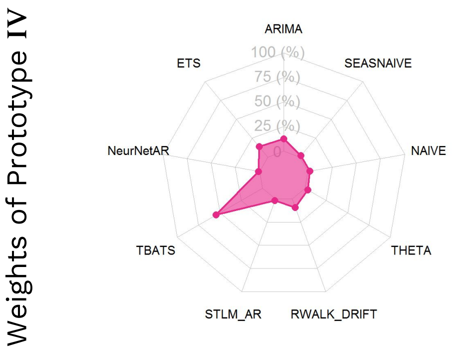
FFORMA: Feature-based FORecast Model Averaging

“Mostly ARIMA”. 16000 Series in M4



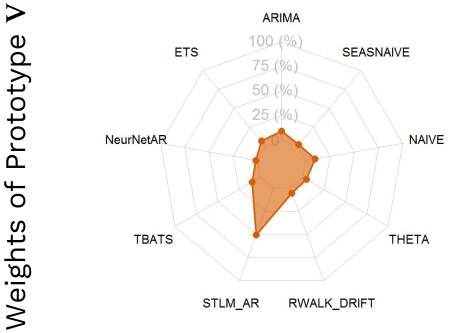
FFORMA: Feature-based FORecast Model Averaging

“Mostly TBATS”. 13000 Series in M4



FFORMA: Feature-based FORecast Model Averaging

“Mostly STLM-AR”. 8000 Series in M4



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