

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

Outline

1 Feature-based visualization

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. © 2000 Elsevier Science B.V. All rights reserved.

M3 competition: 2000



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The M3-Competition: results, conclusions and implications



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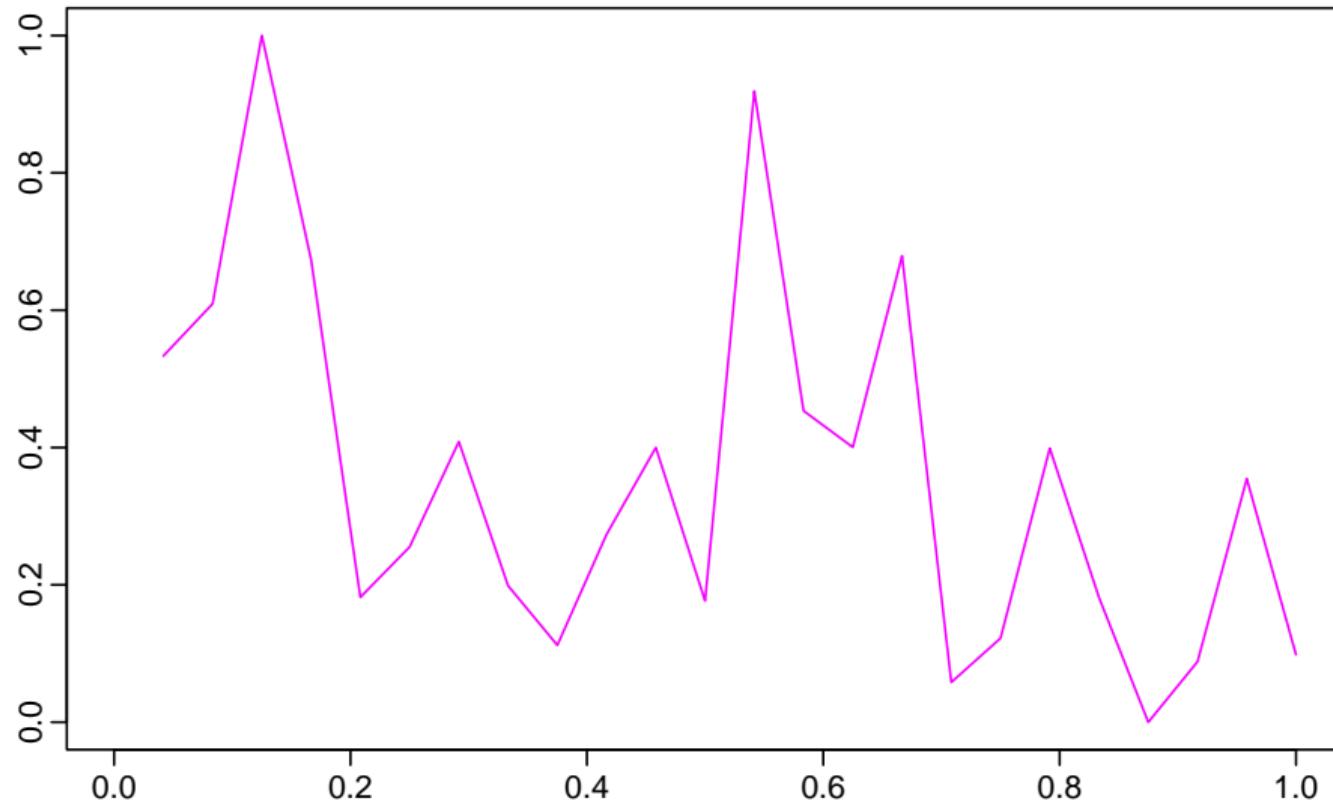
This paper presents the results of the M3-Competition, the latest of the M-Competitions. It explains the main features of the competition and compares its results and conclusions. In addition, the paper compares such results with those obtained in previous competitions as well as with those of other 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. © 2000 Elsevier Science B.V. All rights reserved.

M3 competition: 2000

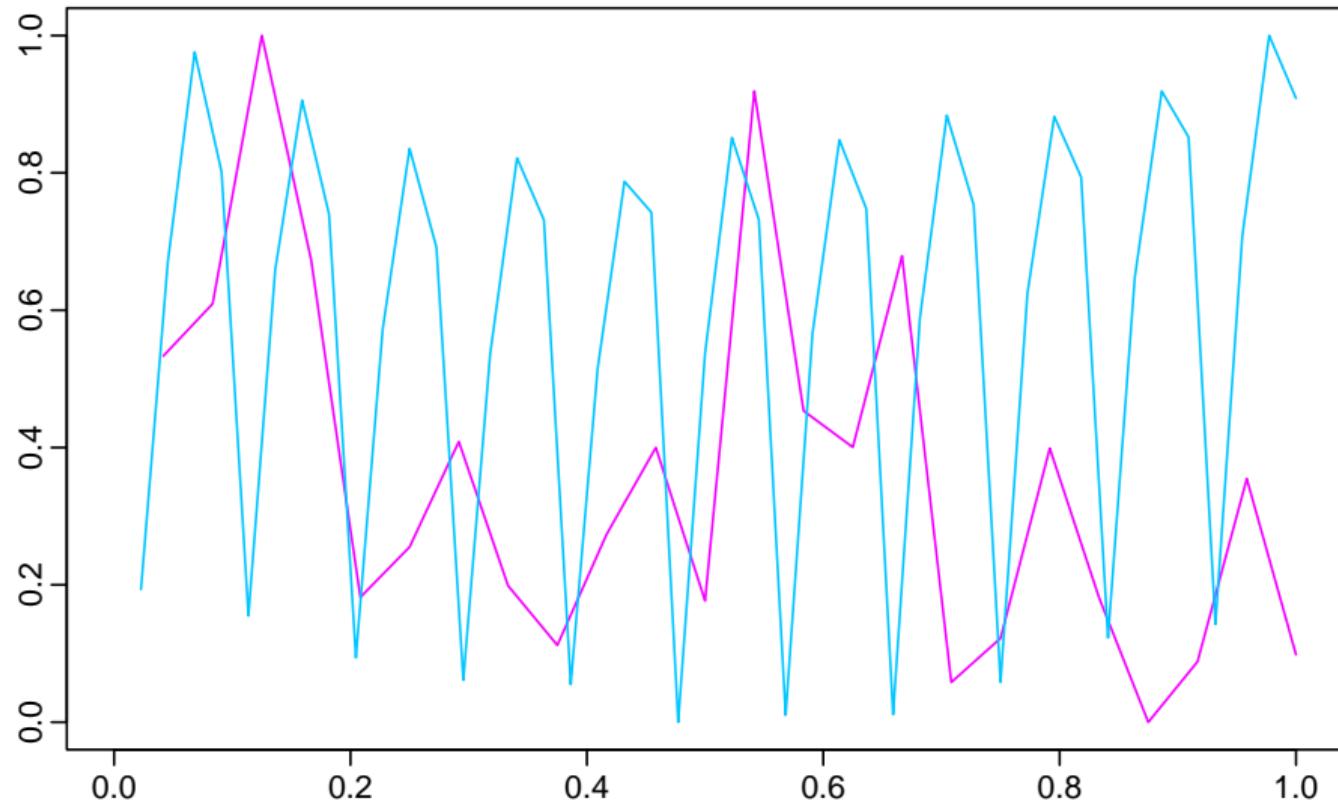
“The M3-Competition is a final attempt by the authors to settle the accuracy issue of various time series methods... The extension involves the inclusion of more methods/ researchers (in particular in the areas of neural networks and expert systems) and more series.”

- 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.

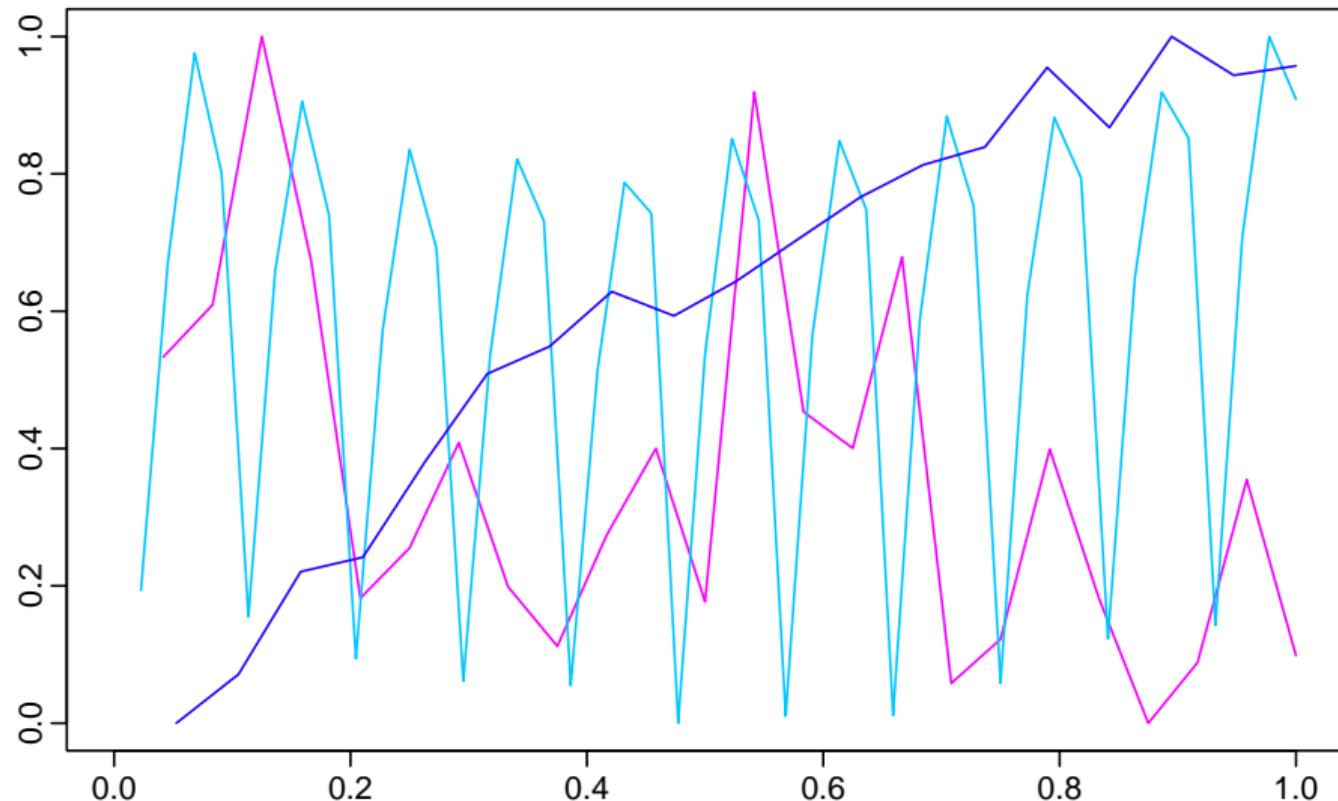
How to plot lots of time series?



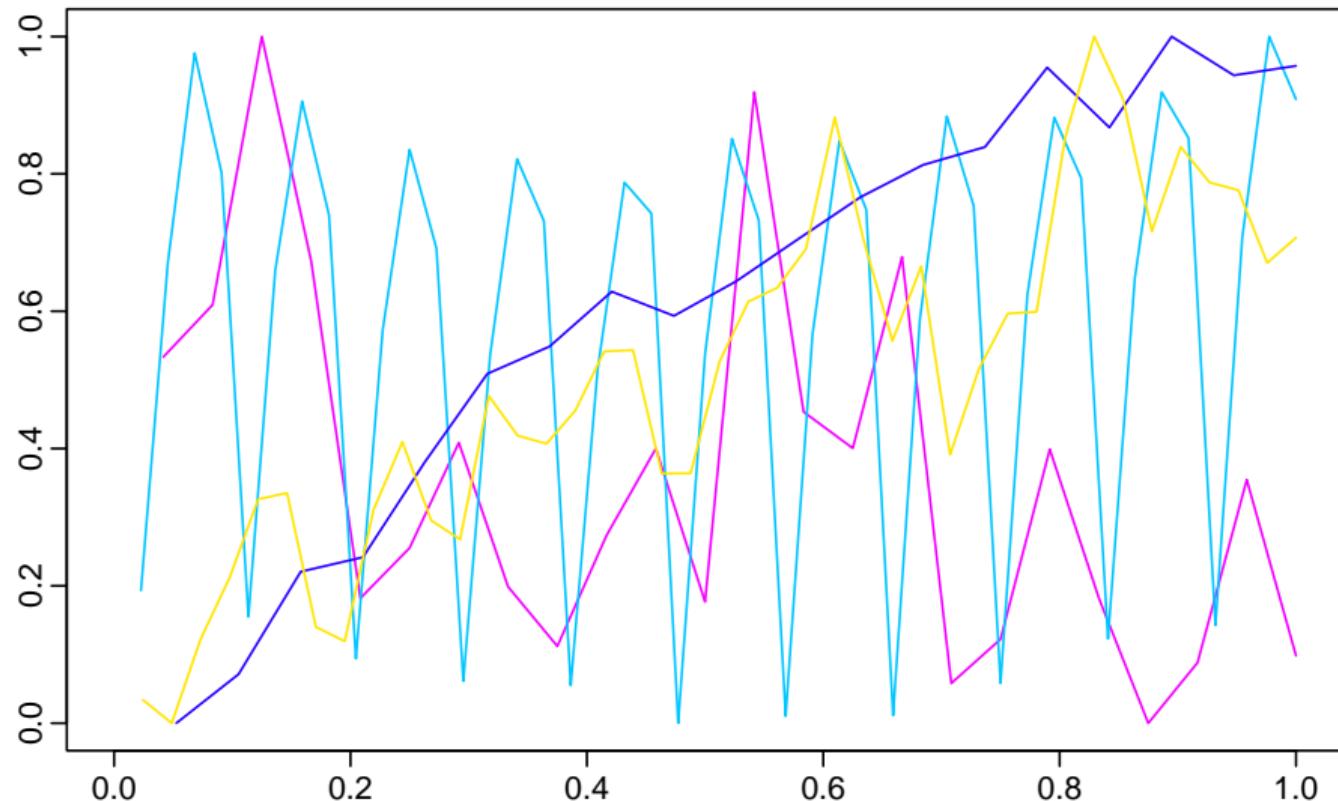
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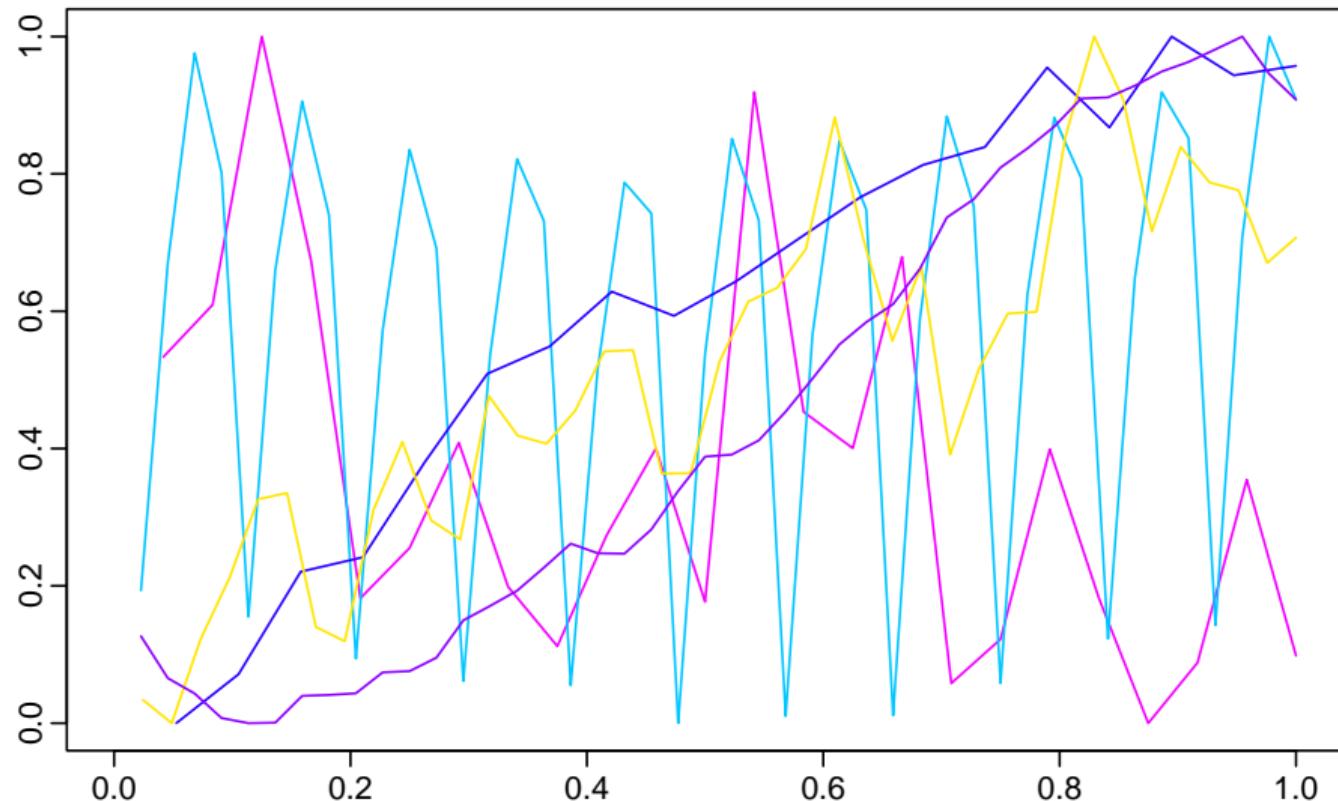
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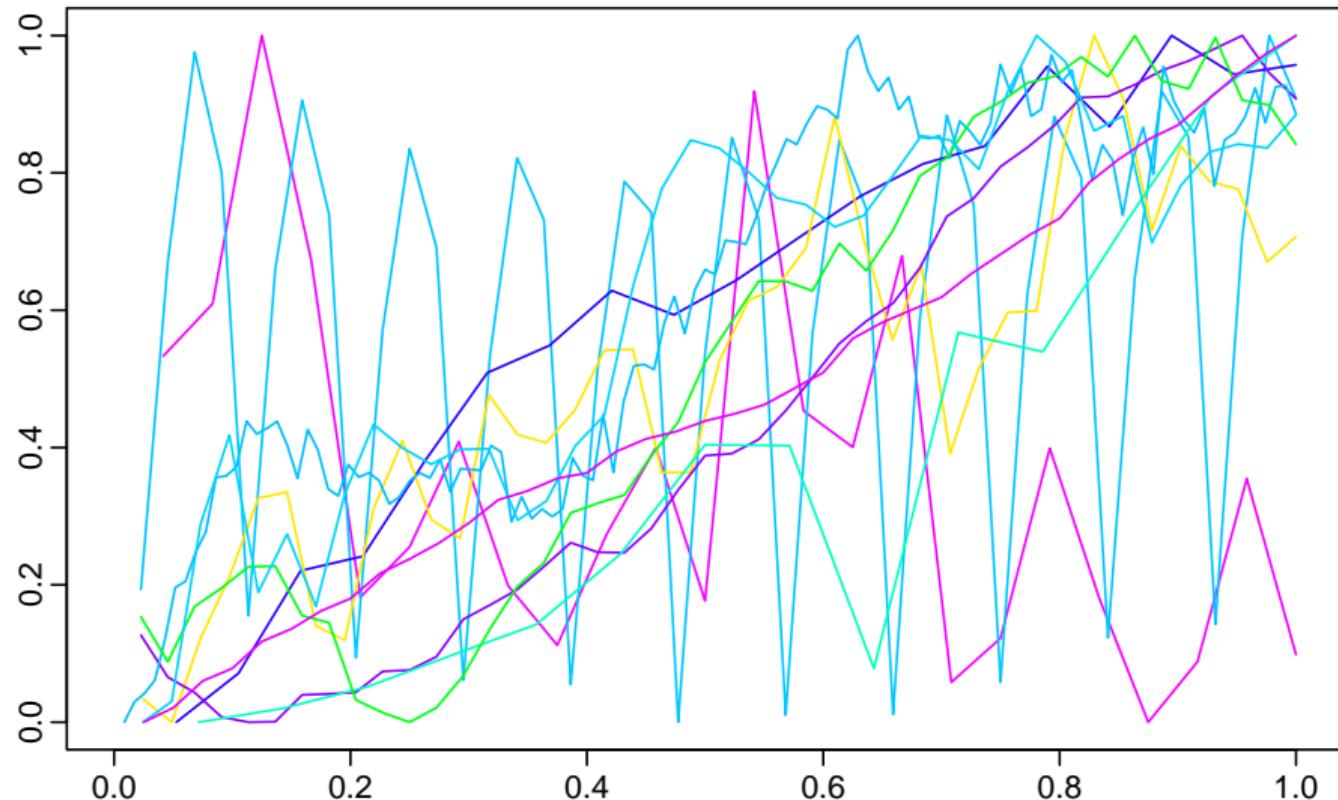
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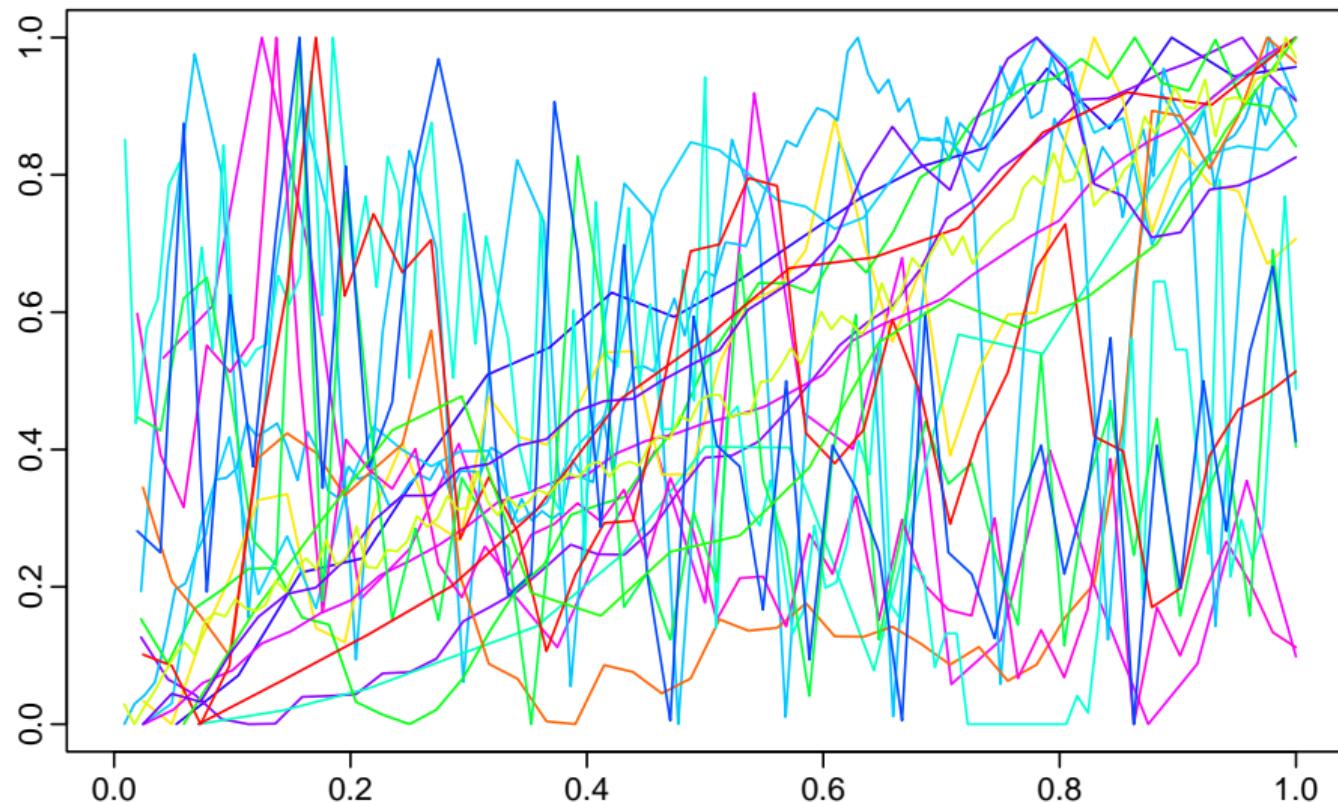
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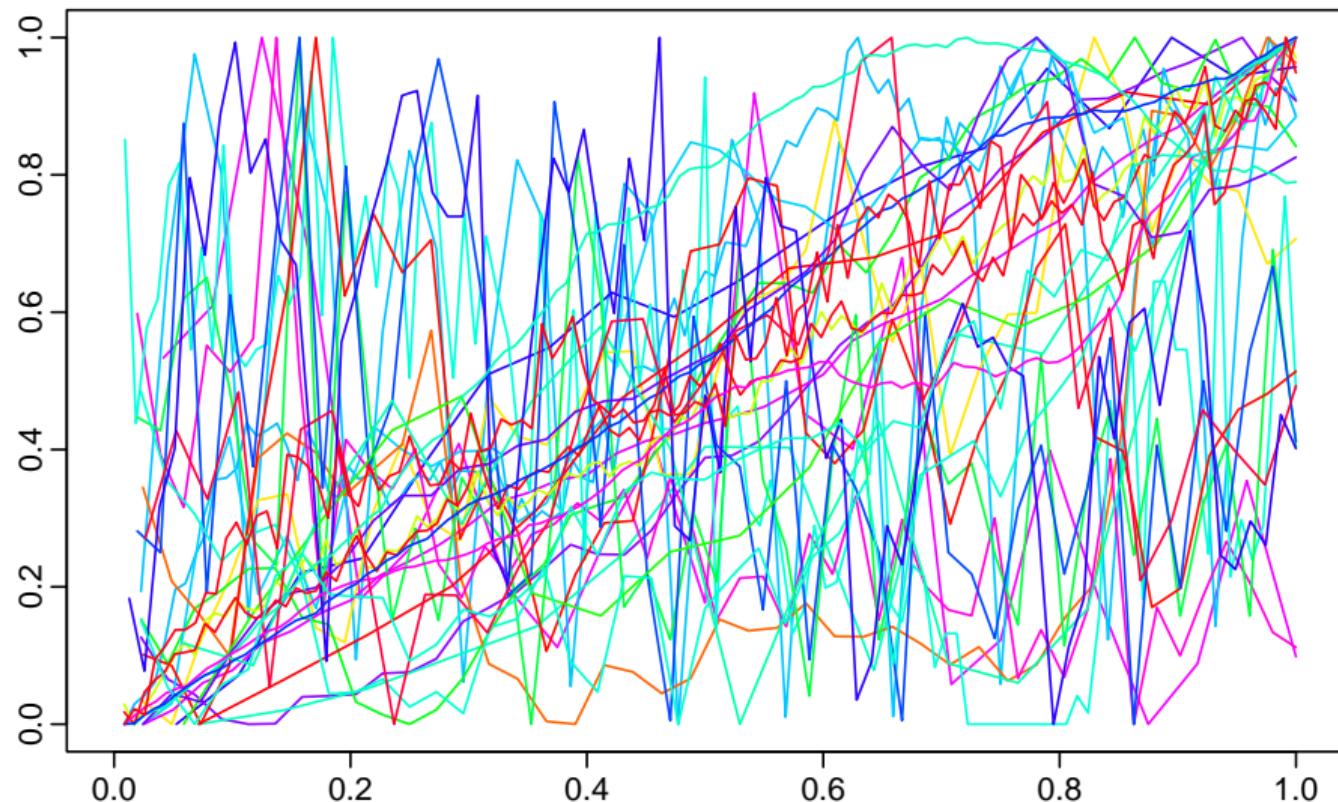
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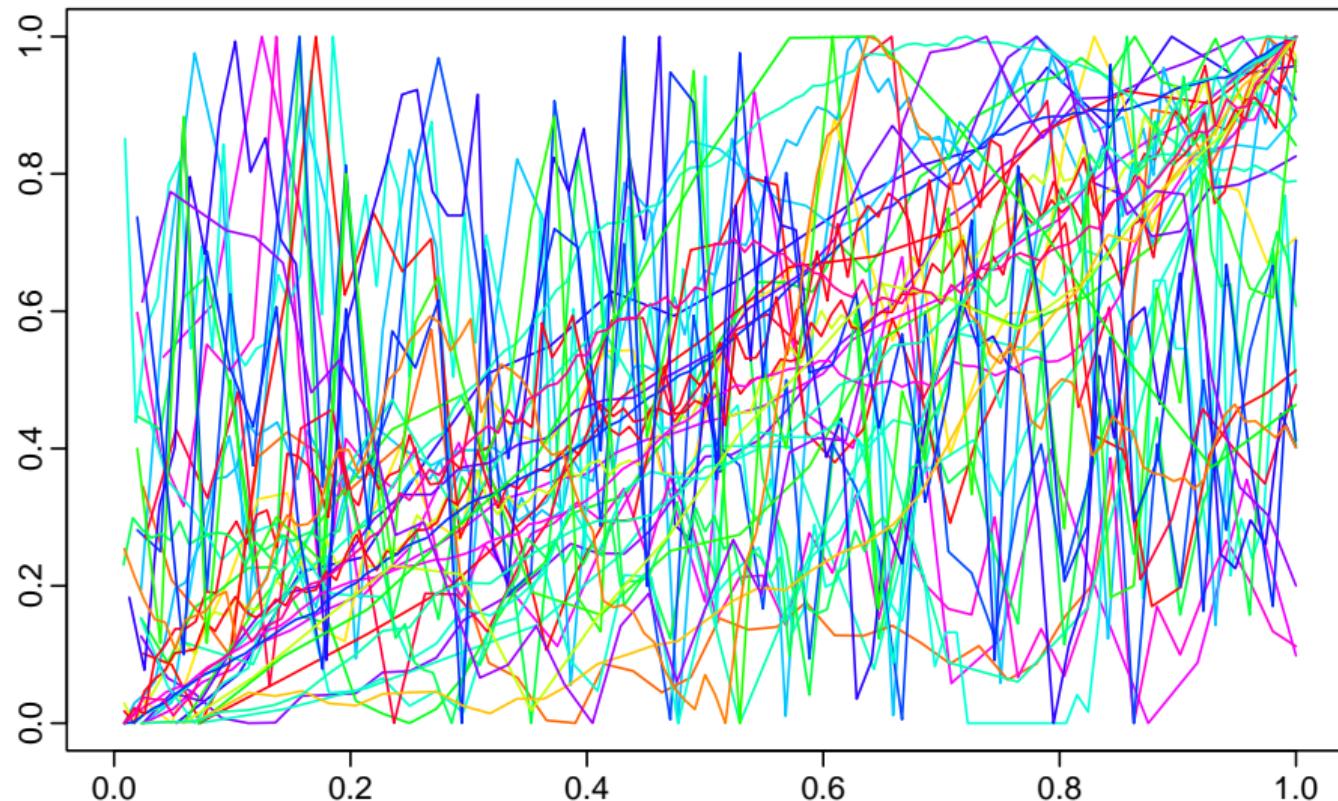
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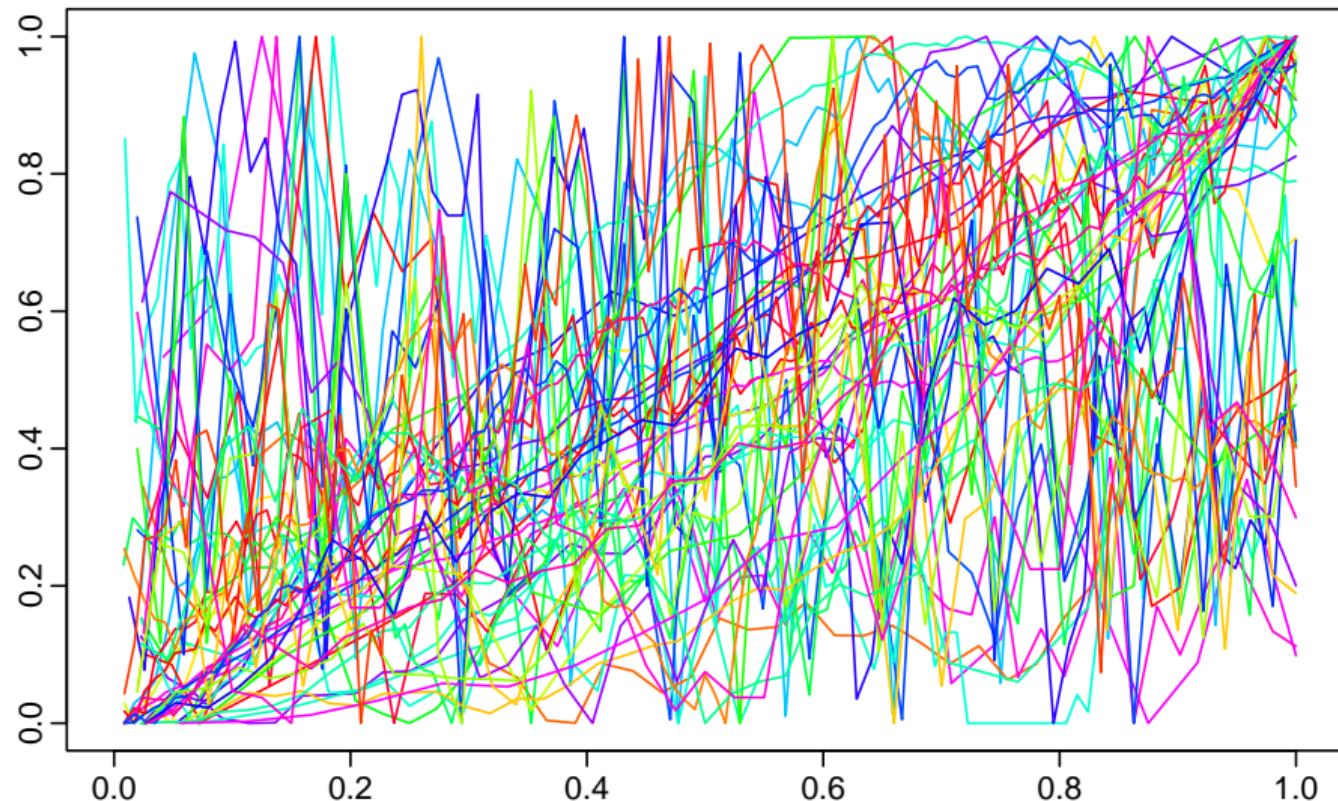
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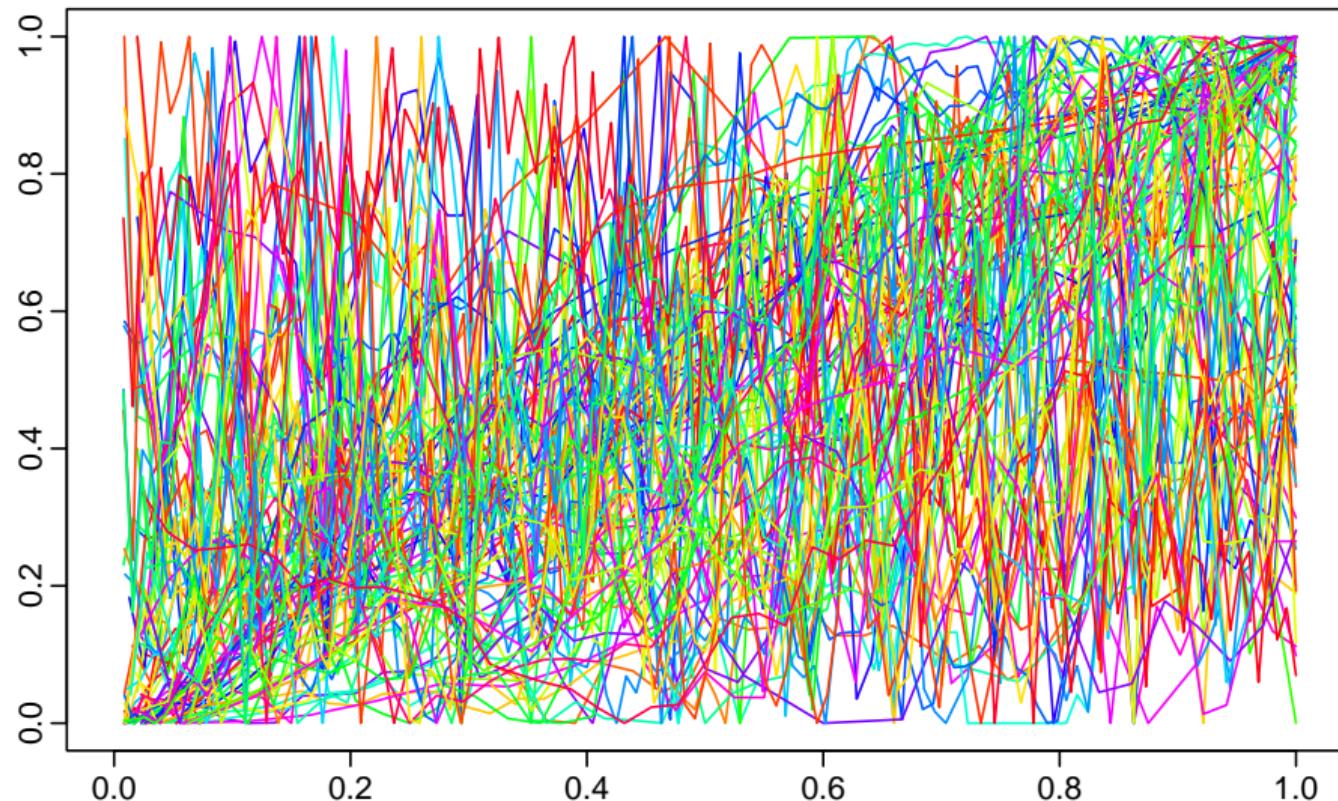
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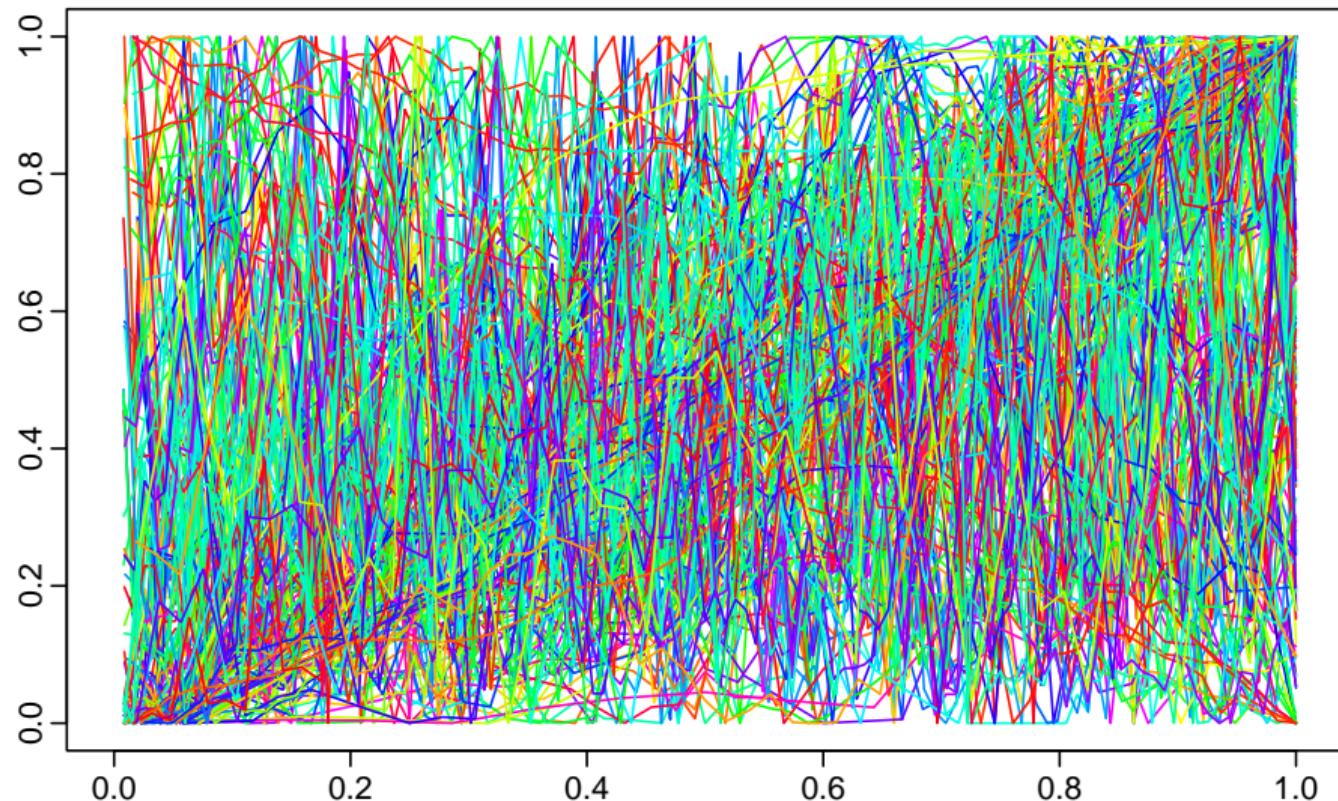
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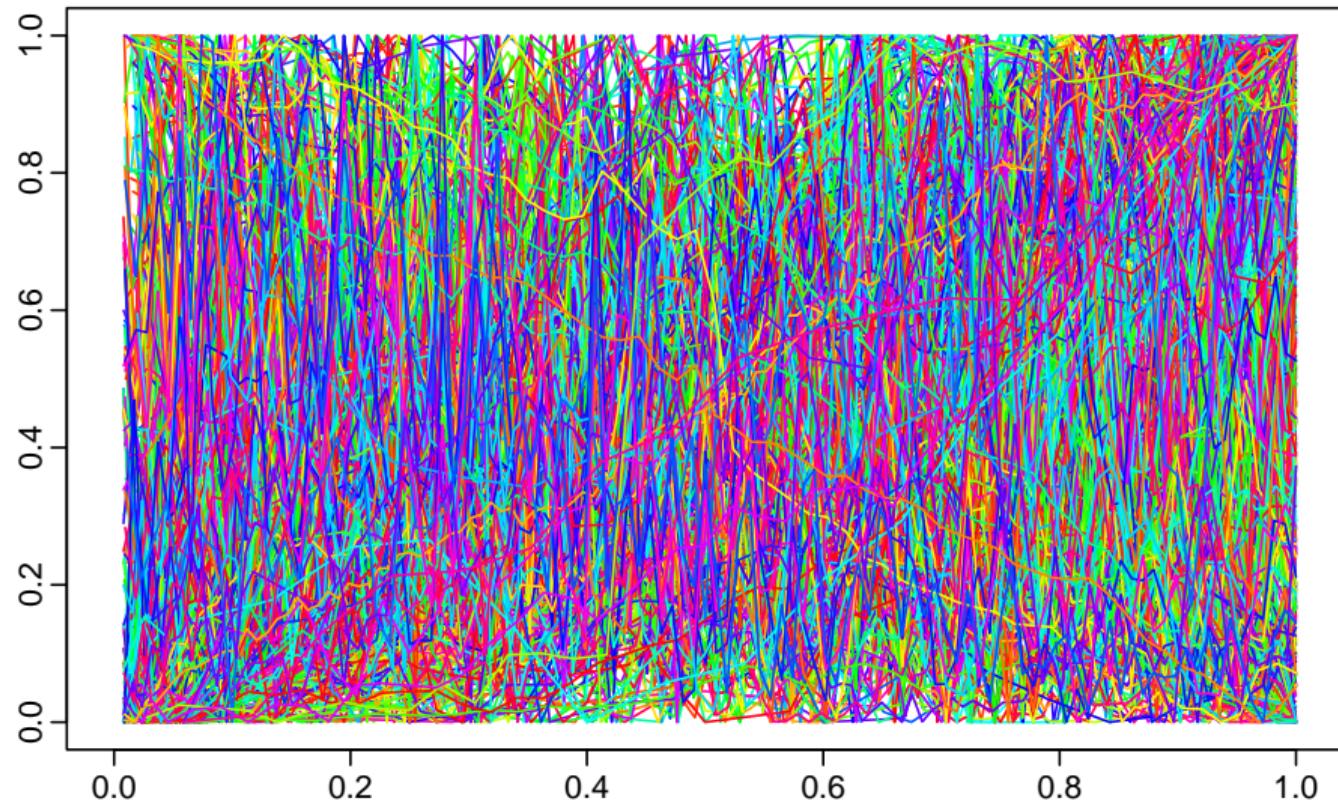
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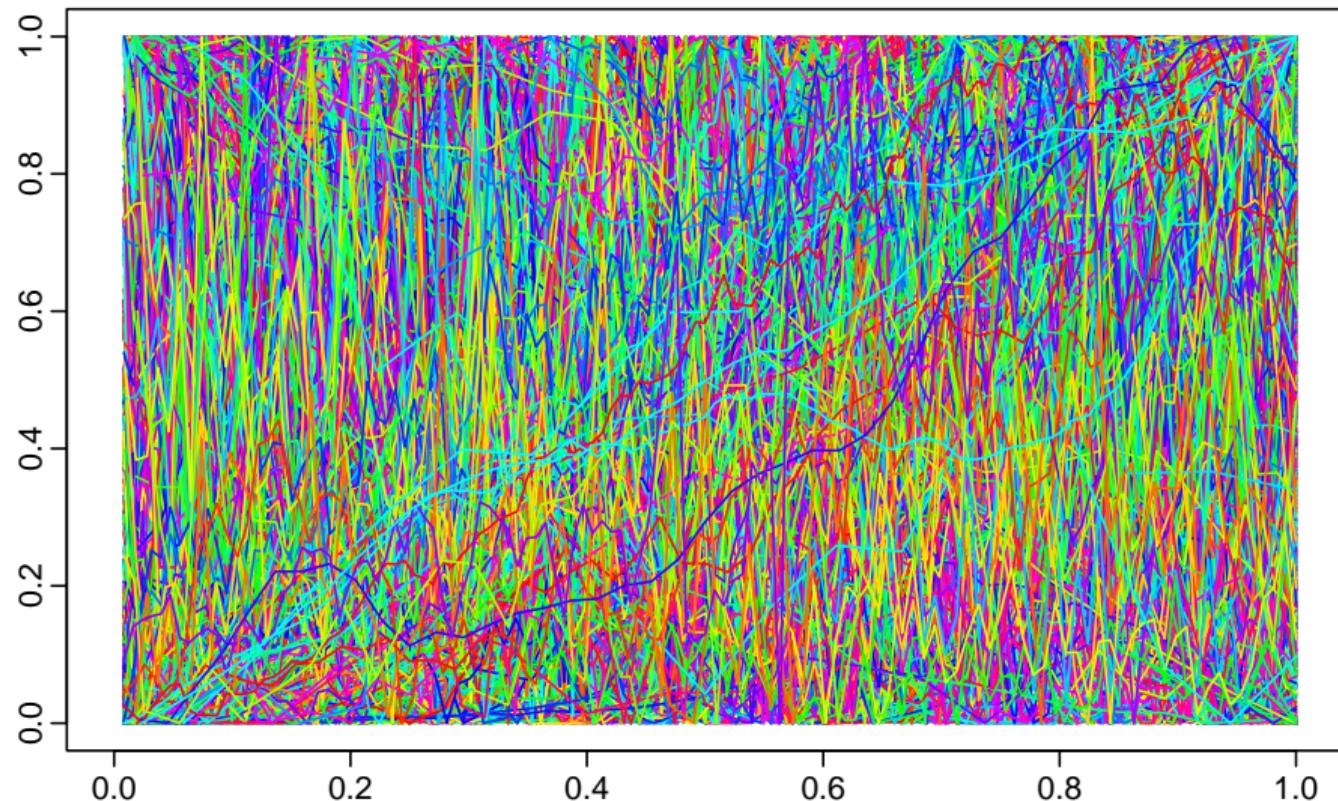
How to plot lots of time series?



How to plot lots of time series?



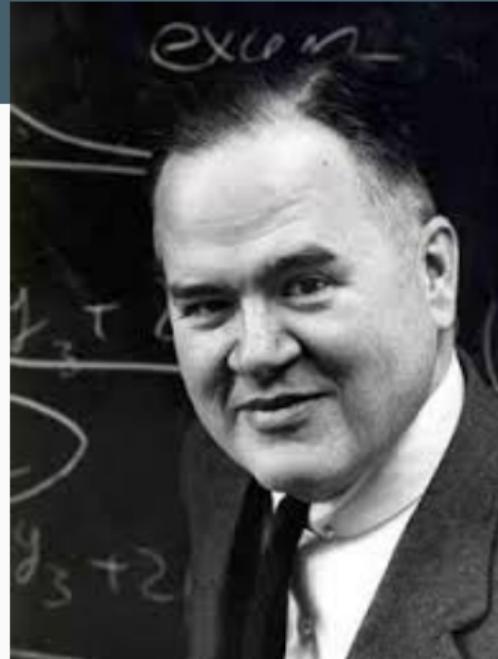
How to plot lots of time series?



Key idea

Cognostics

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



John W Tukey

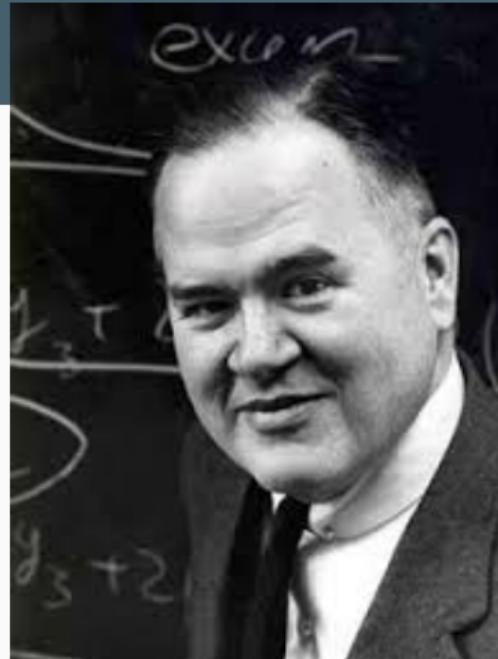
Key idea

Cognostics

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(Tukey and Tukey, 1985).

Examples for time series

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



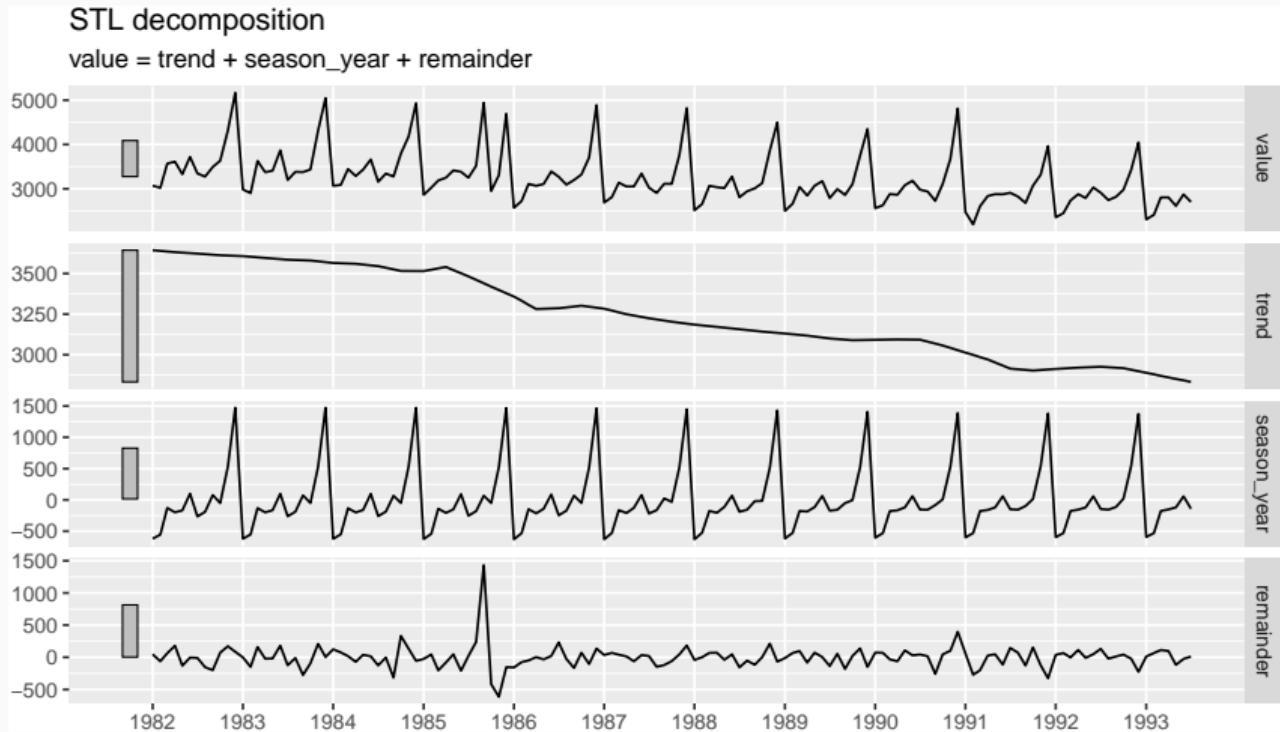
John W Tukey

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

An STL decomposition: N2096

$$Y_t = S_t + T_t + R_t$$

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

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- scale-independent
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- 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

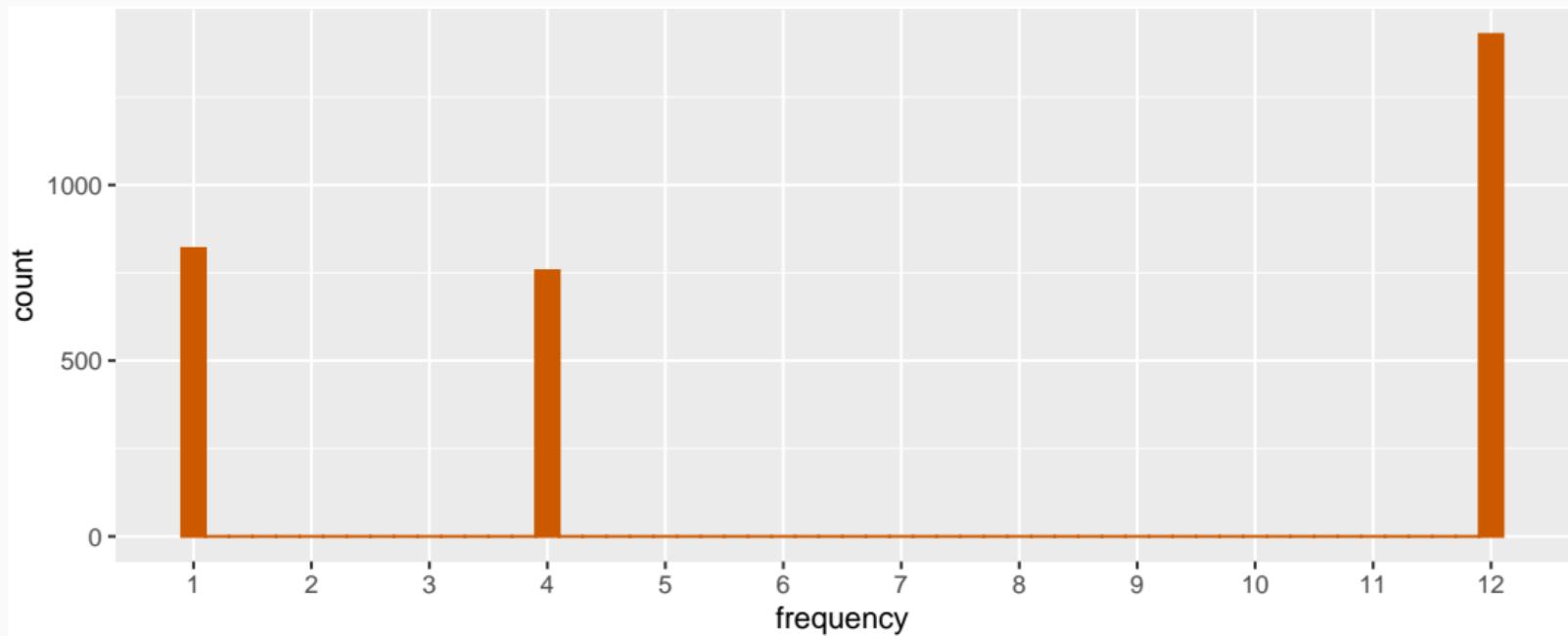
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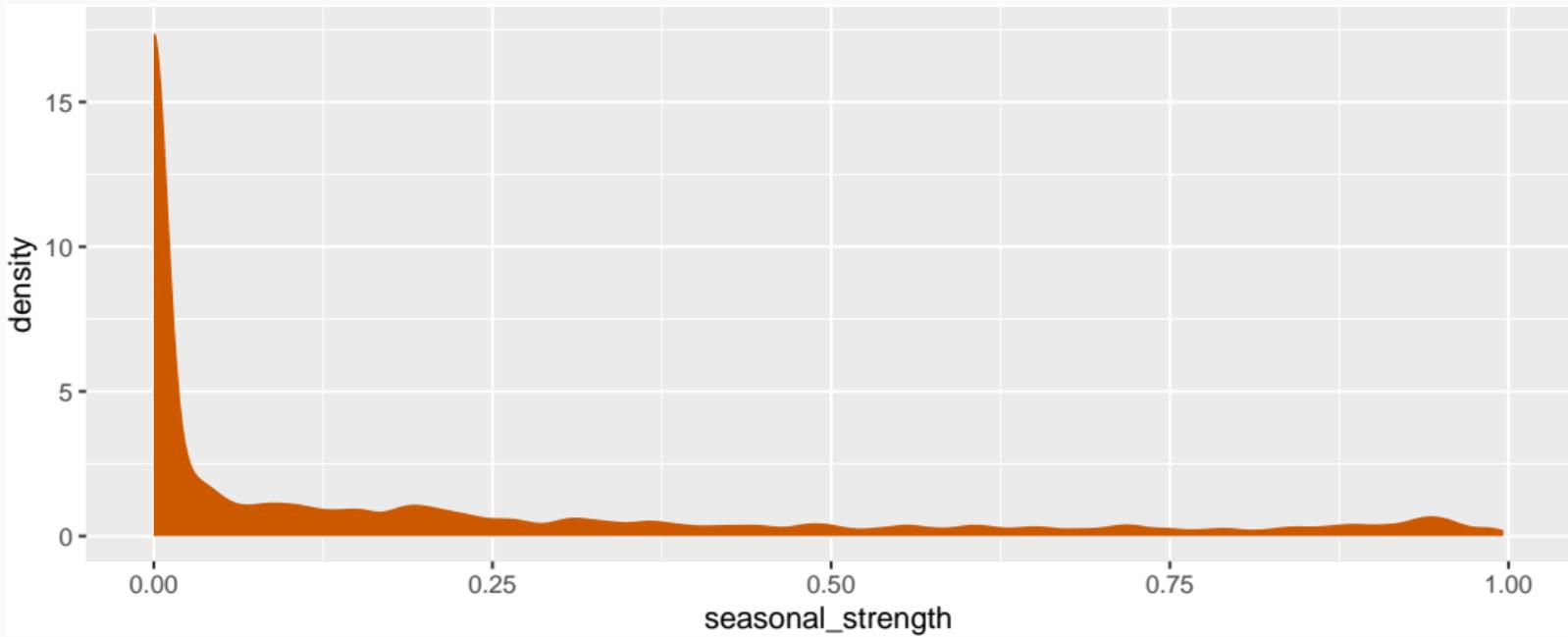
- 1 Seasonal period
- 2 Strength of seasonality
- 3 Strength of trend
- 4 First autocorrelation of STL remainder series
- 5 Spectral entropy
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For other analyses, it may be appropriate to have different requirements.

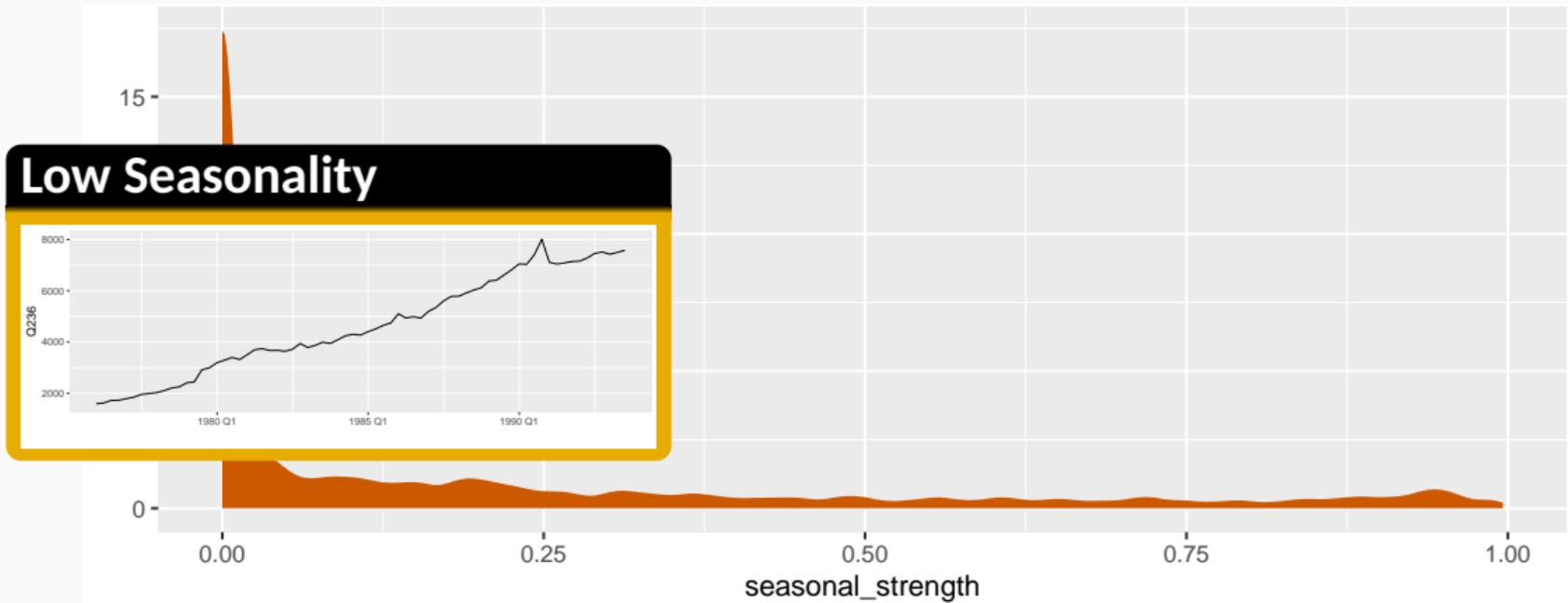
Distribution of Period for M3



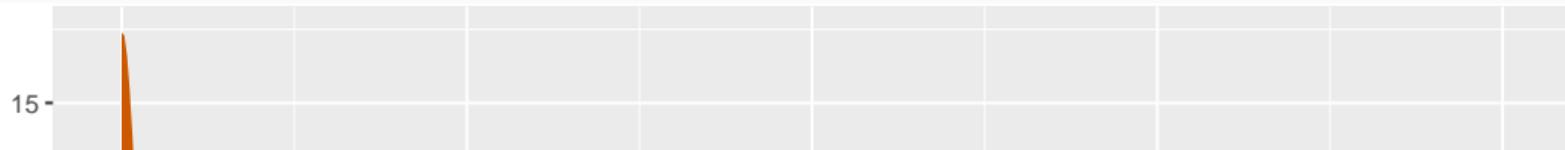
Distribution of Seasonality for M3



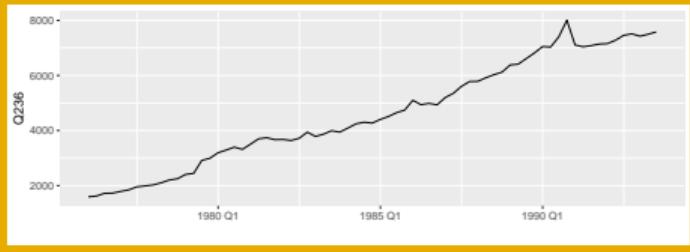
Distribution of Seasonality for M3



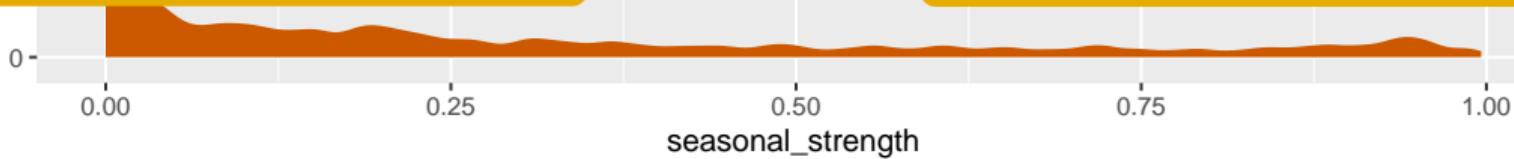
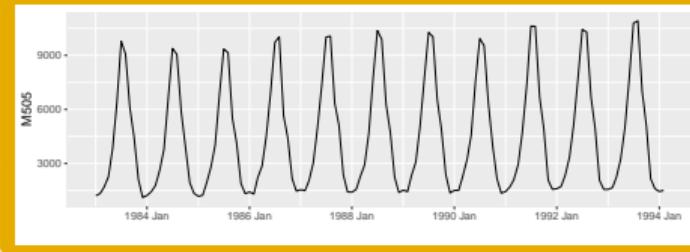
Distribution of Seasonality for M3



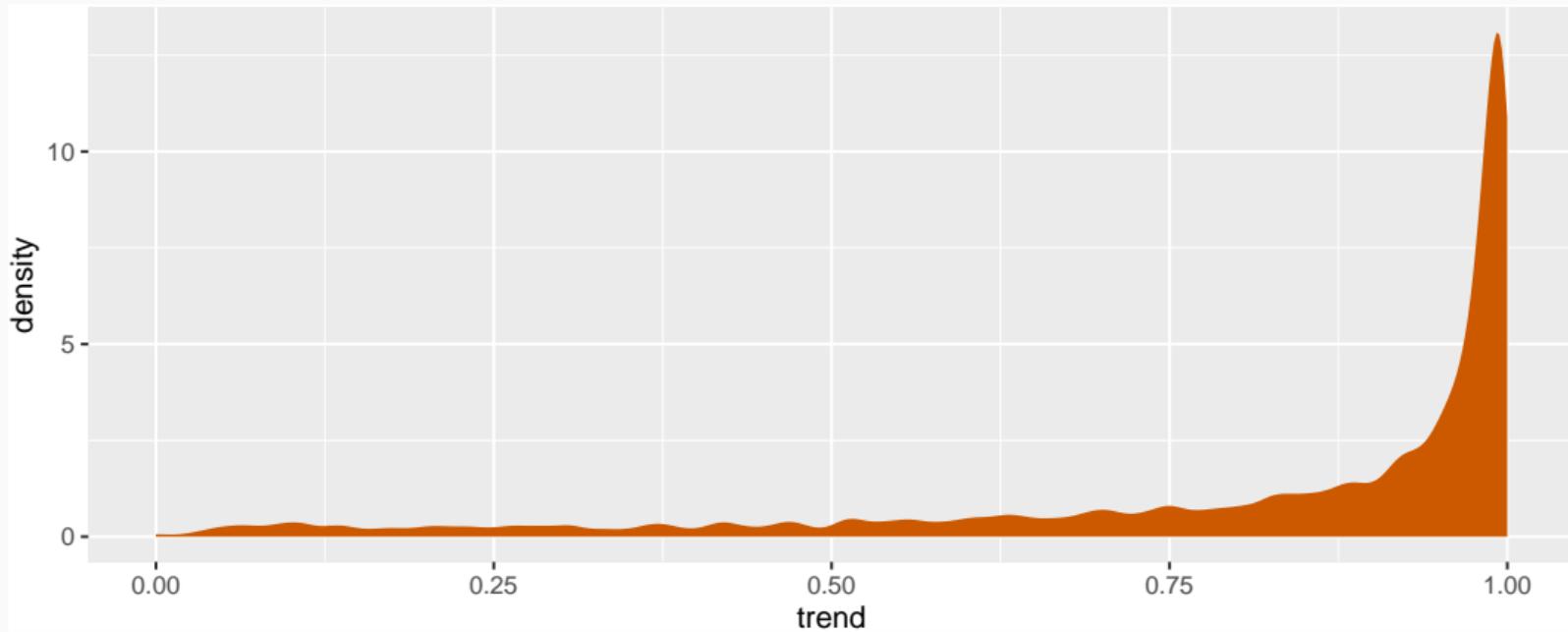
Low Seasonality



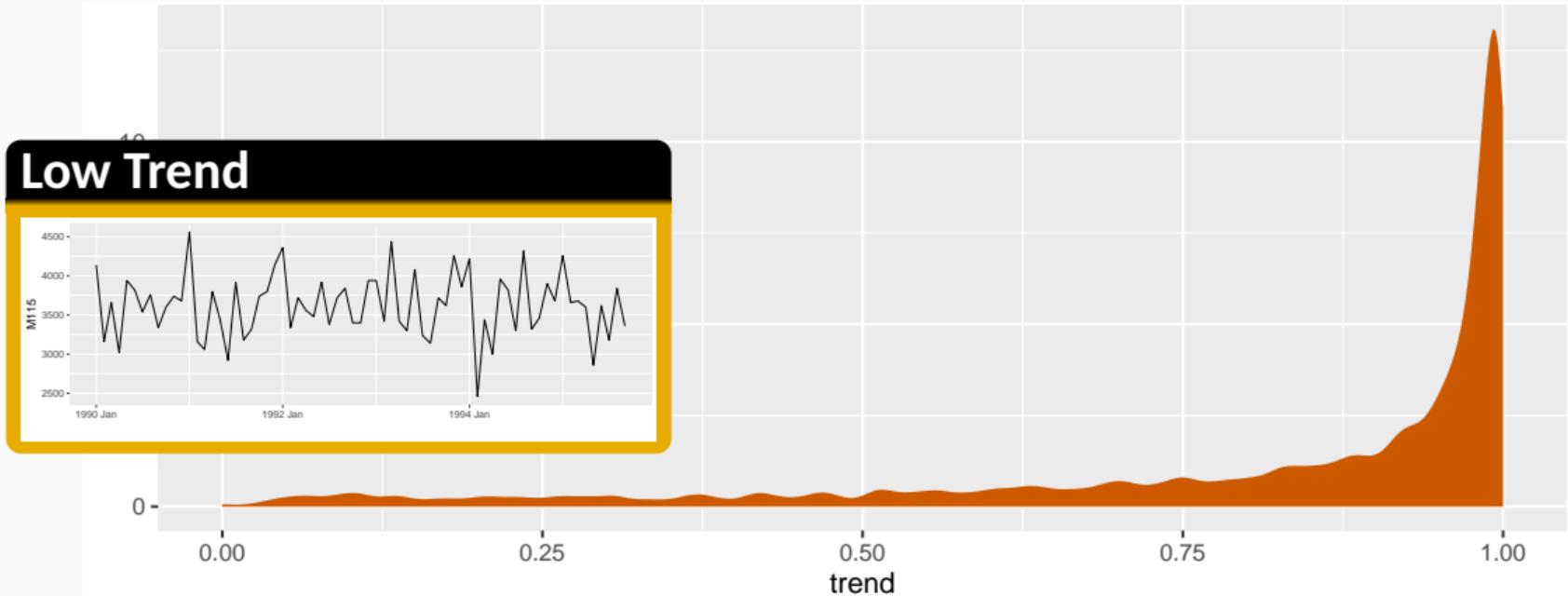
High Seasonality



Distribution of Trend for M3

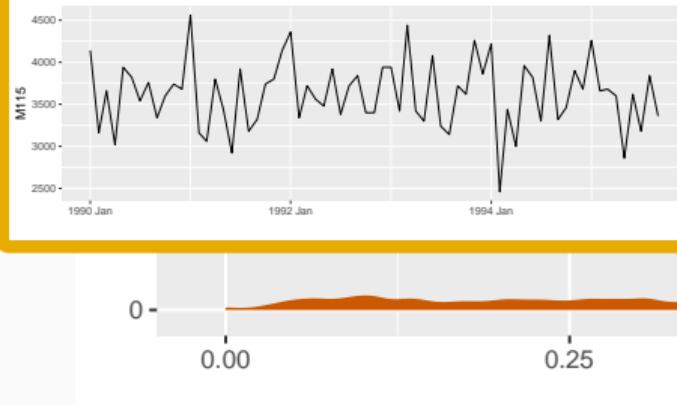


Distribution of Trend for M3

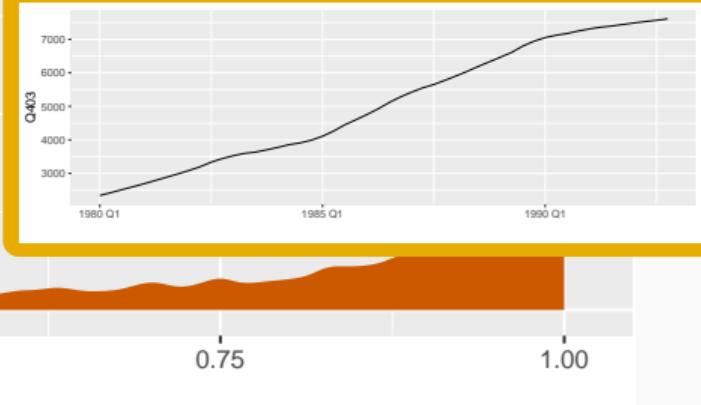


Distribution of Trend for M3

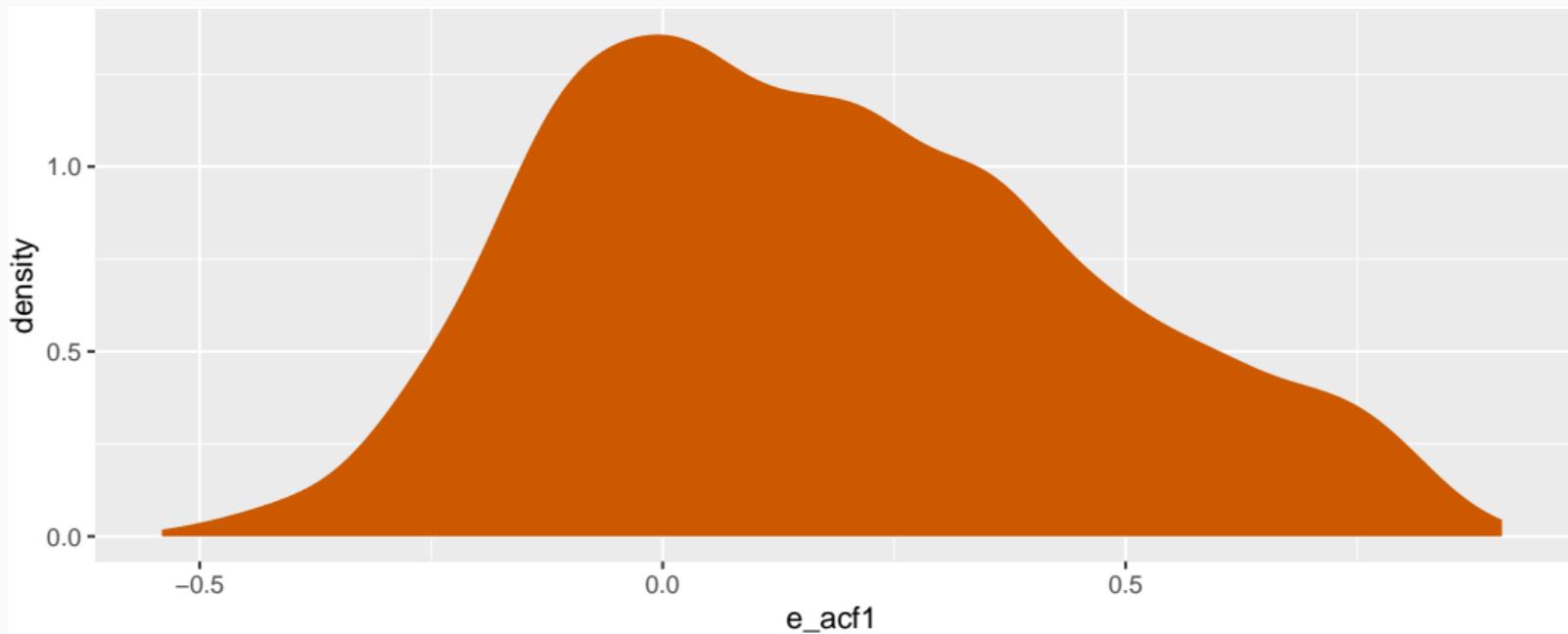
Low Trend



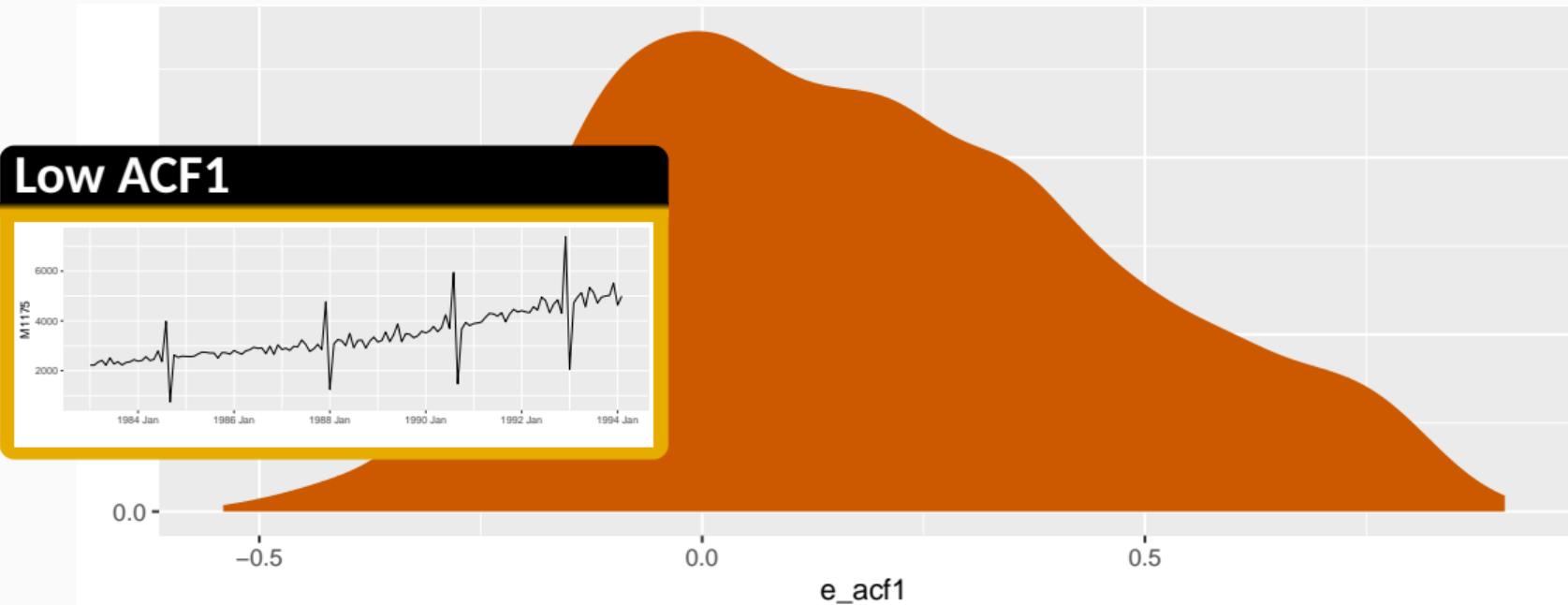
High Trend



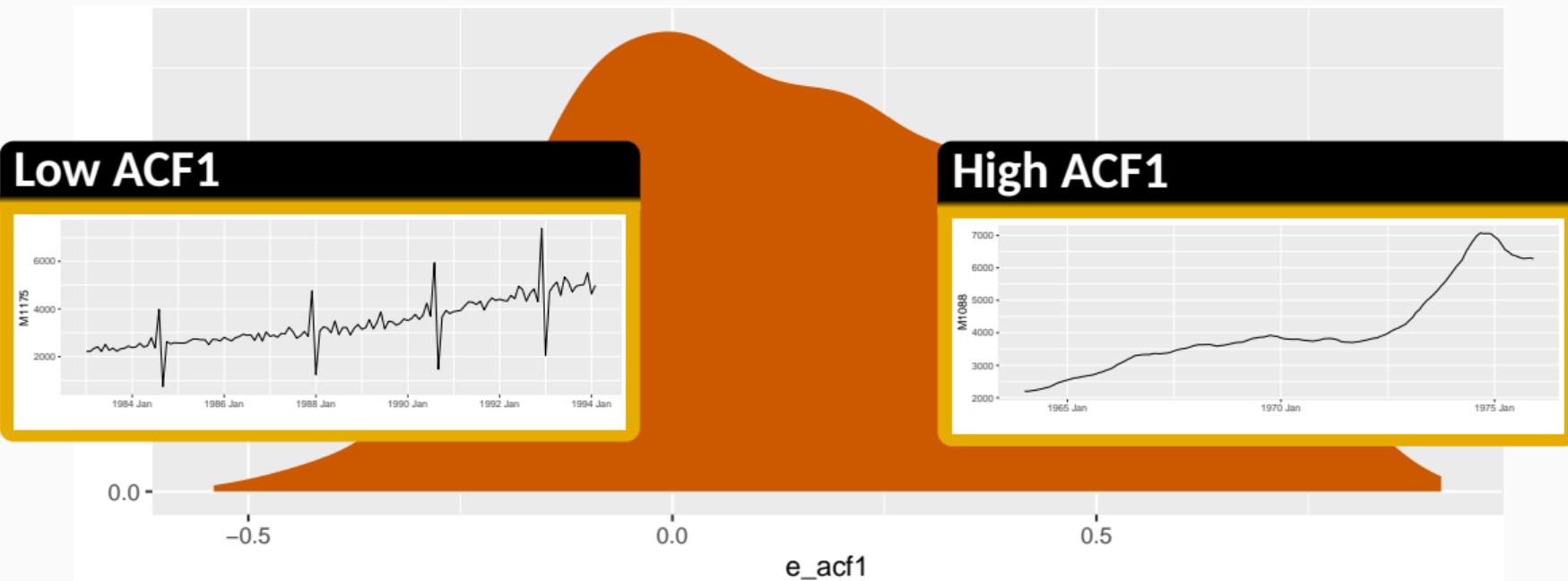
Distribution of Residual ACF1 for M3



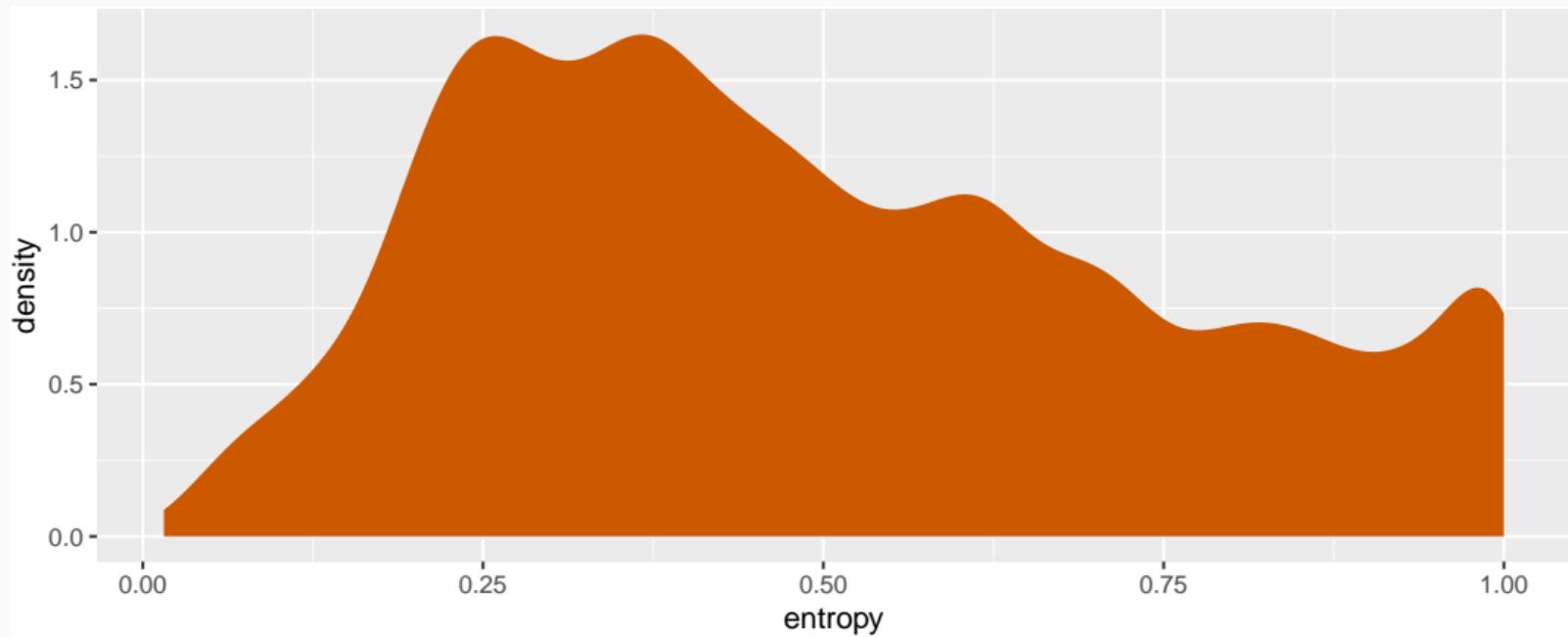
Distribution of Residual ACF1 for M3



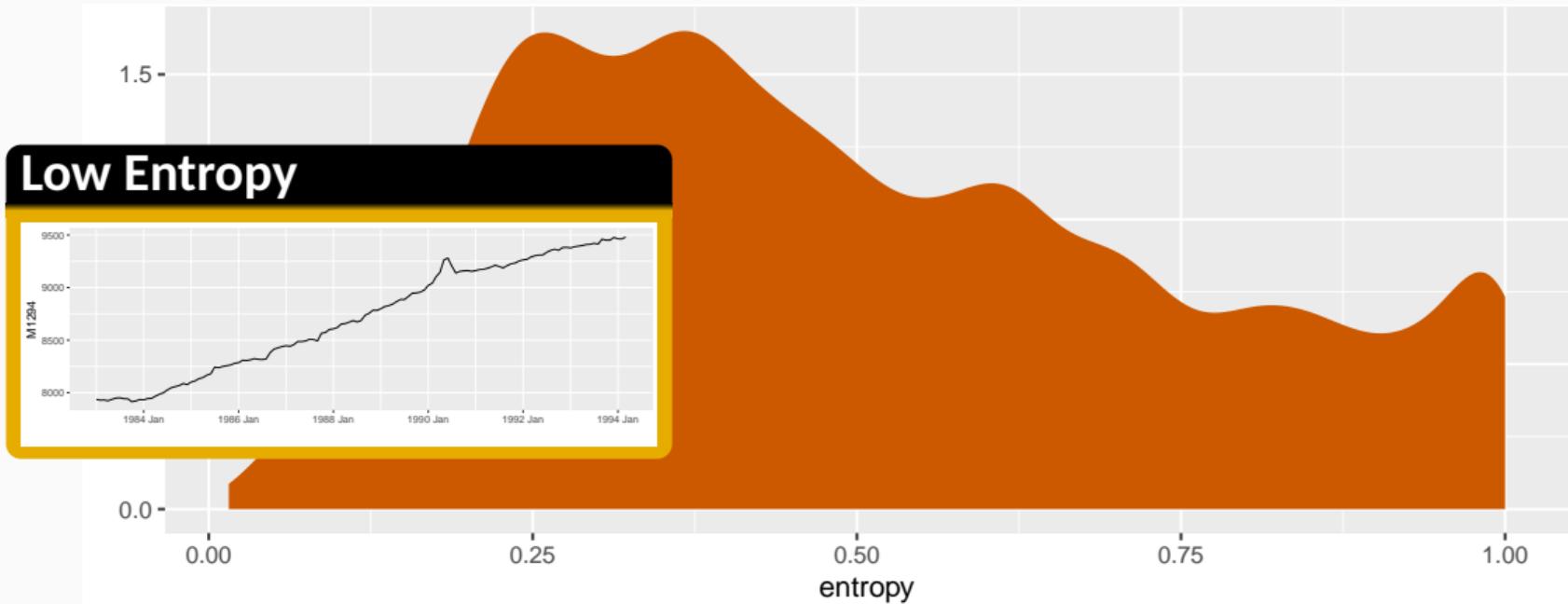
Distribution of Residual ACF1 for M3



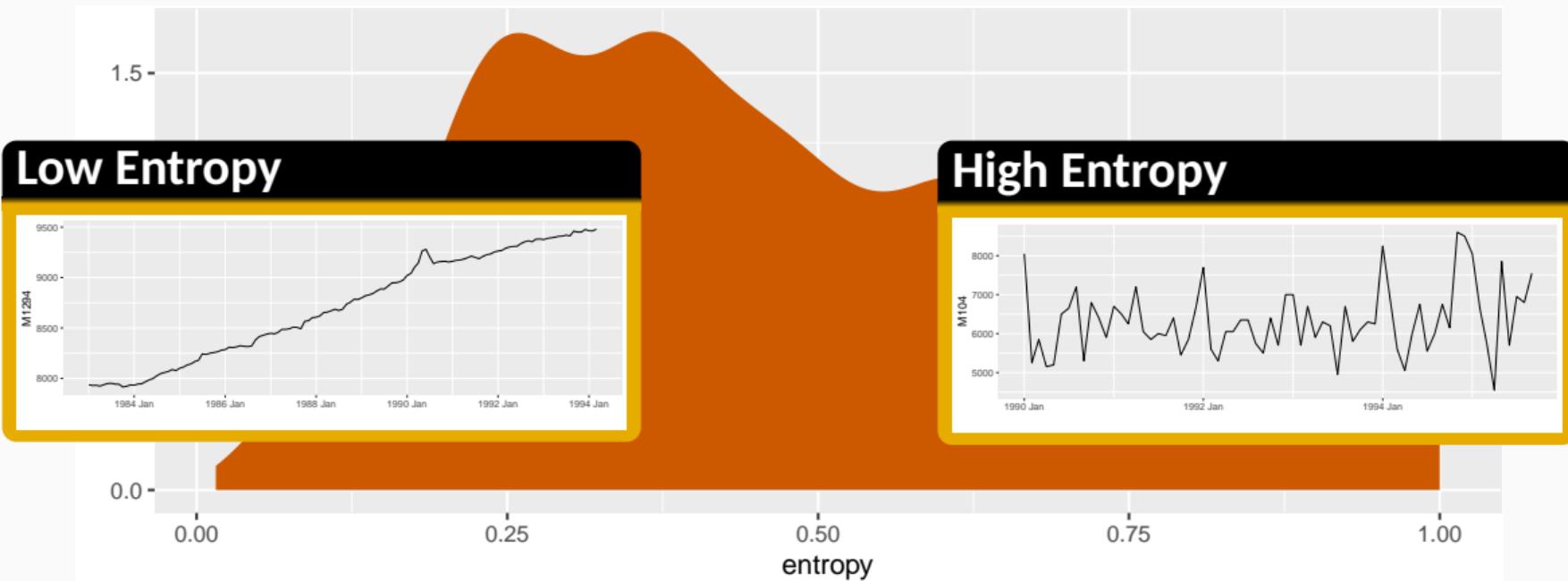
Distribution of Spectral Entropy for M3



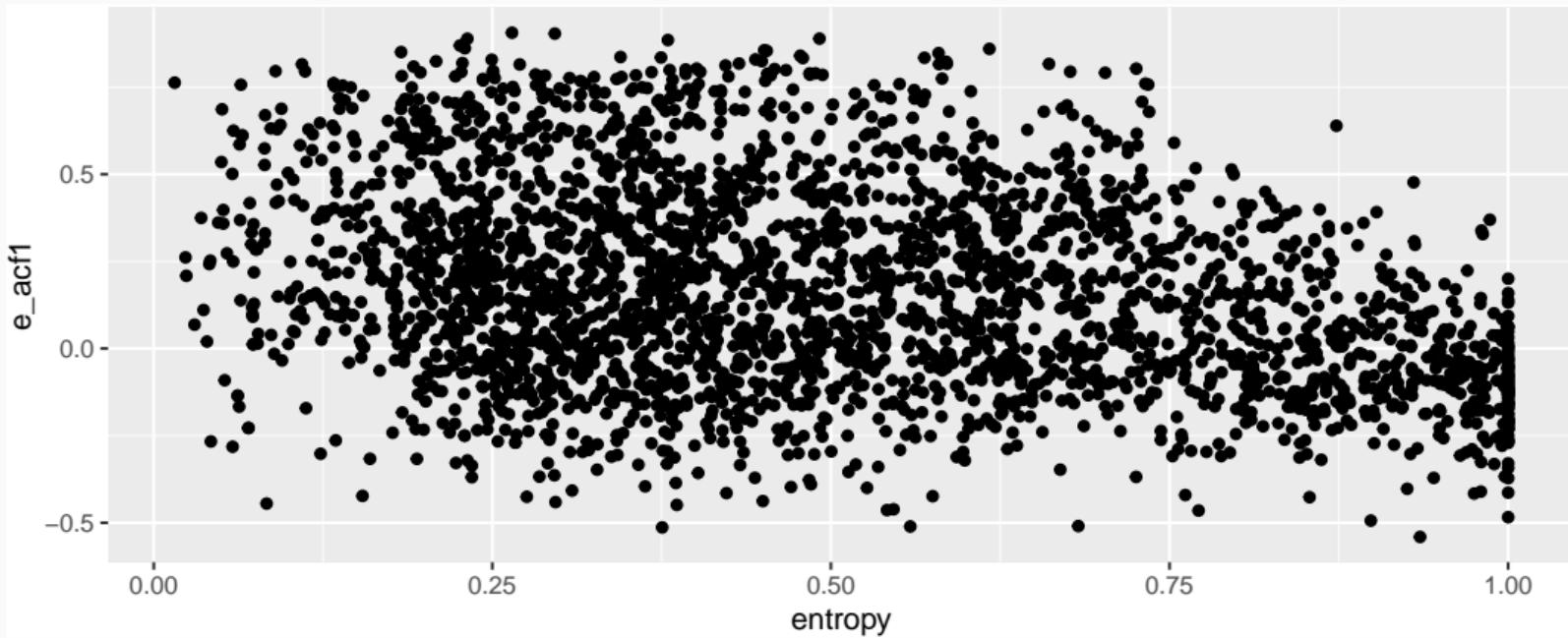
Distribution of Spectral Entropy for M3



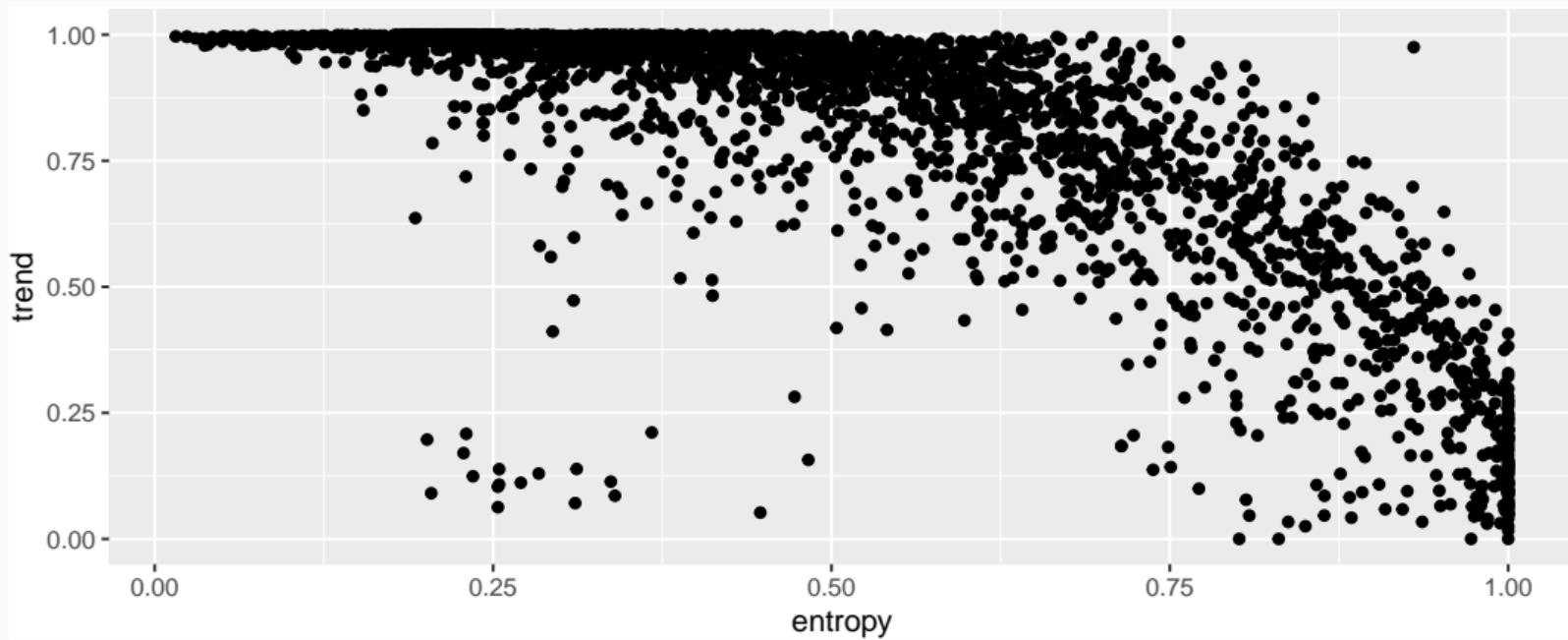
Distribution of Spectral Entropy for M3



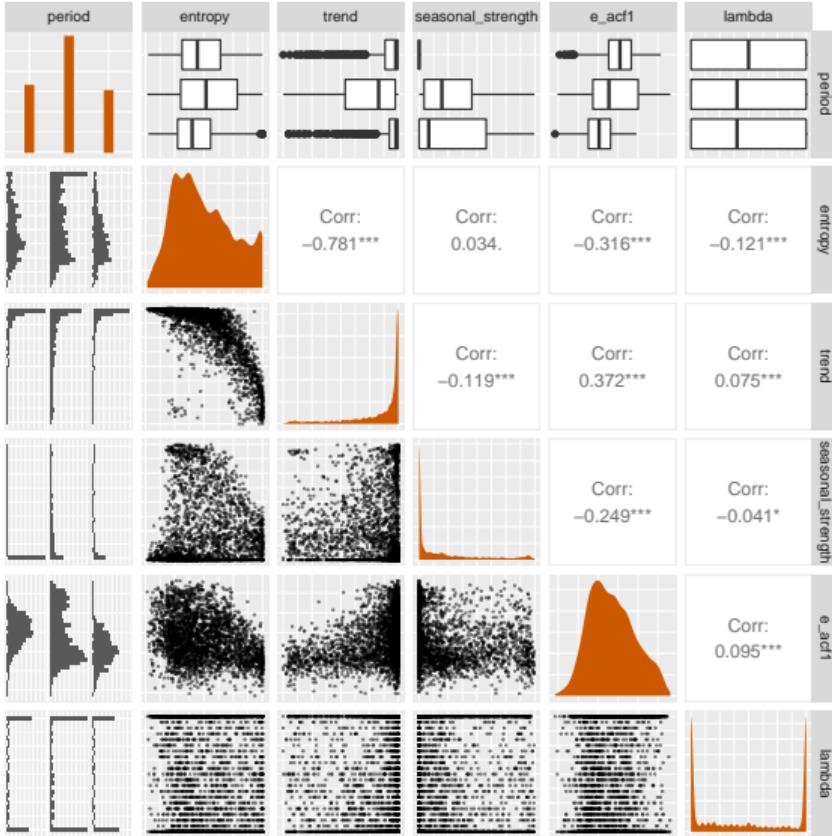
Feature distributions



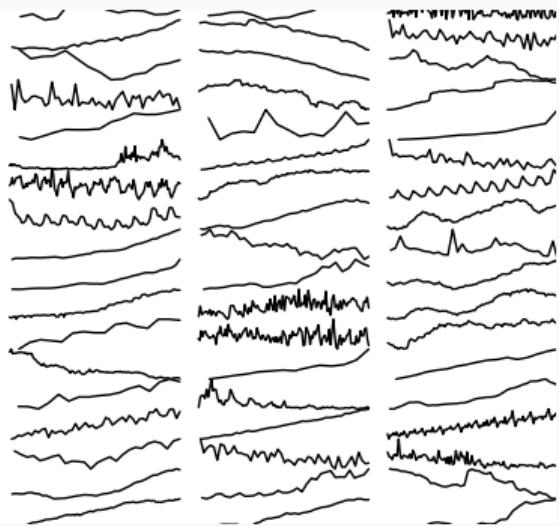
Feature distributions



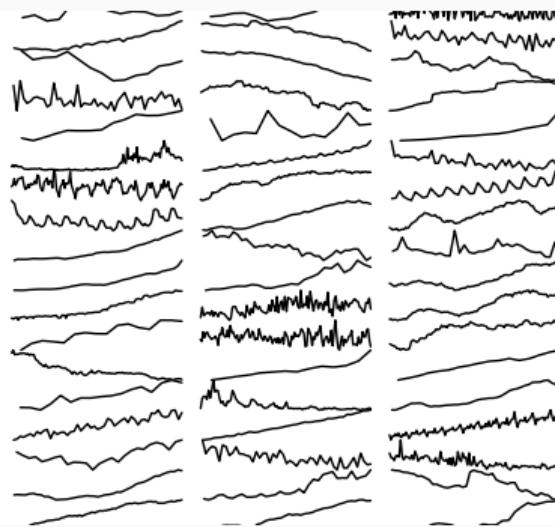
Feature distributions



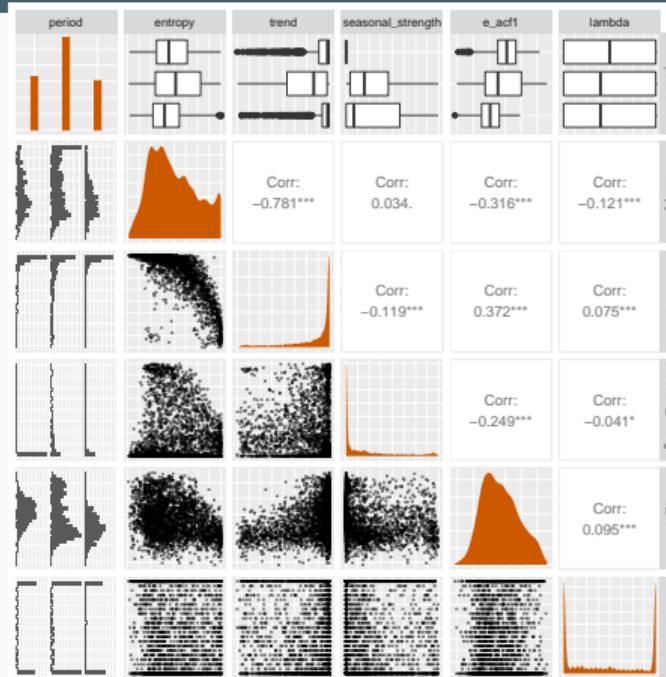
Dimension reduction for time series



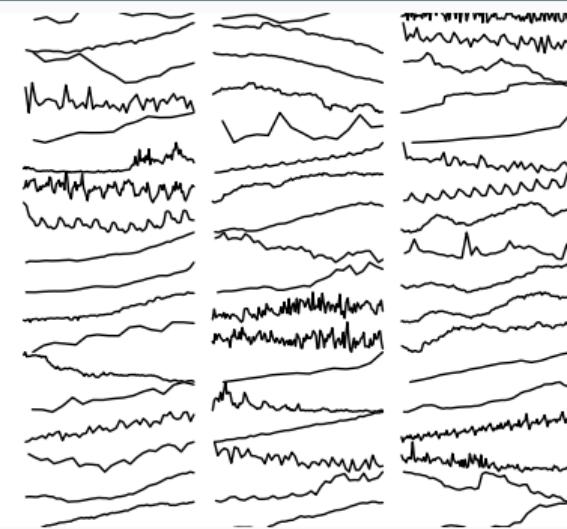
Dimension reduction for time series



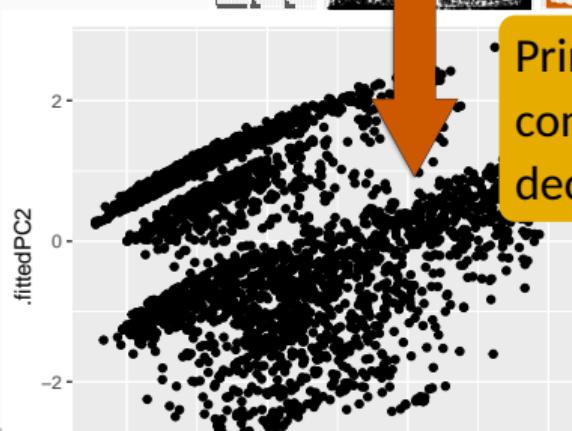
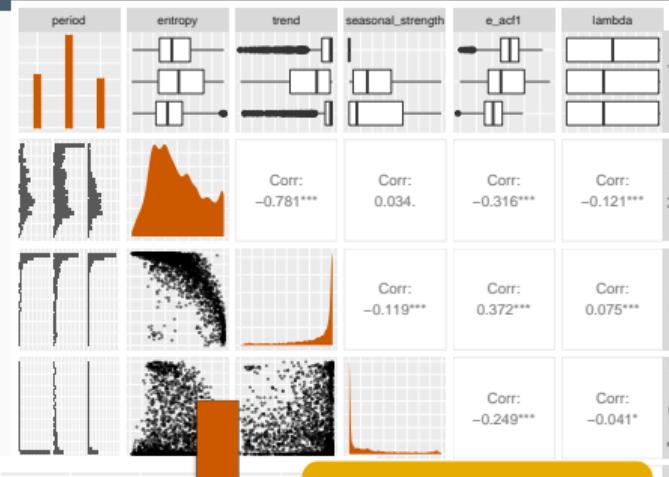
Feature
calculation



Dimension reduction for time series



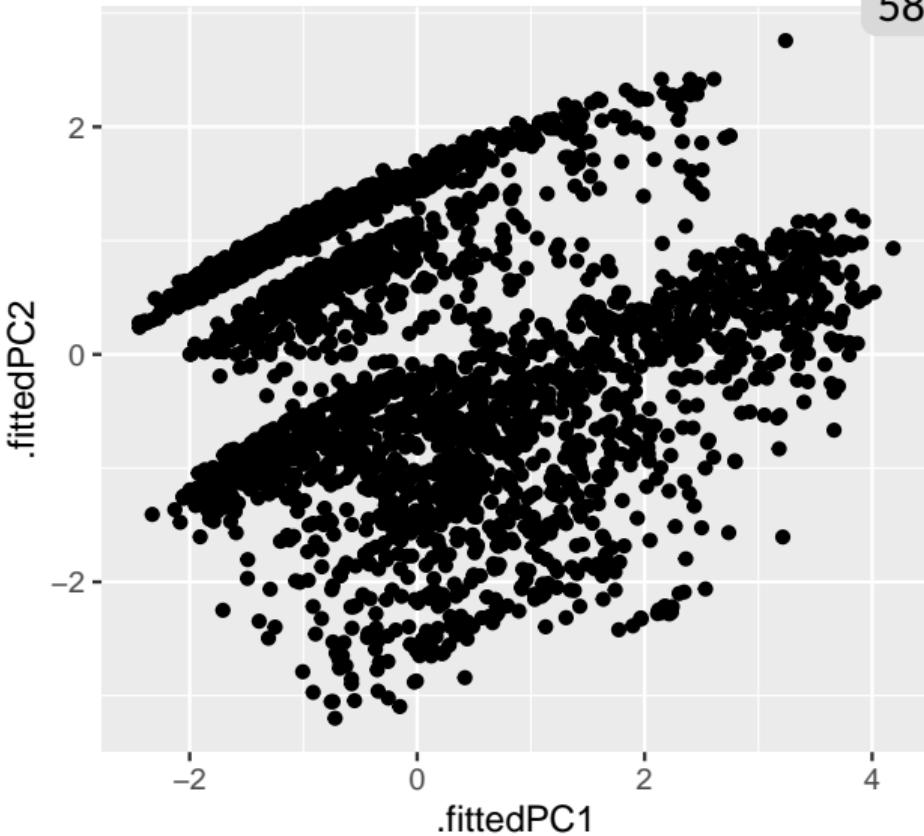
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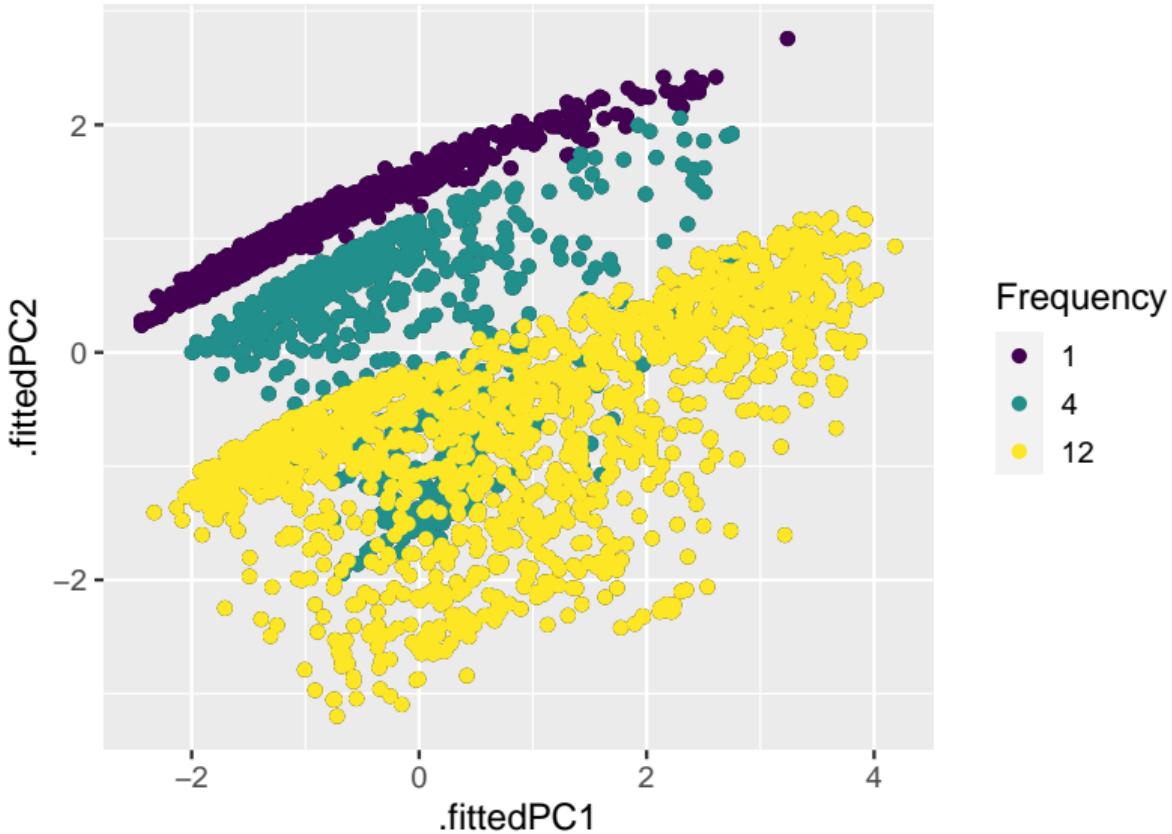
Principal
component
decomposition

M3 feature space

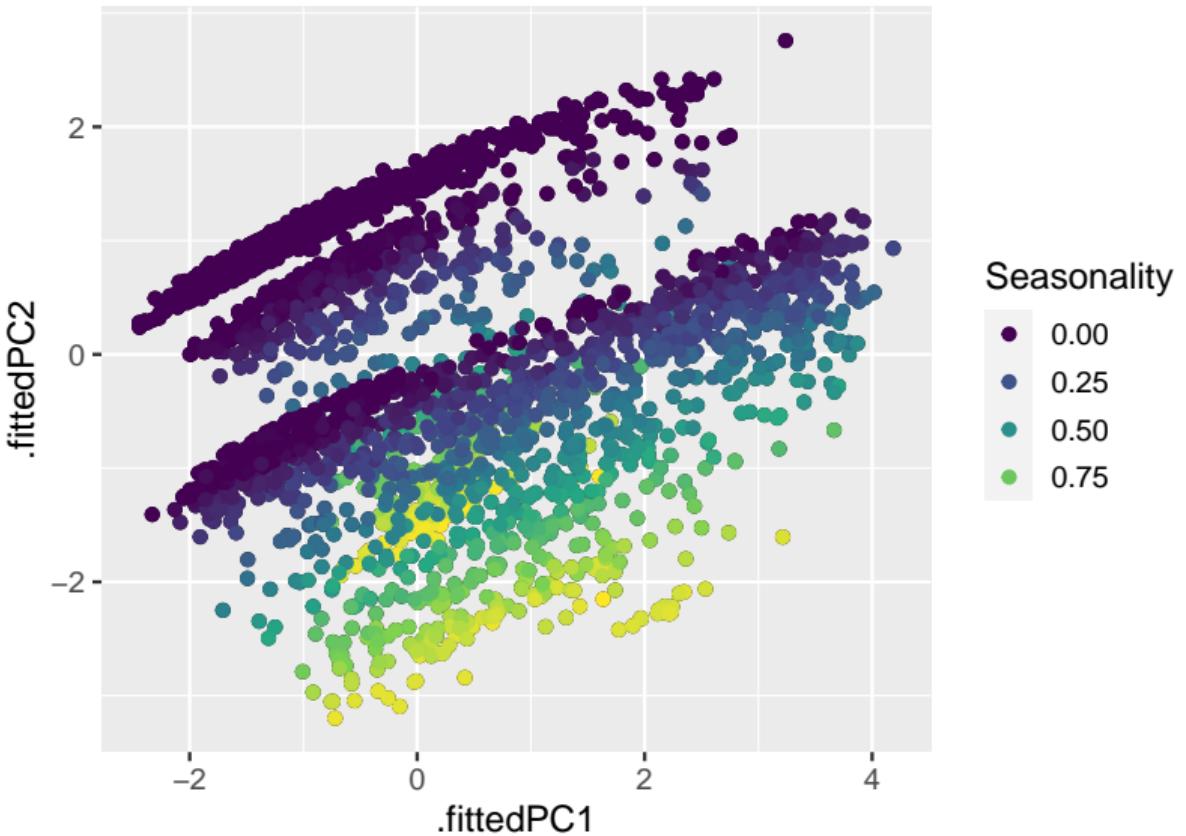
First two PCs explain
58.5% of the variance.



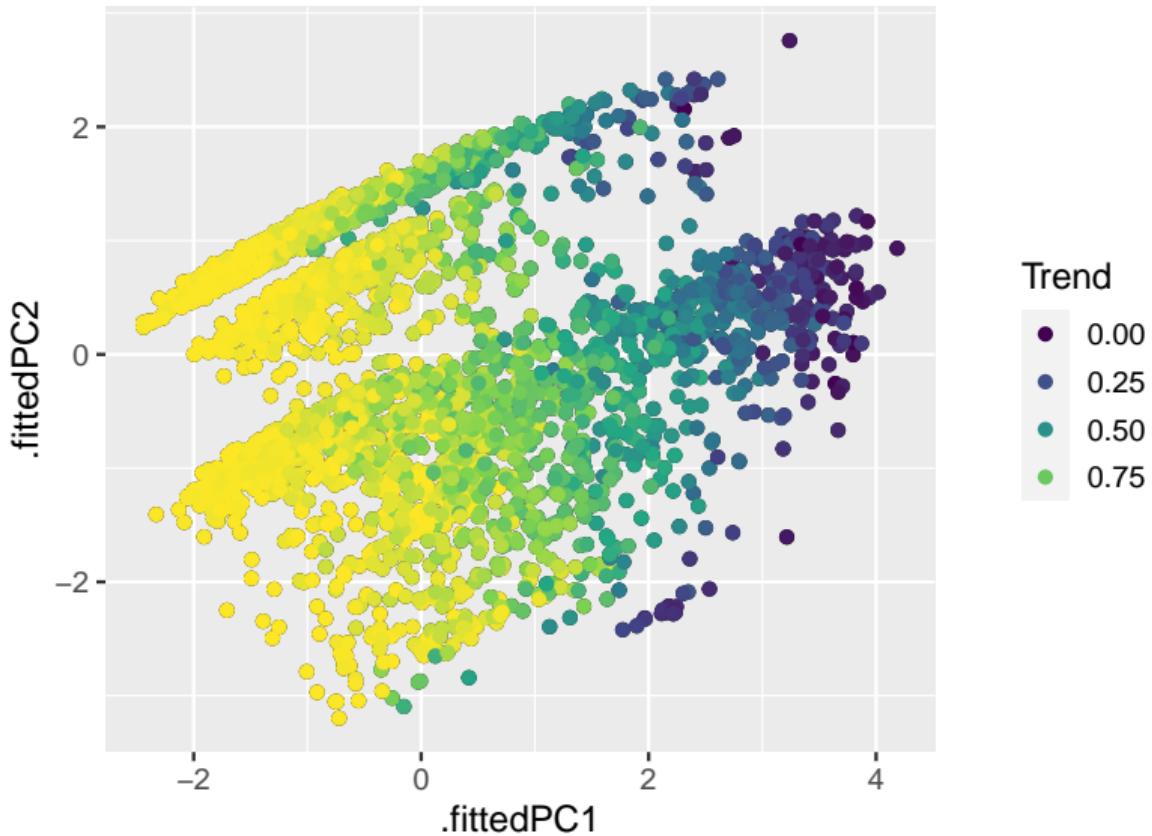
M3 feature space



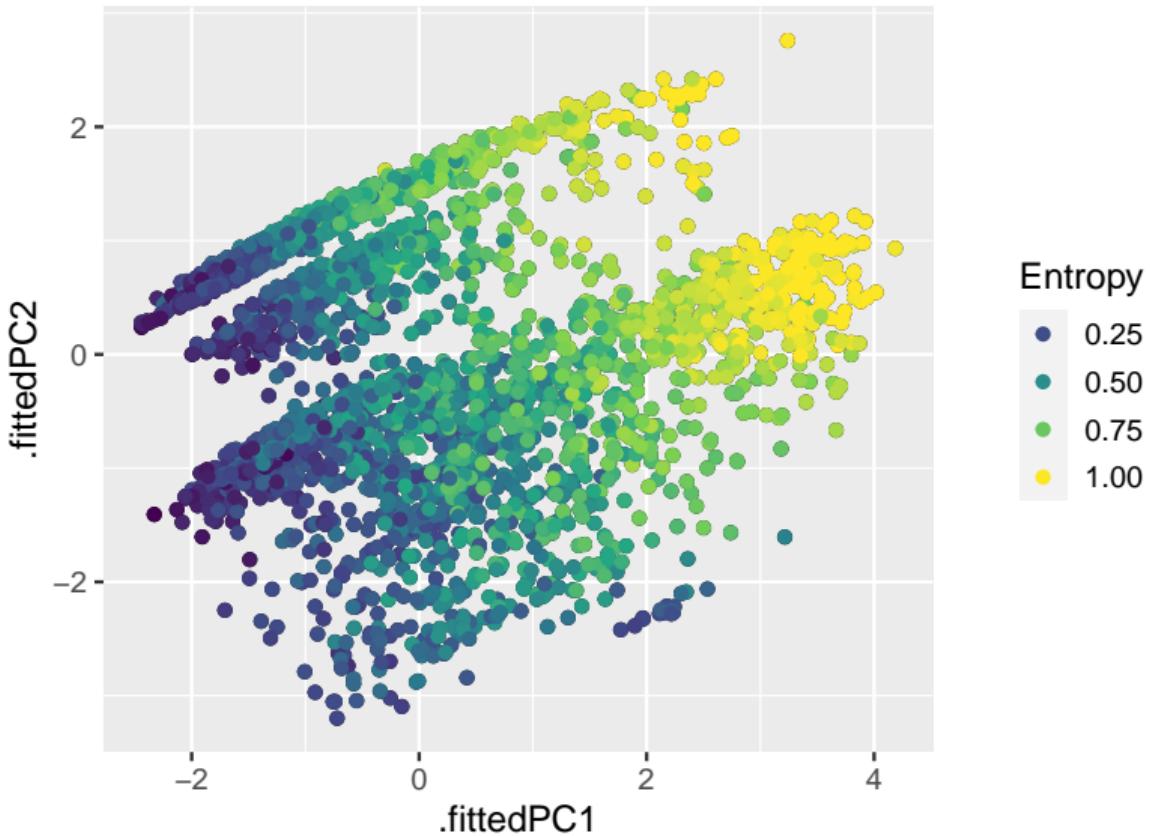
M3 feature space



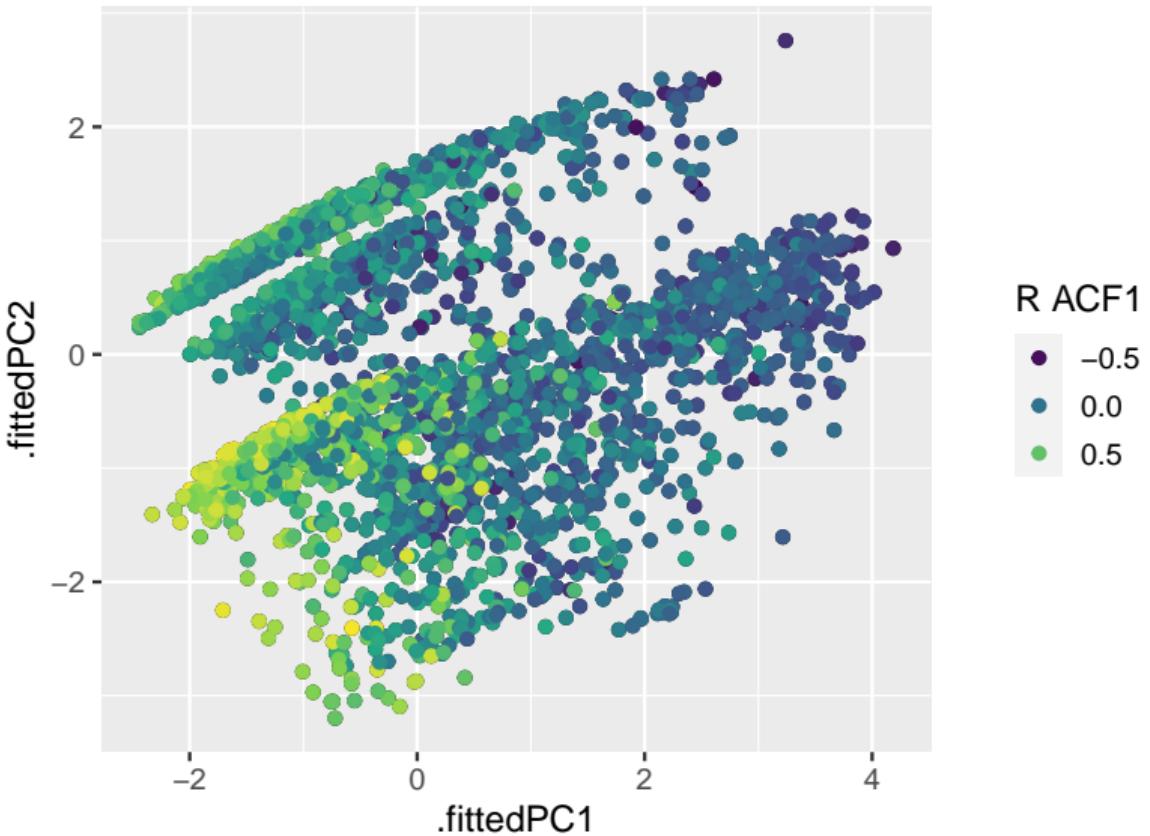
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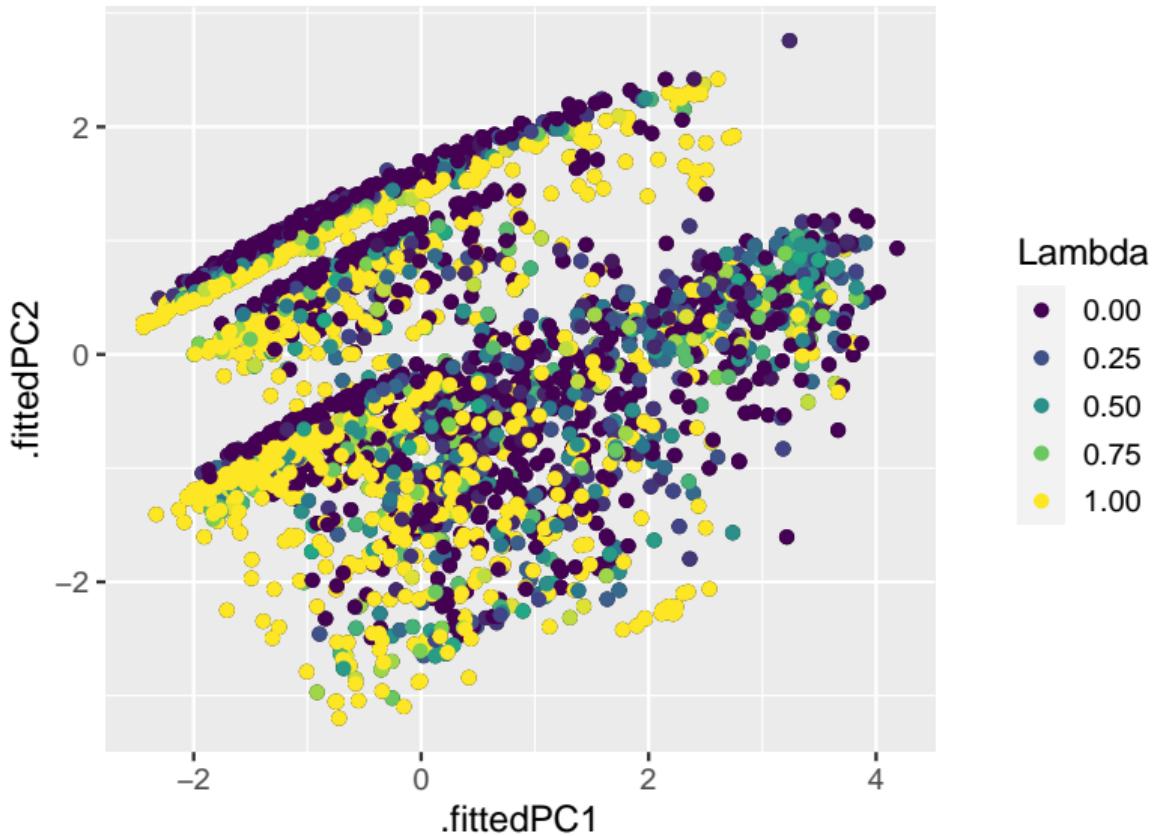
M3 feature space



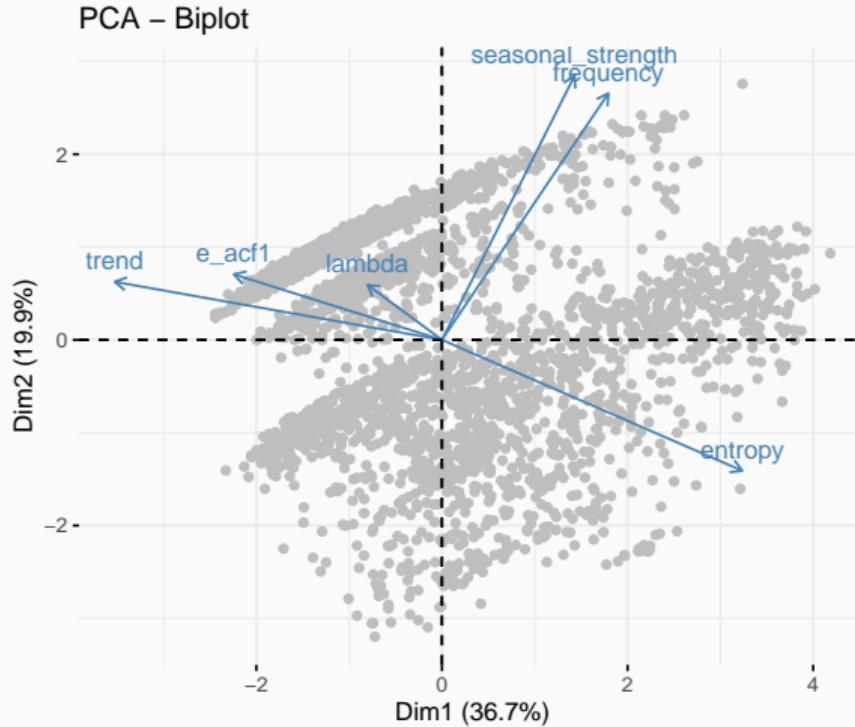
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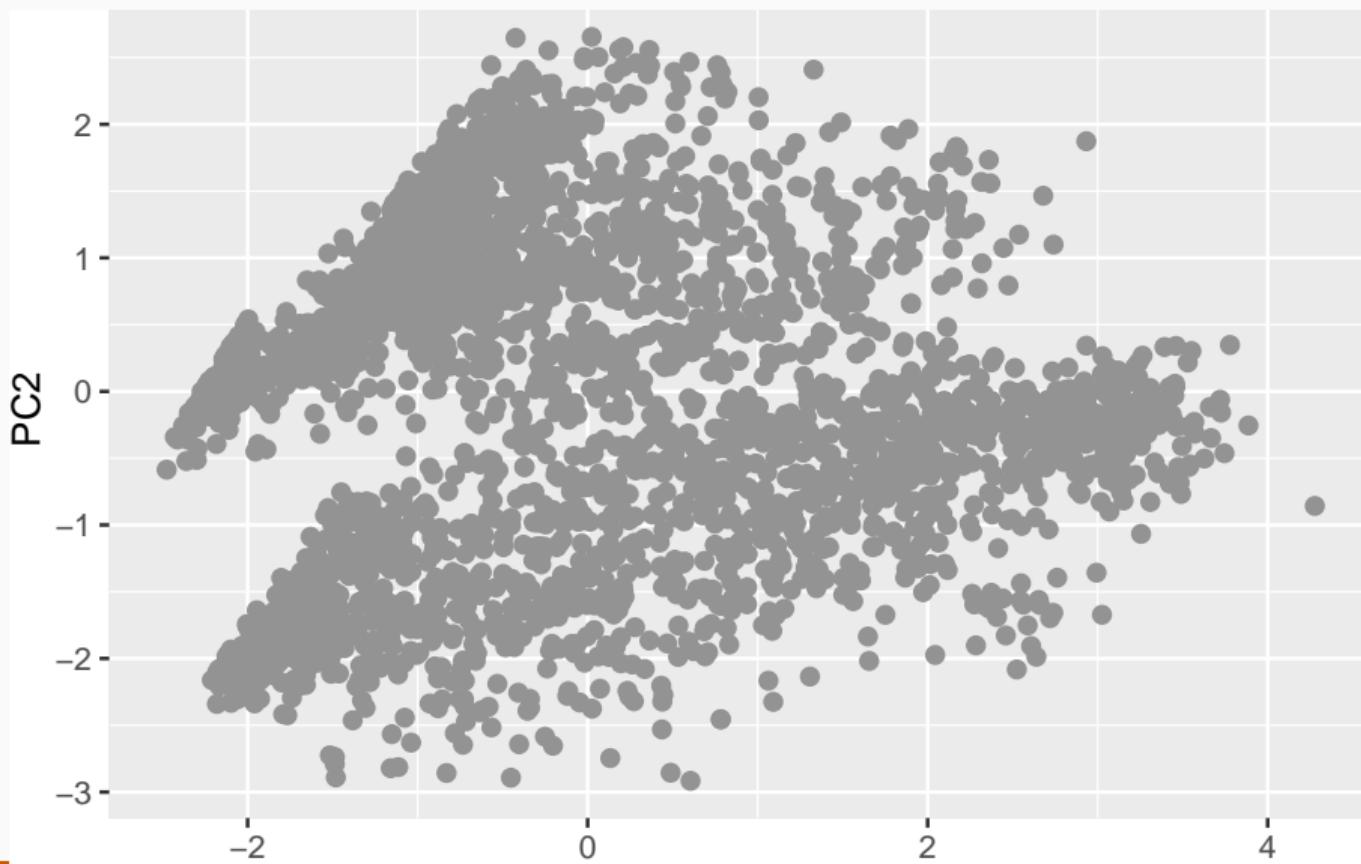
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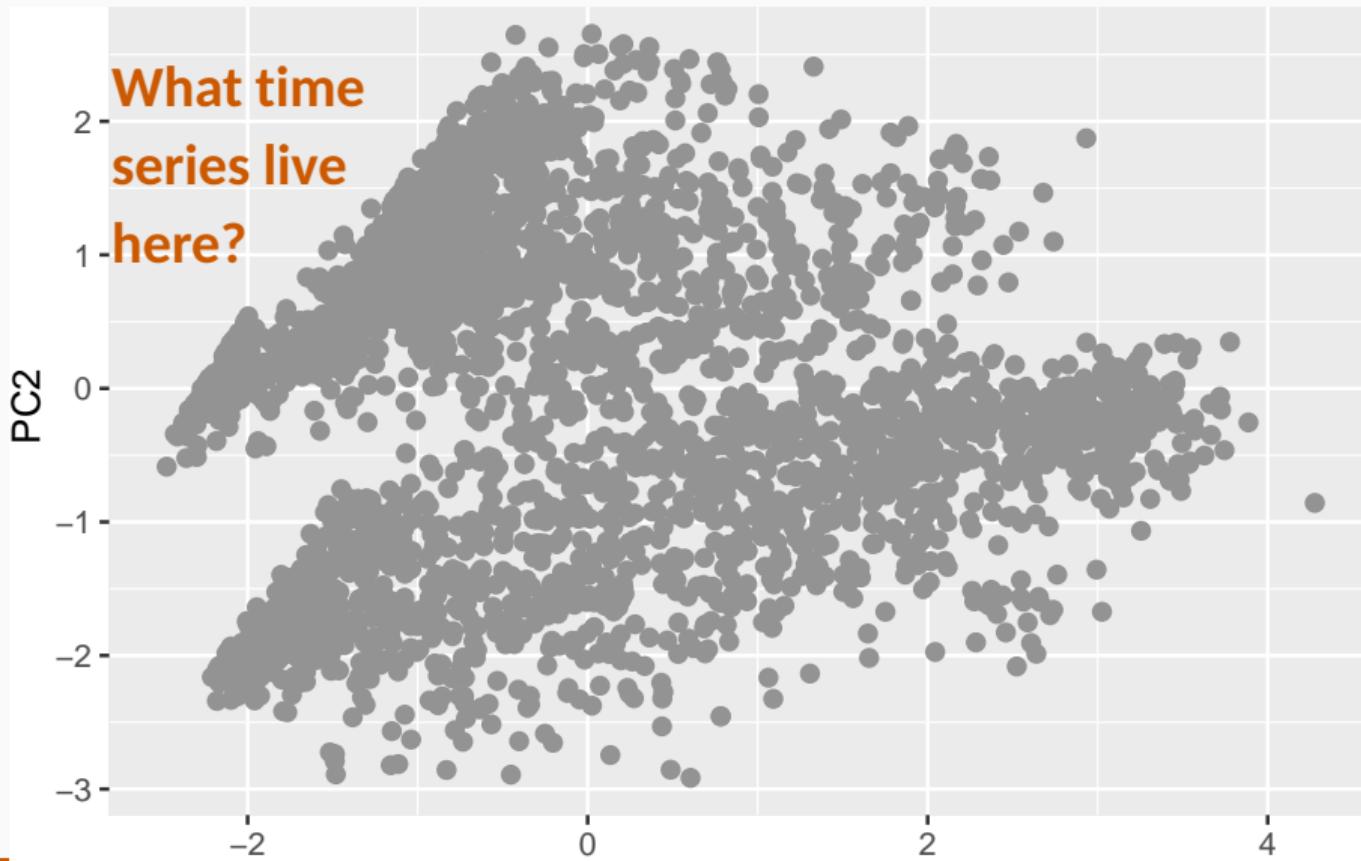
M3 feature space



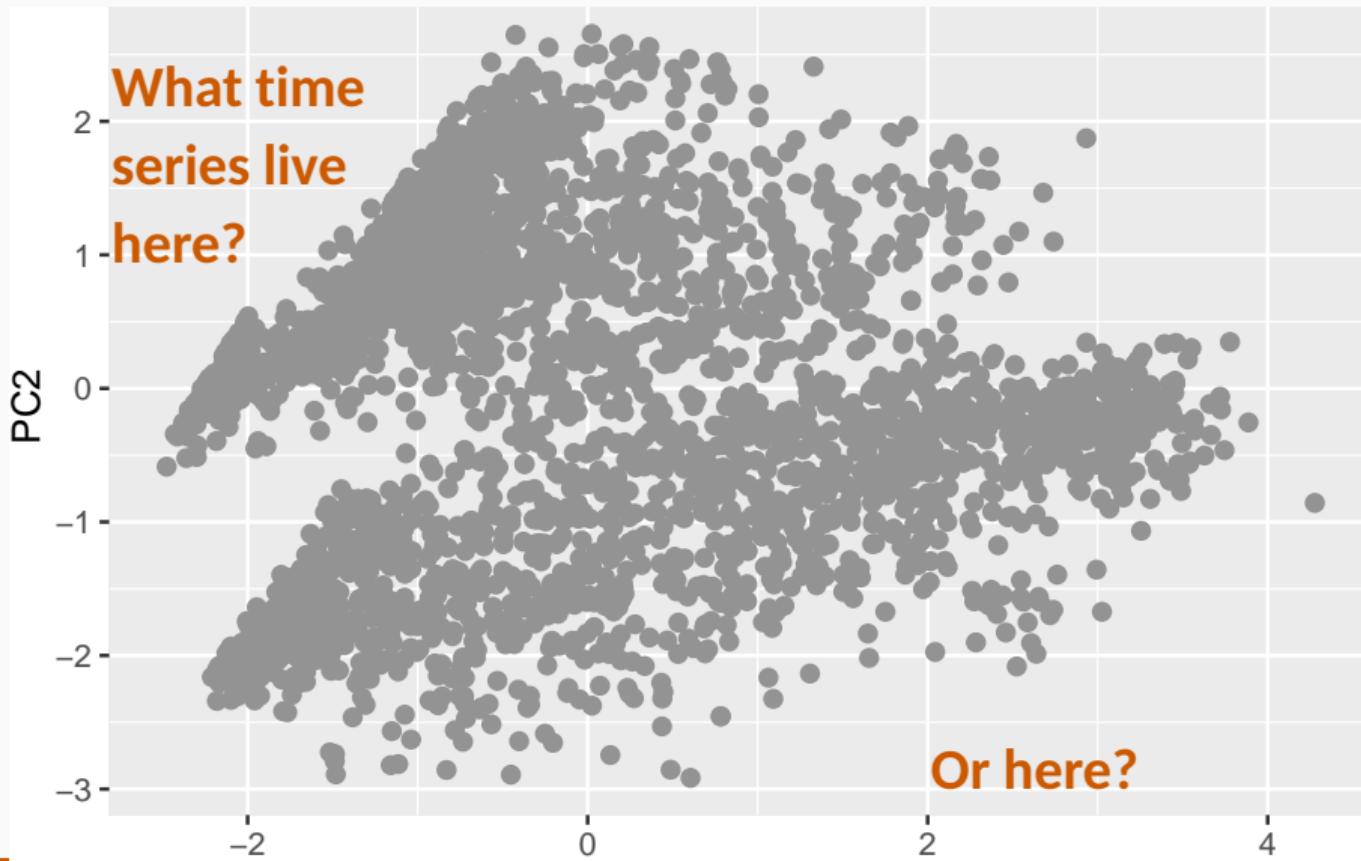
What about the holes?



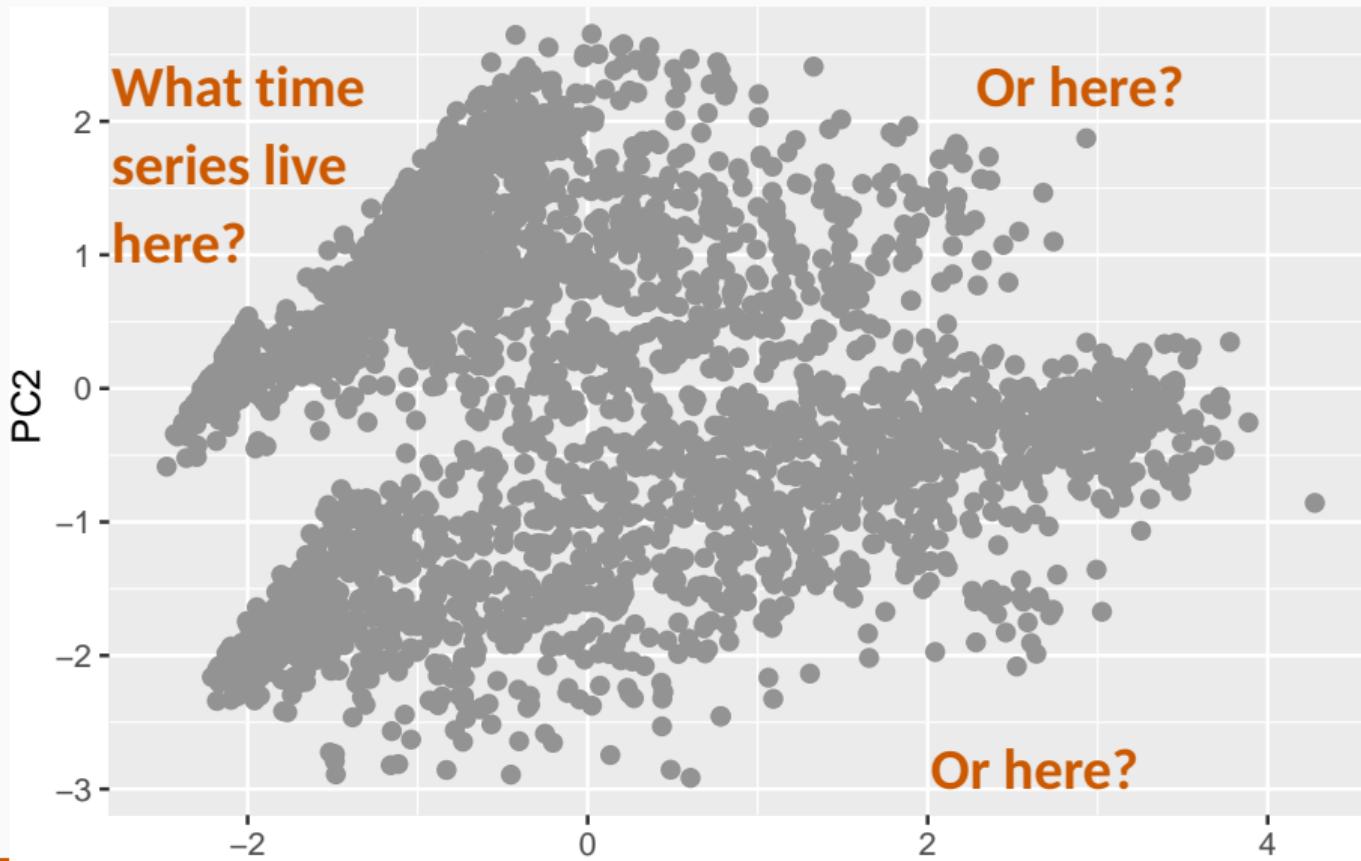
What about the holes?



What about the holes?



What about the holes?



Generating new time series

We can use the feature space to:

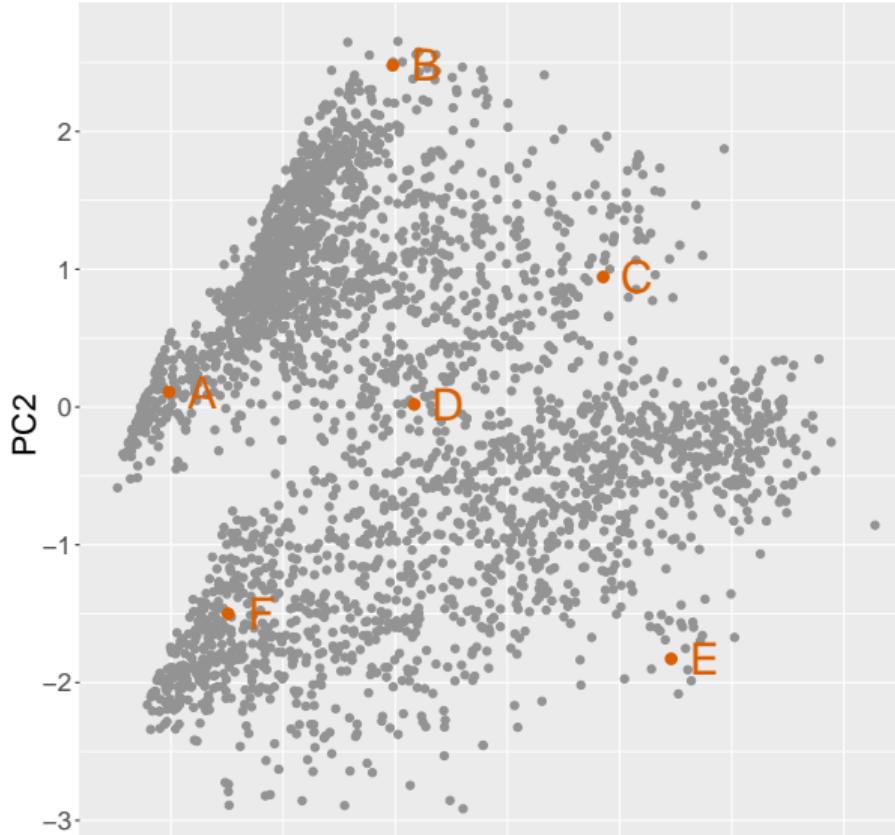
- ➡ Generate new time series with similar features to existing series
- ➡ Generate new time series where there are “holes” in the feature space.

Generating new time series

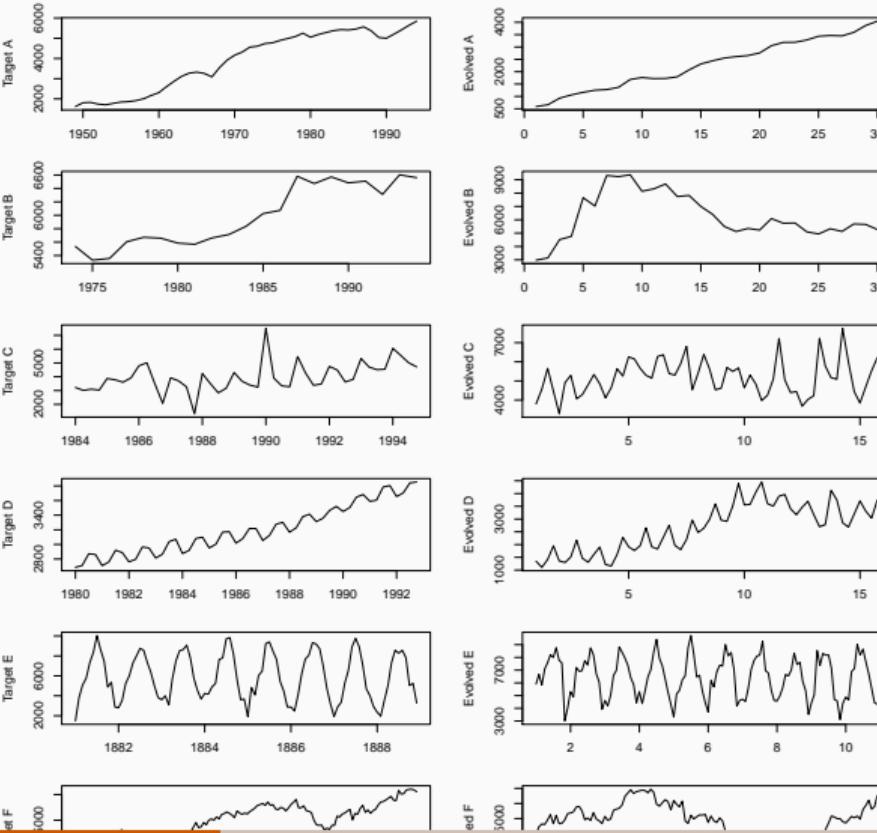
We can use the feature space to:

- ▶ Generate new time series with similar features to existing series
- ▶ Generate new time series where there are “holes” in the feature space.
- Let $\{PC_1, PC_2, \dots, PC_n\}$ 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 (PC_j) = $-\sqrt{(|PC_j - T_i|^2)}$.
- Initial population random with some series in neighbourhood of T_i .

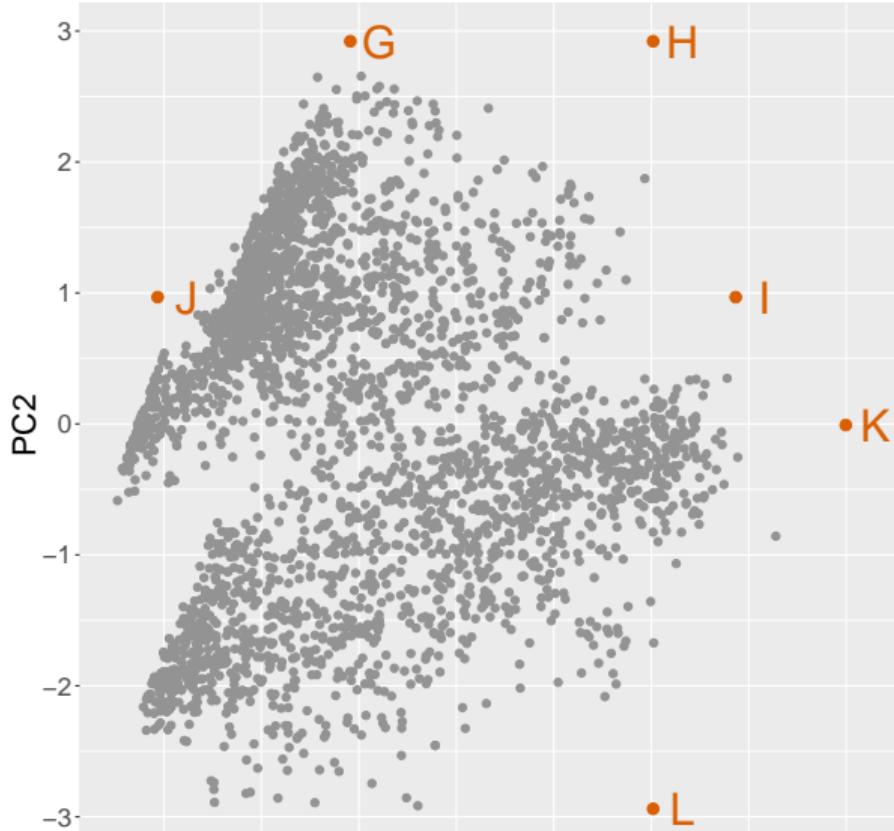
Evolving new time series



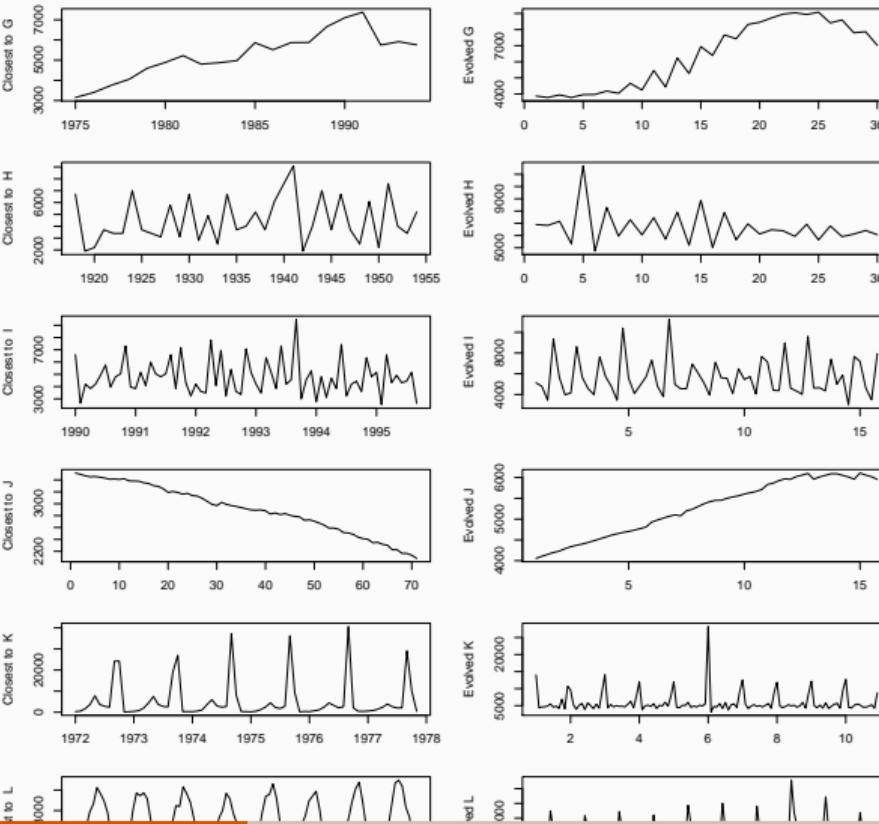
Evolving new time series



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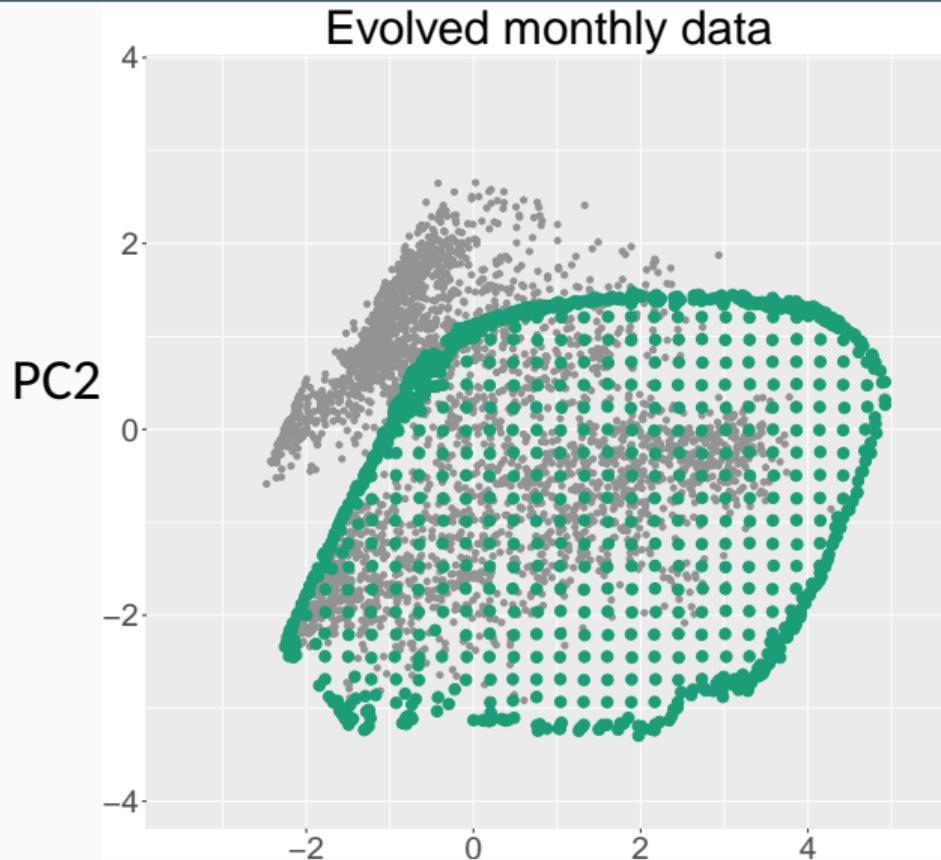
Evolving new time series



Evolving new time series



Evolving new time series



Outline

1 Feature-based visualization

2 R packages

3 Feature-based anomaly detection

4 Feature-based forecasting



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.
```

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## 2 1998 Q2 Adelaide SA Business 110.
## 3 1998 Q3 Adelaide SA Business 166.
## 4 1998 Q4 Adelaide SA Business 127.
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## 6 1999 Q2 Adelaide SA Business 200.
## 7 1999 Q3 Adelaide SA Business 169.
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## # Key:      Region, State, Purpose [304]
## #   Quarter Region  State Purpose Trips
## #   Index     Keys          Measure
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## # 2 1998 Q2 Adelaide SA Business 110.
## # 3 1998 Q3 Adelaide SA Business 166.
## # 4 1998 Q4 Adelaide SA Business 127.
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##   Quarter Region  State Purpose Trips
##   Index    Keys          Measure
## 1 1998 Q1 Adelaide SA Business 135.
## 2 1998 Q2 Adelaide SA Business 110. Domestic visitor
## 3 1998 Q3 Adelaide SA Business 166. nights in thousands
## 4 1998 Q4 Adelaide SA Business 127. by state/region and
## 5 1999 Q1 Adelaide SA Business 137. purpose.
## 6 1999 Q2 Adelaide SA Business 200.
## 7 1999 Q3 Adelaide SA Business 169.
```

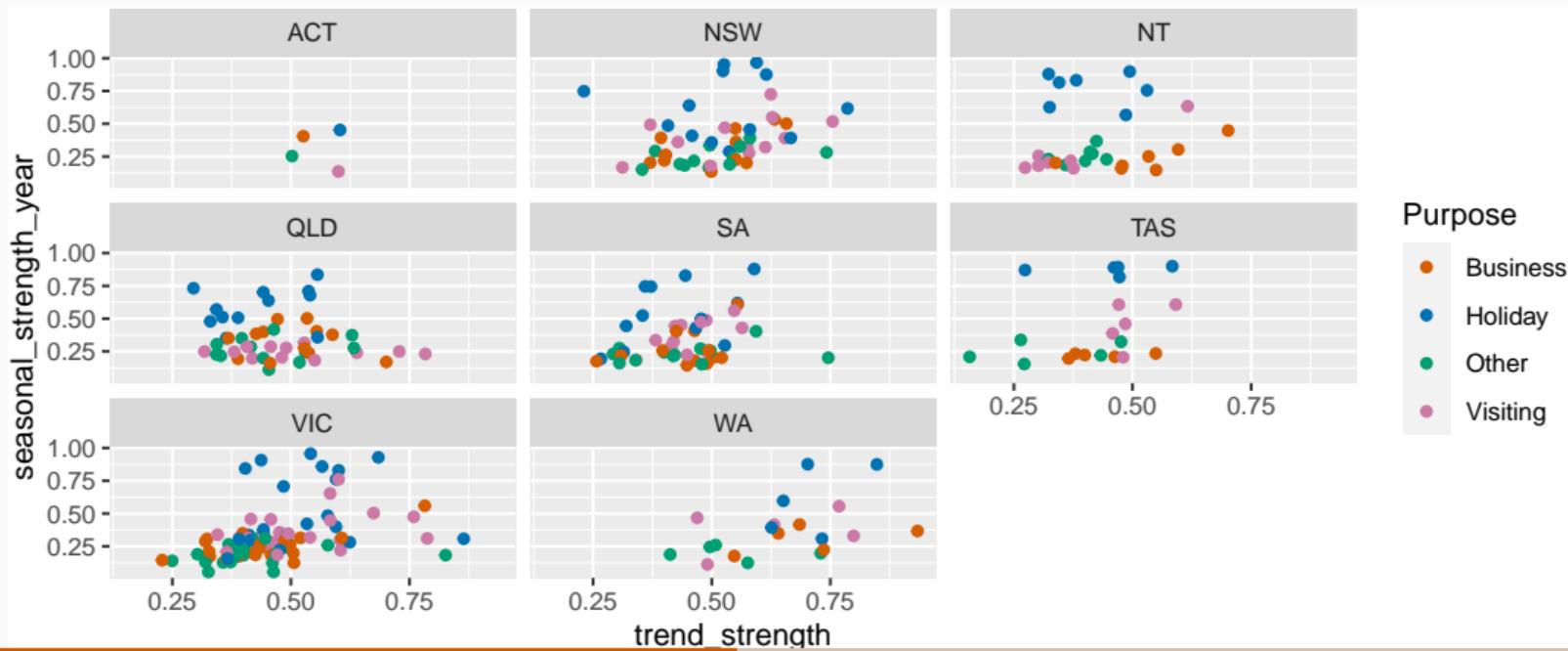
Feature extraction and statistics

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

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

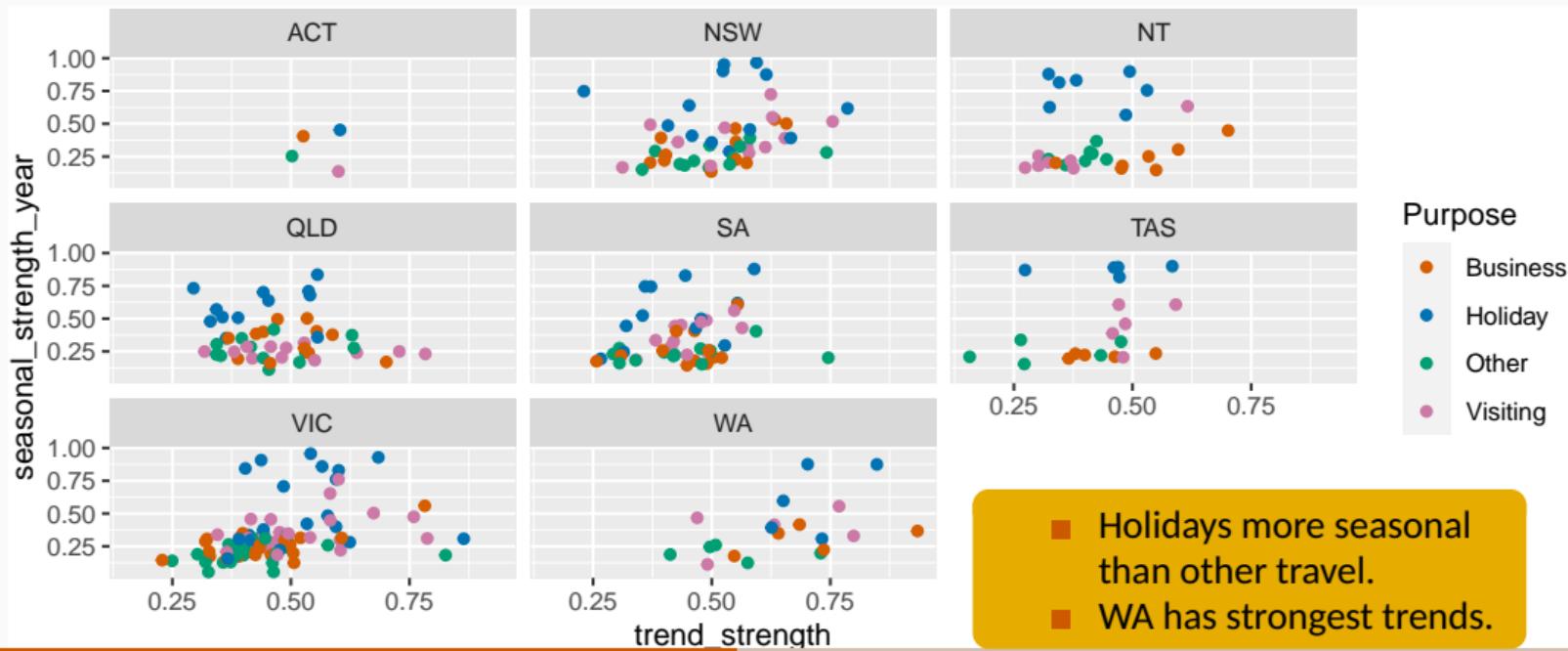
Feature extraction and statistics

```
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))
```



Feature extraction and statistics

Find the most seasonal time series:

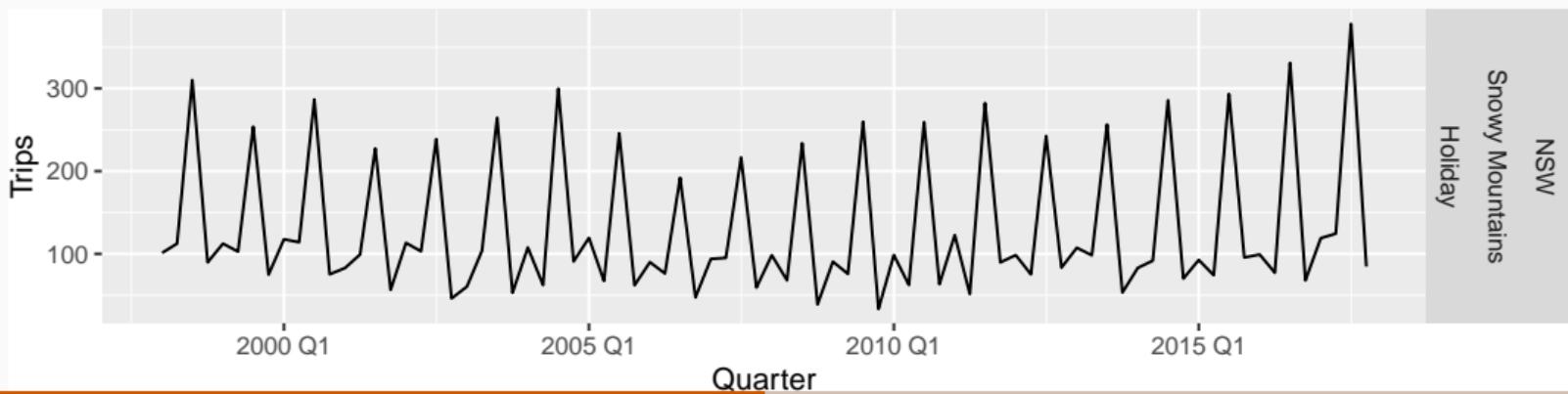
```
most_seasonal <- tourism %>%
  features(Trips, feature_set(tags="stl")) %>%
  filter(seasonal_strength_year == max(seasonal_strength_year))
```

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

```
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~ seasonal_peak_y~ seasonal_trough~
##   <chr>   <chr>  <chr>        <dbl>            <dbl>            <dbl>
## 1 Adelai~ SA     Busine~      0.464           0.407            3
## 2 Adelai~ SA     Holiday       0.554           0.619            1
## 3 Adelai~ SA     Other         0.746           0.202            2
## 4 Adelai~ SA     Visiti~      0.435           0.452            1
## 5 Adelai~ SA     Busine~      0.464           0.179            3
## 6 Adelai~ SA     Holiday       0.528           0.296            2
## 7 Adelai~ SA     Other         0.593           0.404            2
## 8 Adelai~ SA     Visiti~      0.488           0.254            0
## 9 Alice ~ NT     Busine~      0.534           0.251            0
## 10 Alice ~ NT    Holiday       0.381           0.832            3
## # ... with 294 more rows, and 44 more variables: 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>
```

Feature manifolds

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

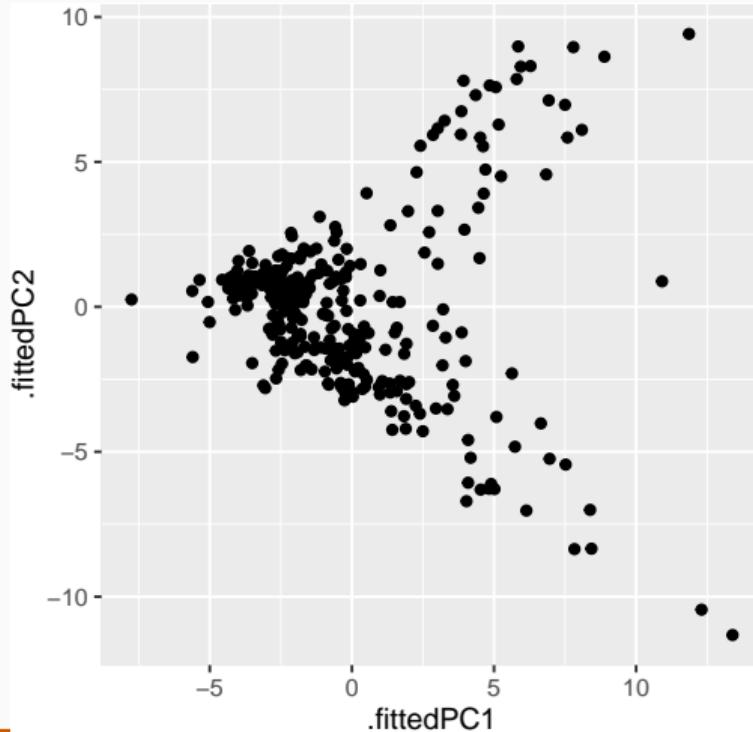
```
## # A tibble: 304 x 100  
##   .rownames Region      State Purpose trend_streng~ seasonal_peak_y~  
##   <chr>     <chr>      <chr> <chr>    <dbl>                <dbl>  
## 1 1        Adelaide    SA    Busine~ 0.407                3  
## 2 2        Adelaide    SA    Holiday  0.619                1  
## 3 3        Adelaide    SA    Other    0.202                2  
## 4 4        Adelaide    SA    Visiti~ 0.452                1  
## 5 5        Adelaide Hills SA    Busine~ 0.179                3  
## 6 6        Adelaide Hills SA    Holiday  0.528                2  
## 7 7        Adelaide Hills SA    Other    0.593                2  
## 8 8        Adelaide Hills SA    Visiti~ 0.488                0  
## 9 9        Alice Springs NT    Busine~ 0.534                0  
## 10 10      Alice Springs NT    Holiday  0.381                3  
## # ... with 294 more rows, and 93 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>
```

Principal components based on all features from the feasts package

Feature manifolds

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

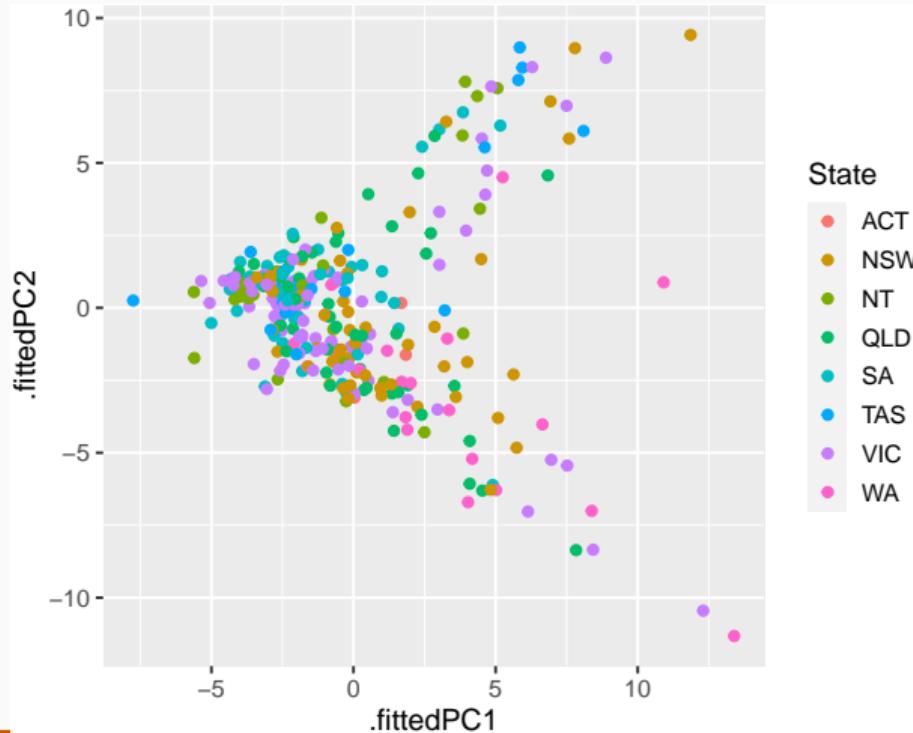
Principal components
based on all features
from the feasts
package



Feature manifolds

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

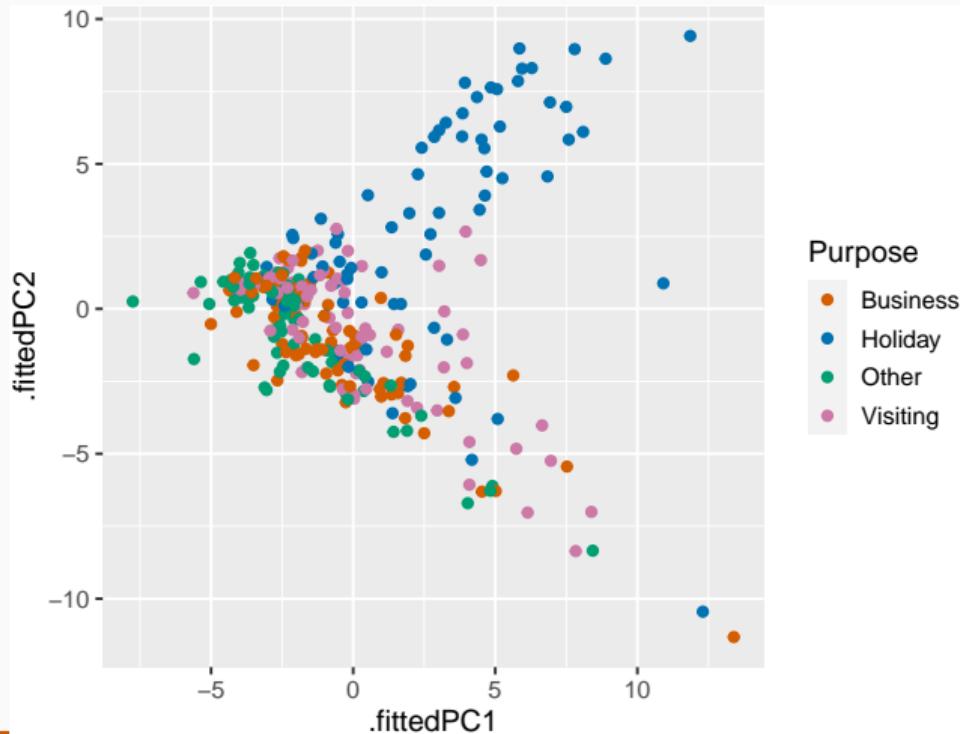
Principal components
based on all features
from the feasts
package



Feature manifolds

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

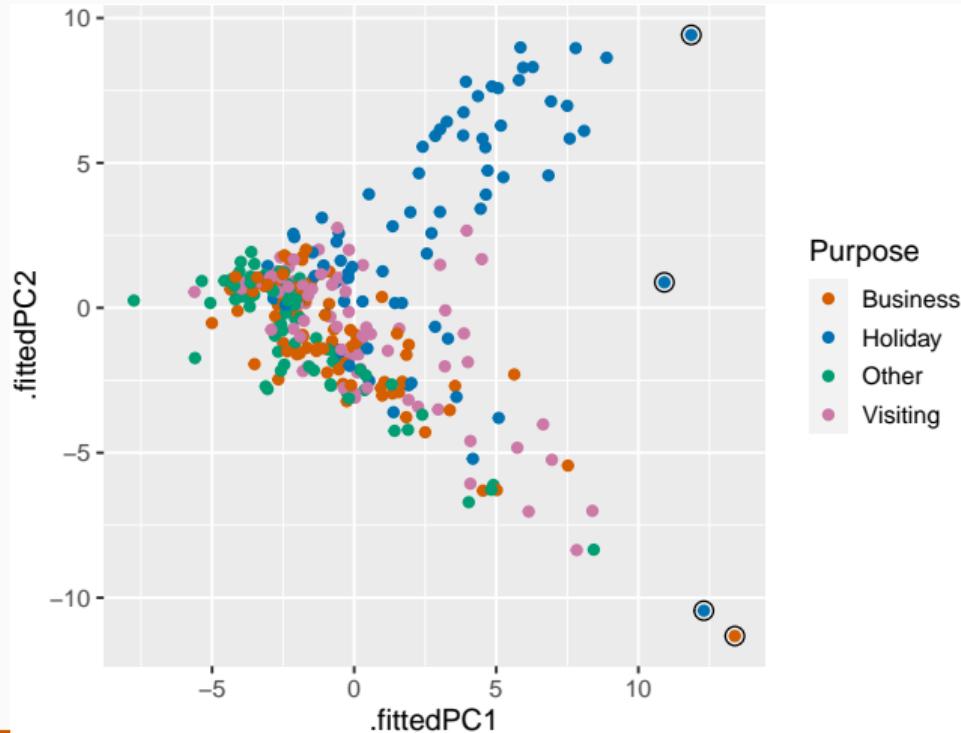
Principal components
based on all features
from the feasts
package



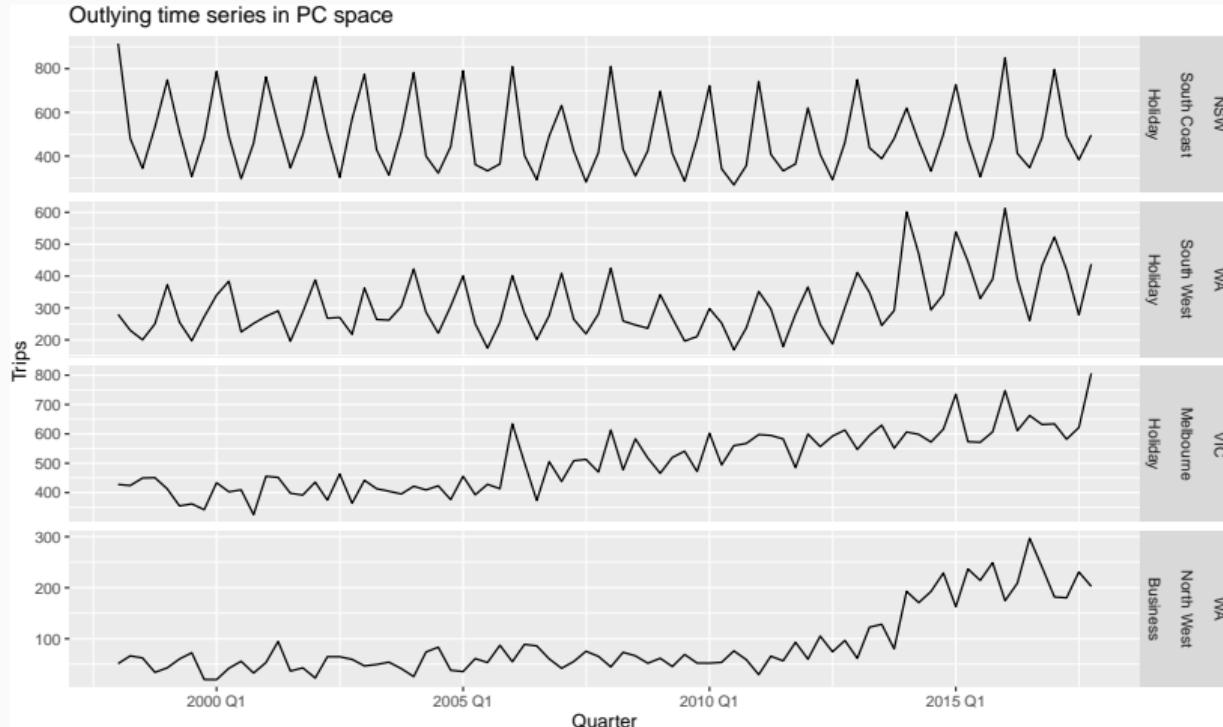
Anomaly detection using time series features

```
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



Anomaly detection using time series features



Outline

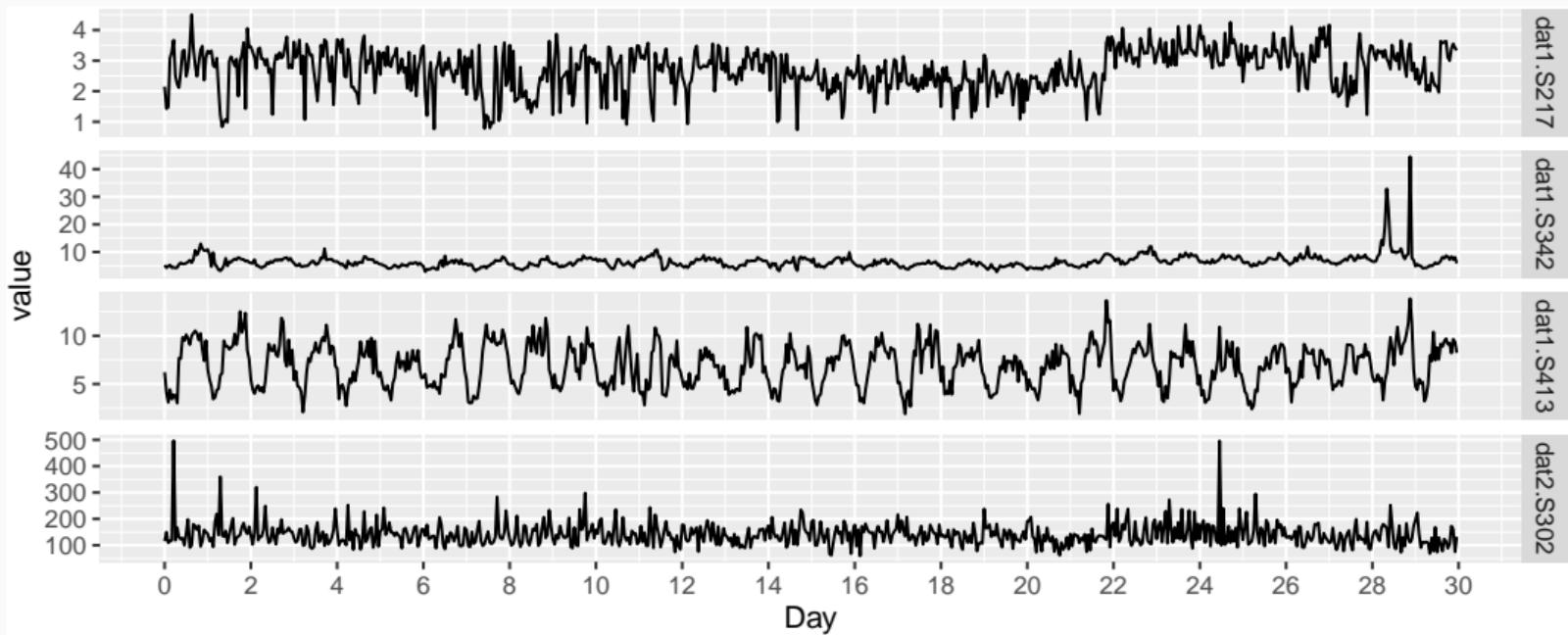
- 1 Feature-based visualization
- 2 R packages
- 3 Feature-based anomaly detection
- 4 Feature-based forecasting

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.



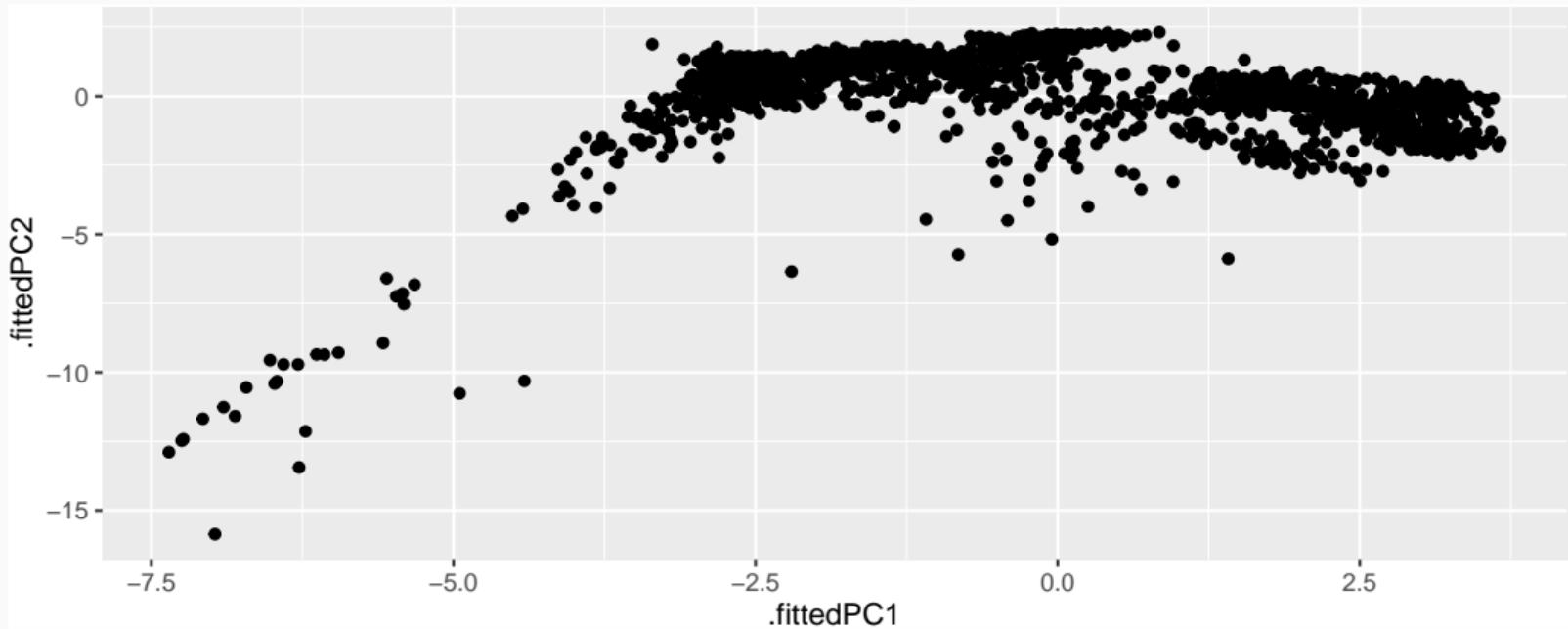
Yahoo server metrics



Yahoo server metrics

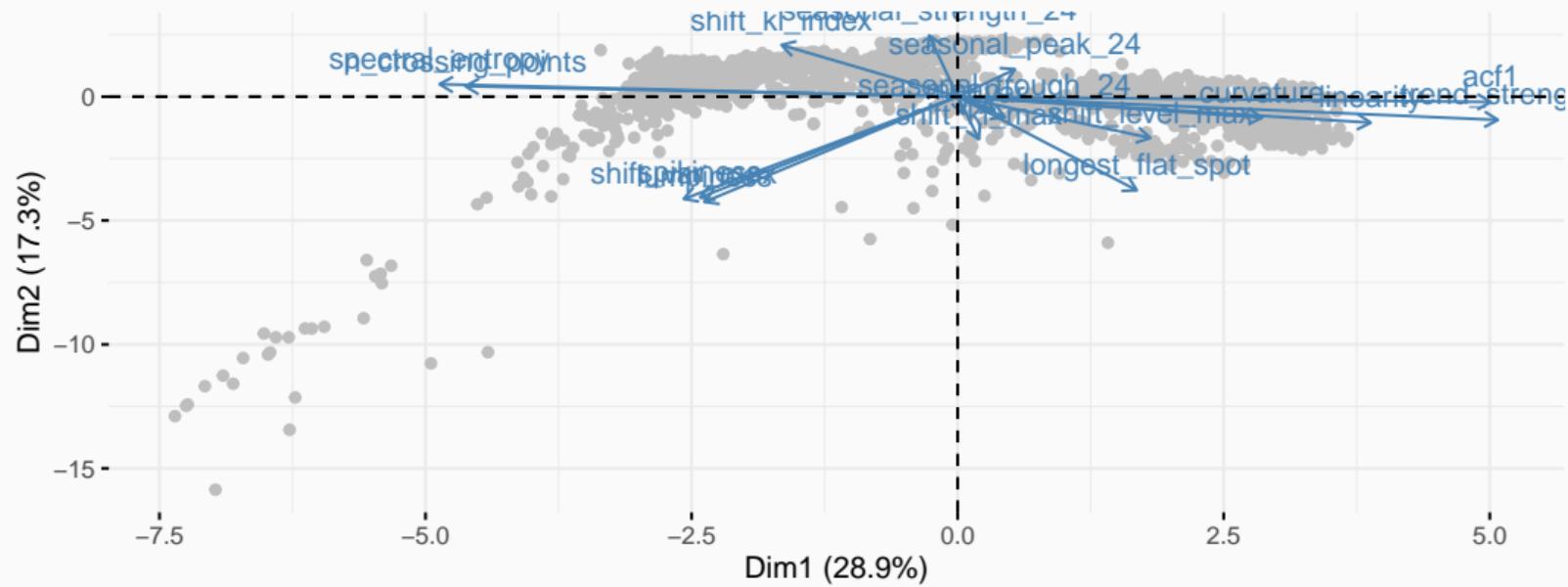
- **ACF1:** first order autocorrelation = $\text{Corr}(Y_t, Y_{t-1})$
- Strength of **trend** and **seasonality** based on STL
- Size of seasonal **peak** and **trough**
- Spectral **entropy**
- **Lumpiness:** variance of block variances (block size 24).
- **Spikiness:** variances of leave-one-out variances 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



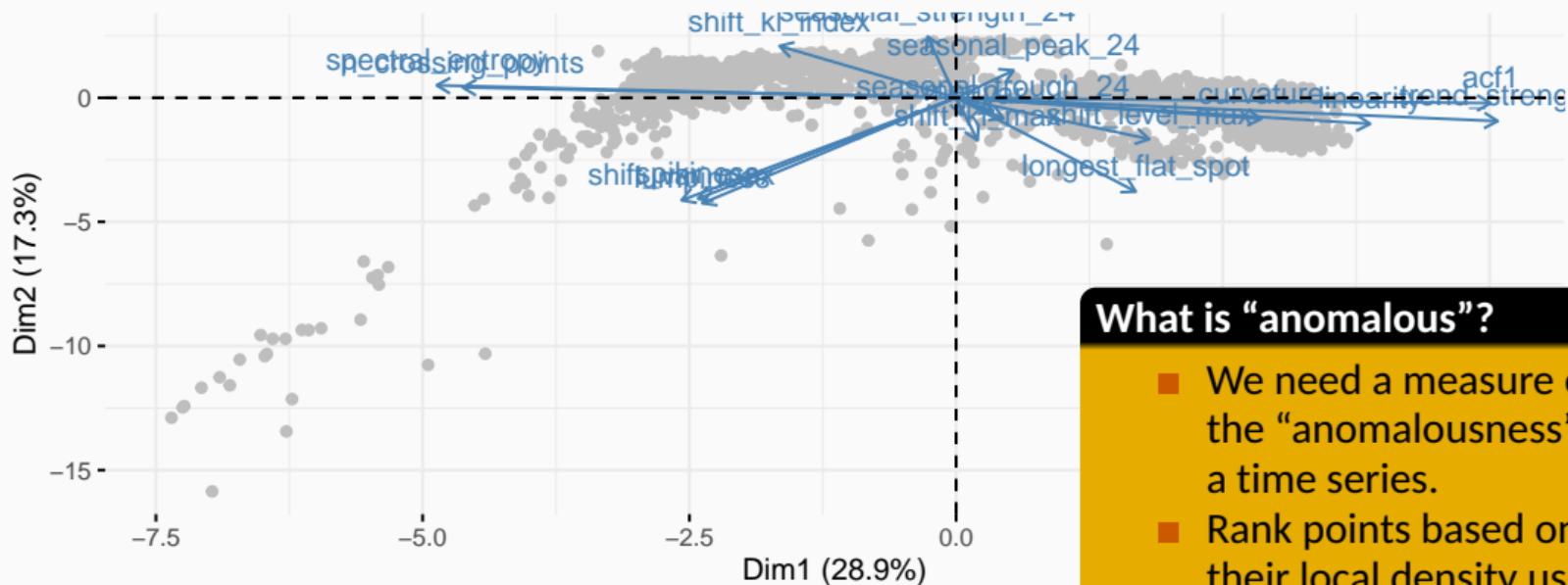
Feature space

PCA – Biplot



Feature space

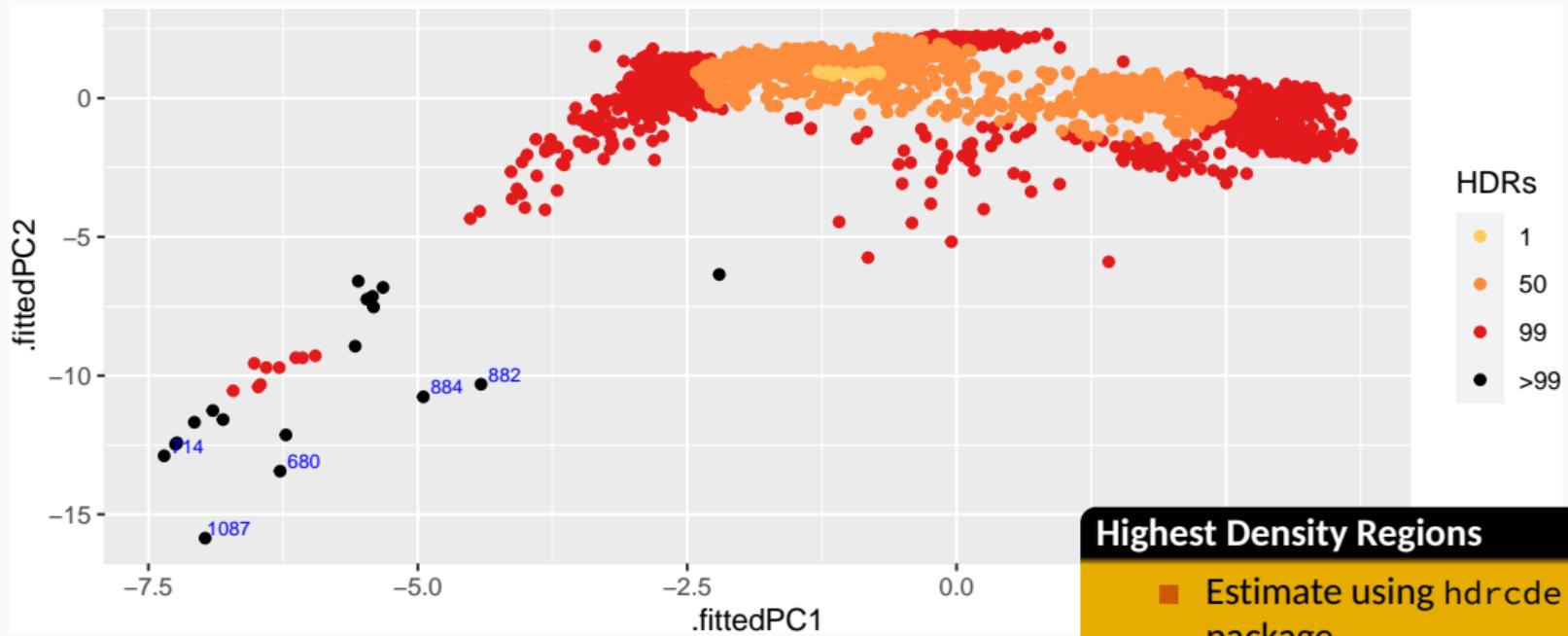
PCA – Biplot



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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Indiana University, Bloomington, U.S.A.

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. © 2000 Elsevier Science B.V. All rights reserved.

M4 competition: 2018

International Journal of Forecasting 34 (2018) 802–808



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Contents lists available at [ScienceDirect](#)

International Journal of Forecasting

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



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



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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

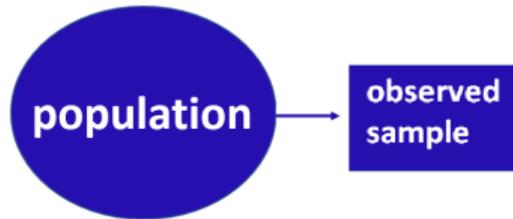
Why these features?

- 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

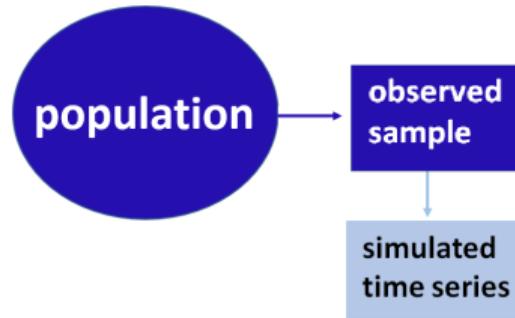
FFORMS: Feature-based FOrecast Model Selection



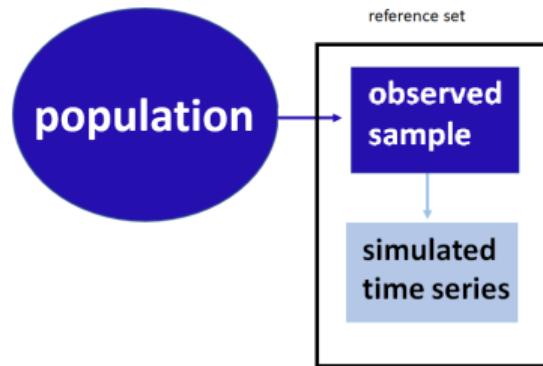
FFORMS: Feature-based FOrecast Model Selection



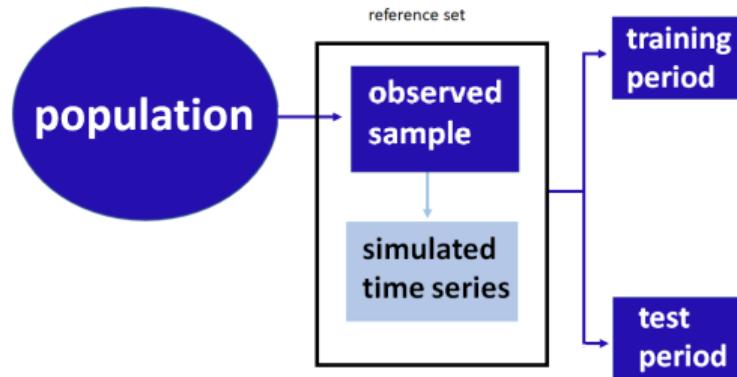
FFORMS: Feature-based FOrecast Model Selection



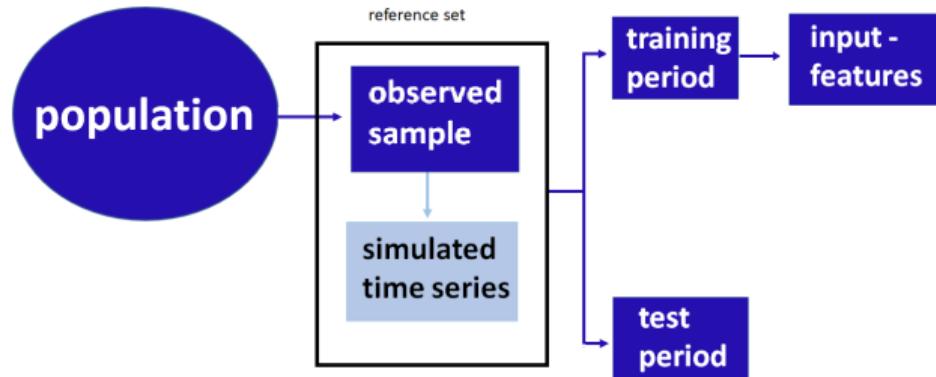
FFORMS: Feature-based FOrecast Model Selection



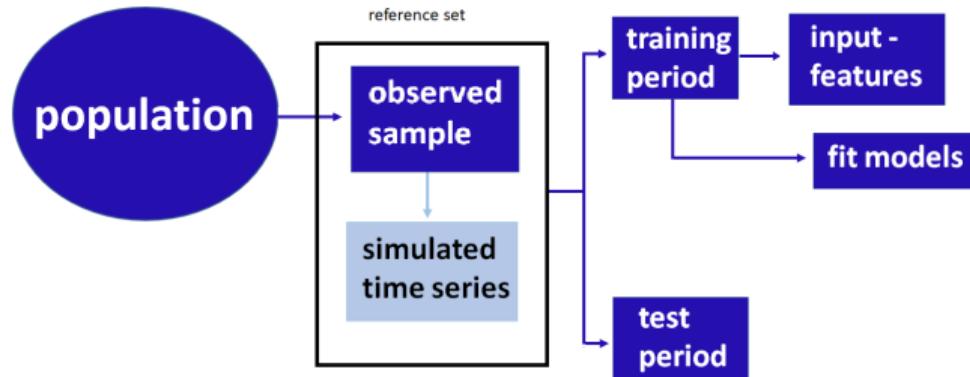
FFORMS: Feature-based FOrecast Model Selection



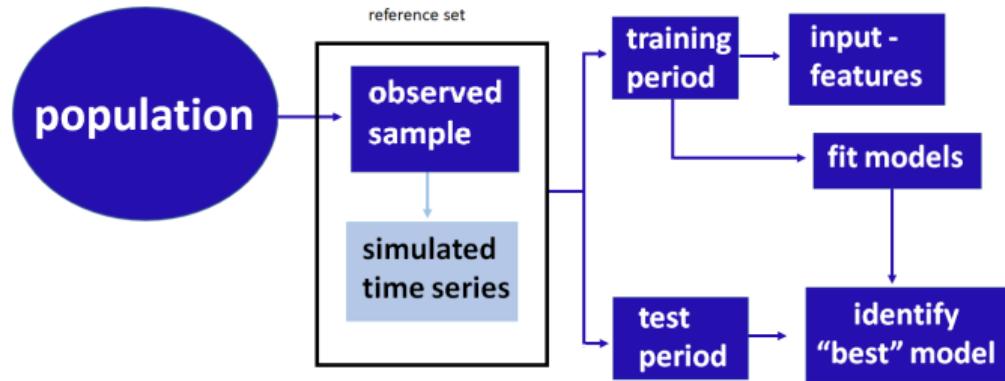
FFORMS: Feature-based FOrecast Model Selection



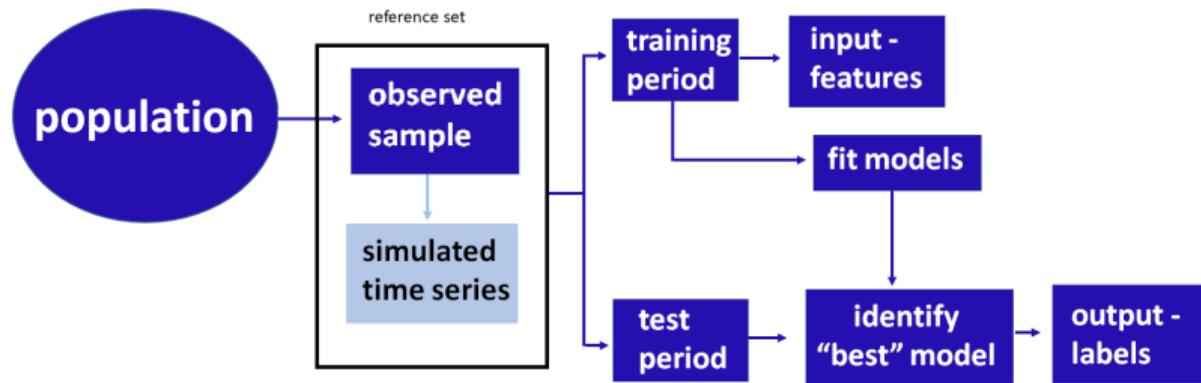
FFORMS: Feature-based FOrecast Model Selection



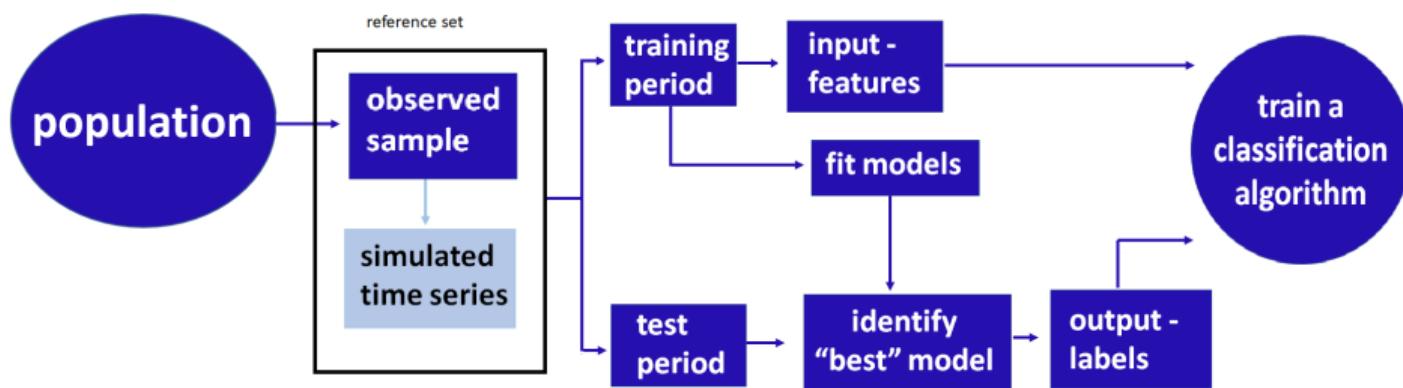
FFORMS: Feature-based FOrecast Model Selection



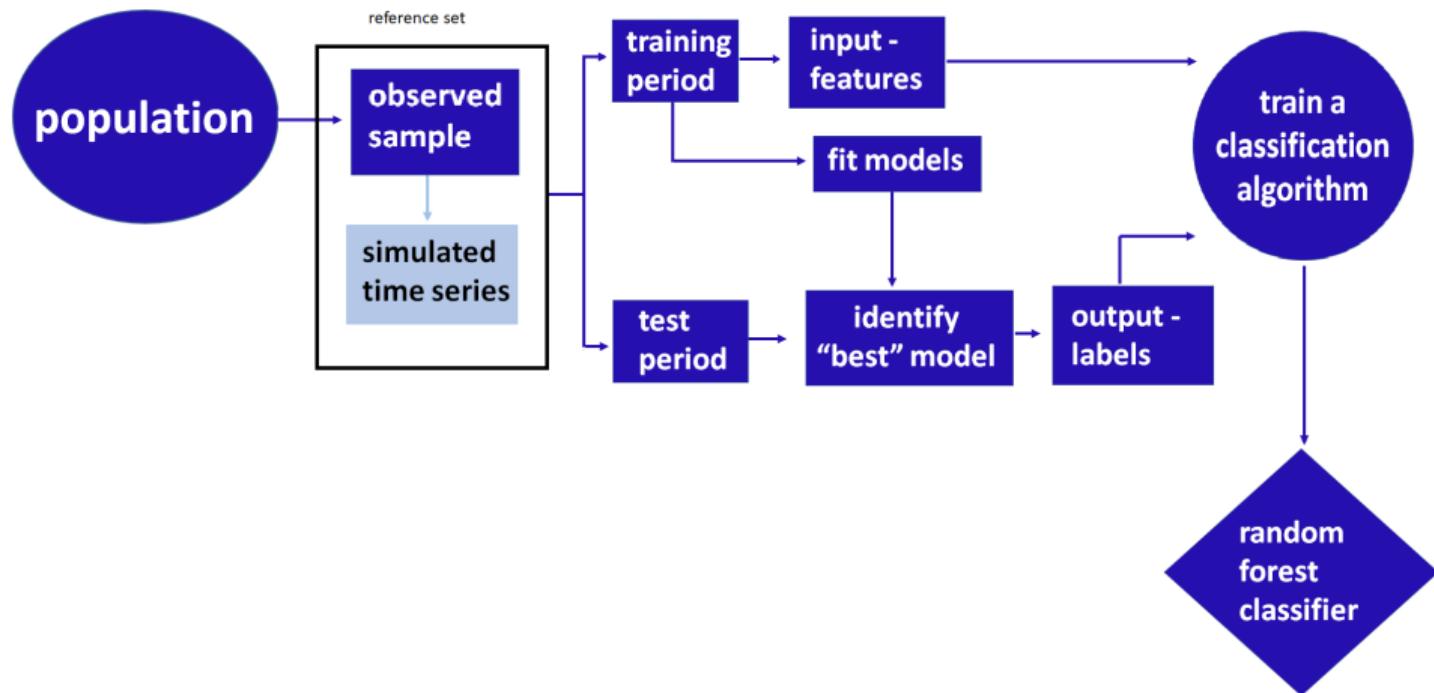
FFORMS: Feature-based FOrecast Model Selection



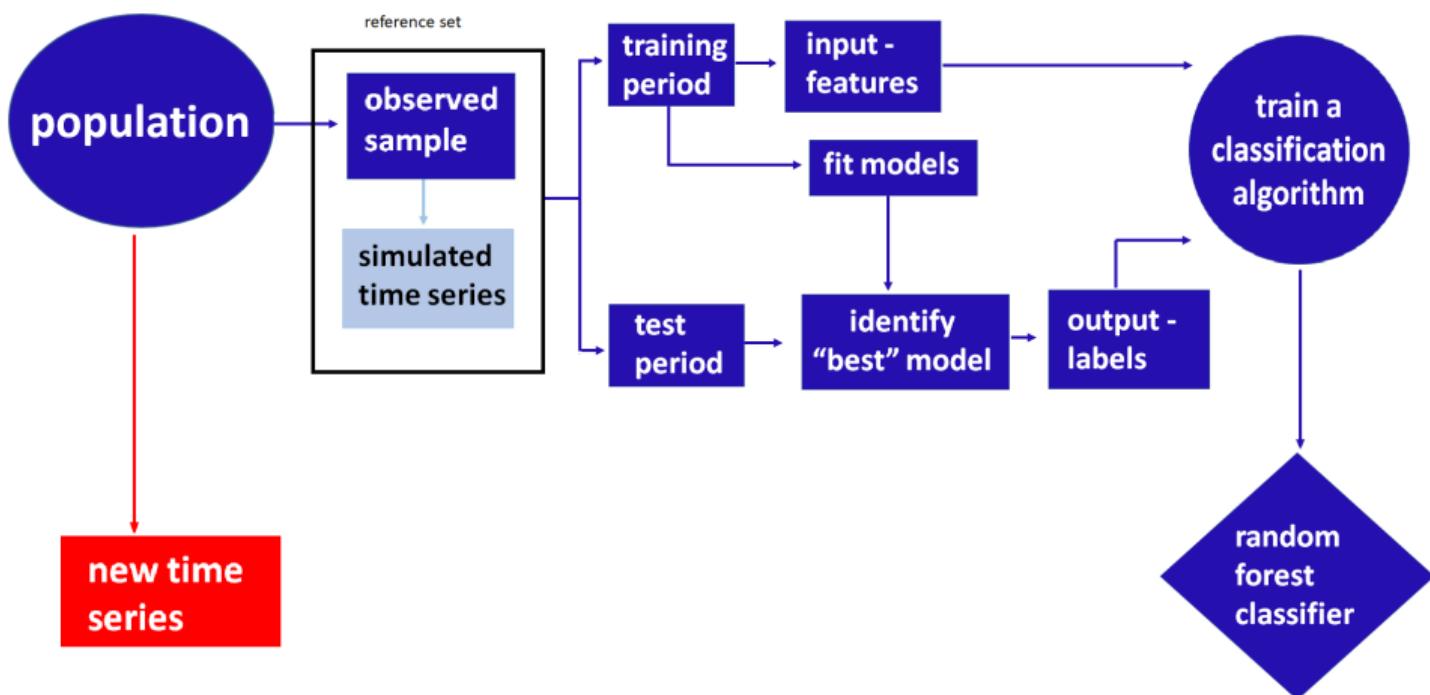
FFORMS: Feature-based FOrecast Model Selection



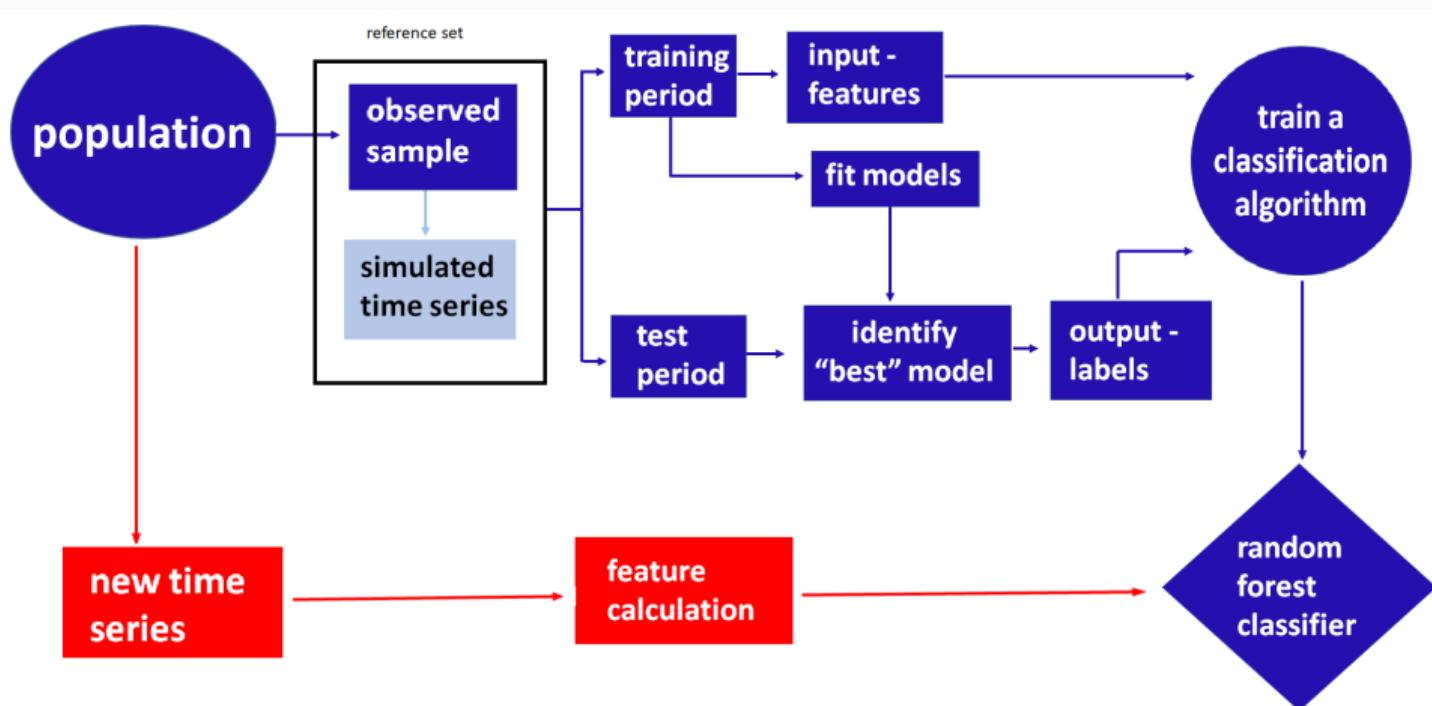
FFORMS: Feature-based FOrecast Model Selection



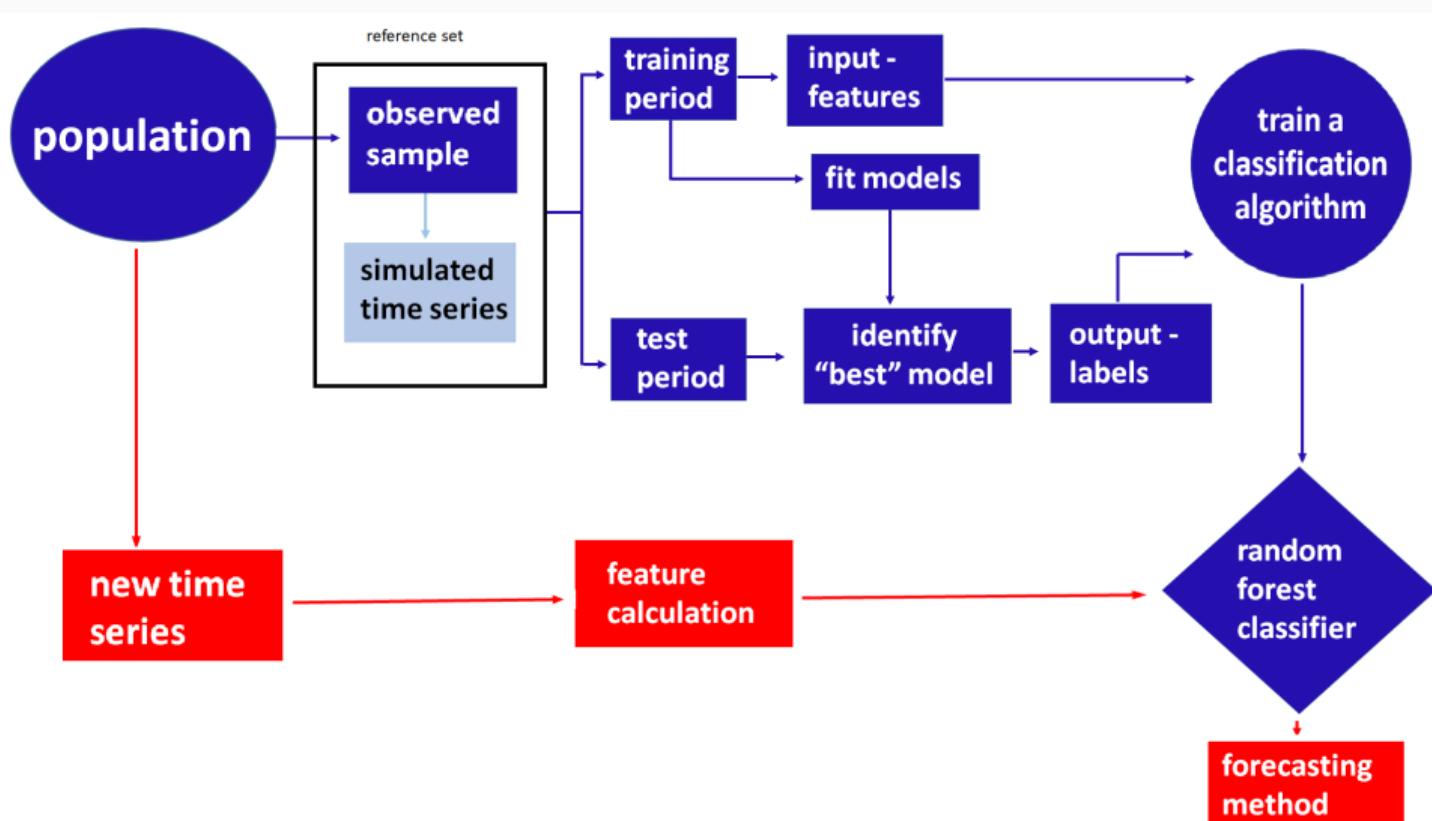
FFORMS: Feature-based FOrecast Model Selection



FFORMS: Feature-based FOrecast Model Selection



FFORMS: Feature-based FOrecast Model Selection



Application to M competition data

Experiment 1

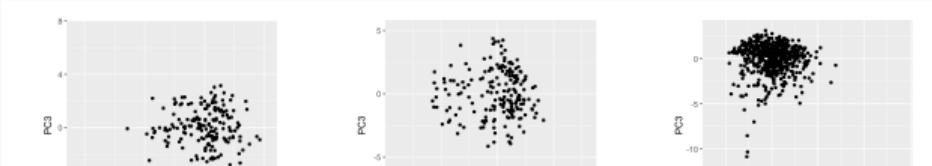
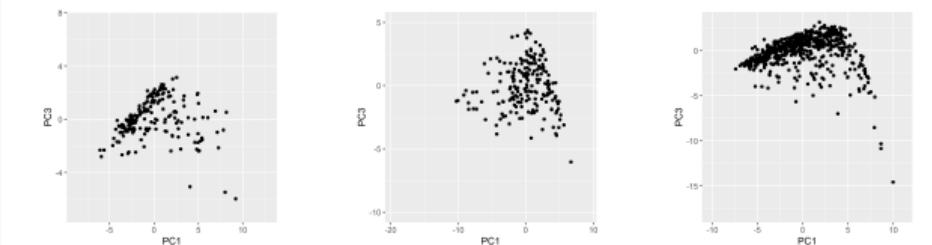
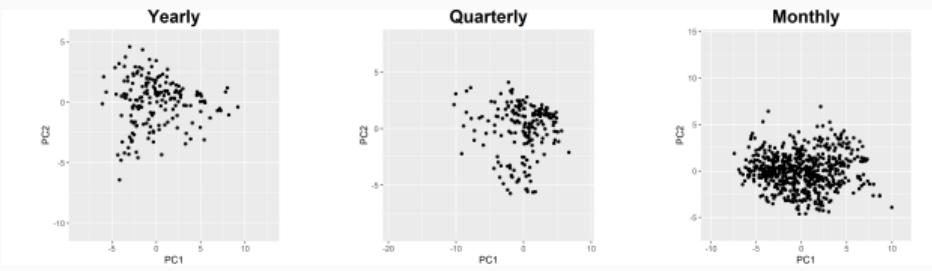
	Source	Y	Q	M
Observed series	M1	181	203	617
Simulated series		362000	406000	123400
New series	M3	645	756	1428

Experiment 2

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

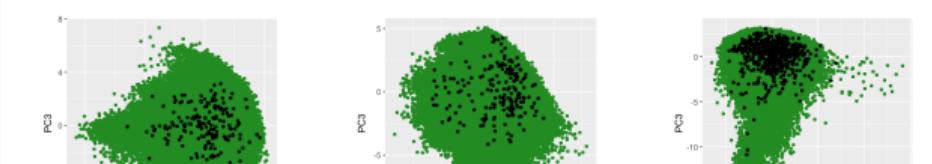
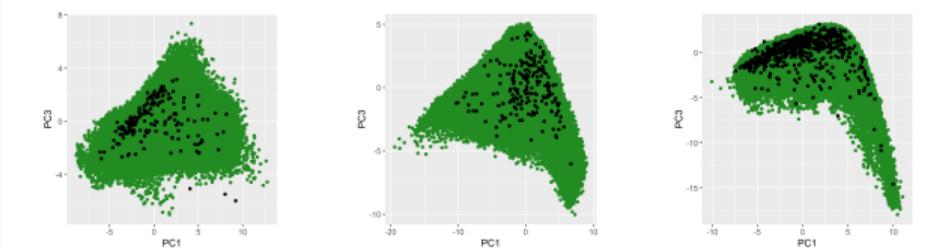
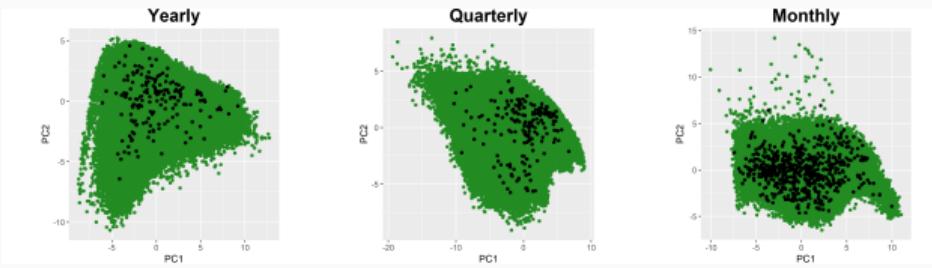
Experiment 1: Distribution of time series in PCA space

observed - M1



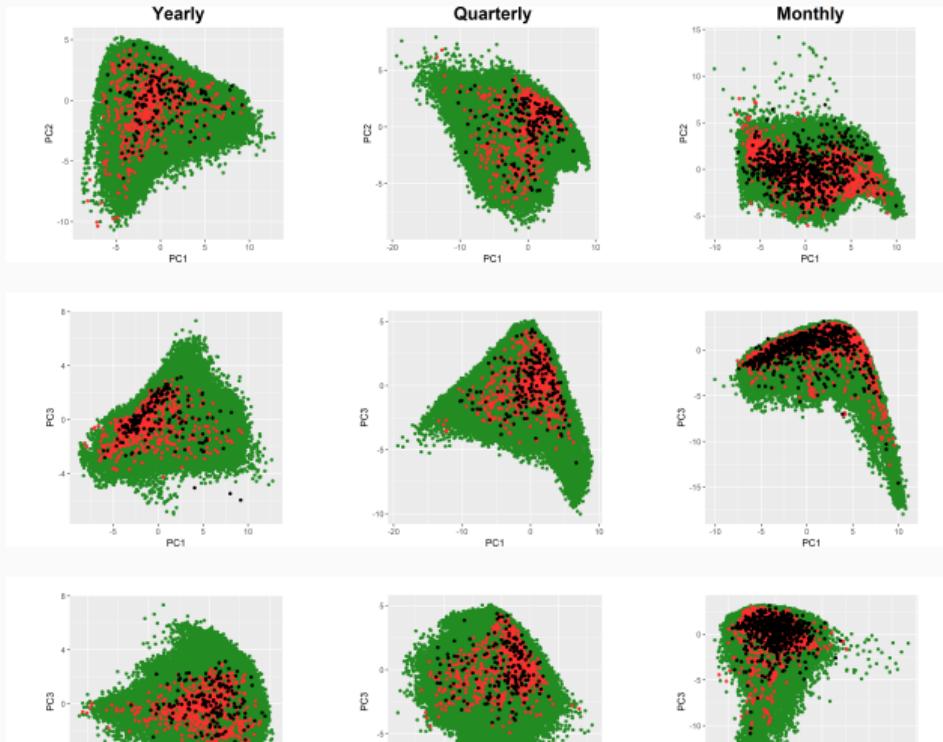
Experiment 1: Distribution of time series in PCA space

observed - M1 simulated



Experiment 1: Distribution of time series in PCA space

observed - M1 simulated new - M3



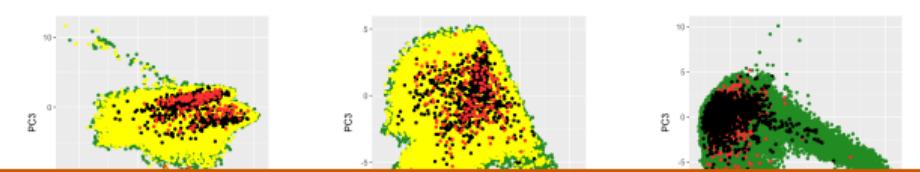
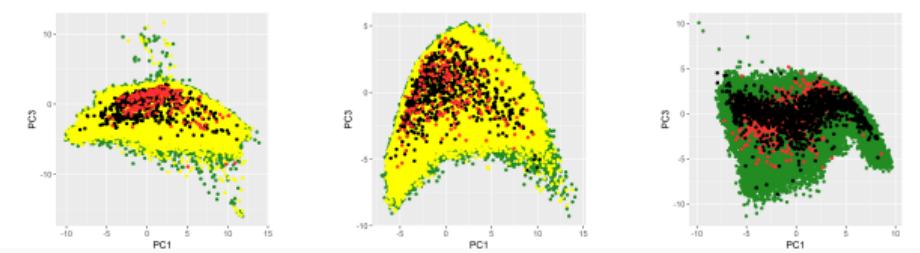
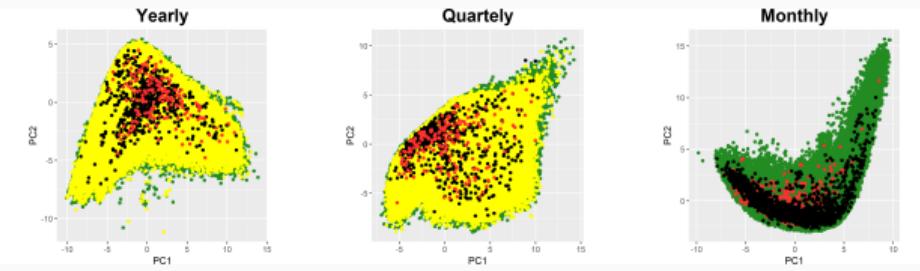
Experiment 2: Distribution of time series in PCA space

observed - M3

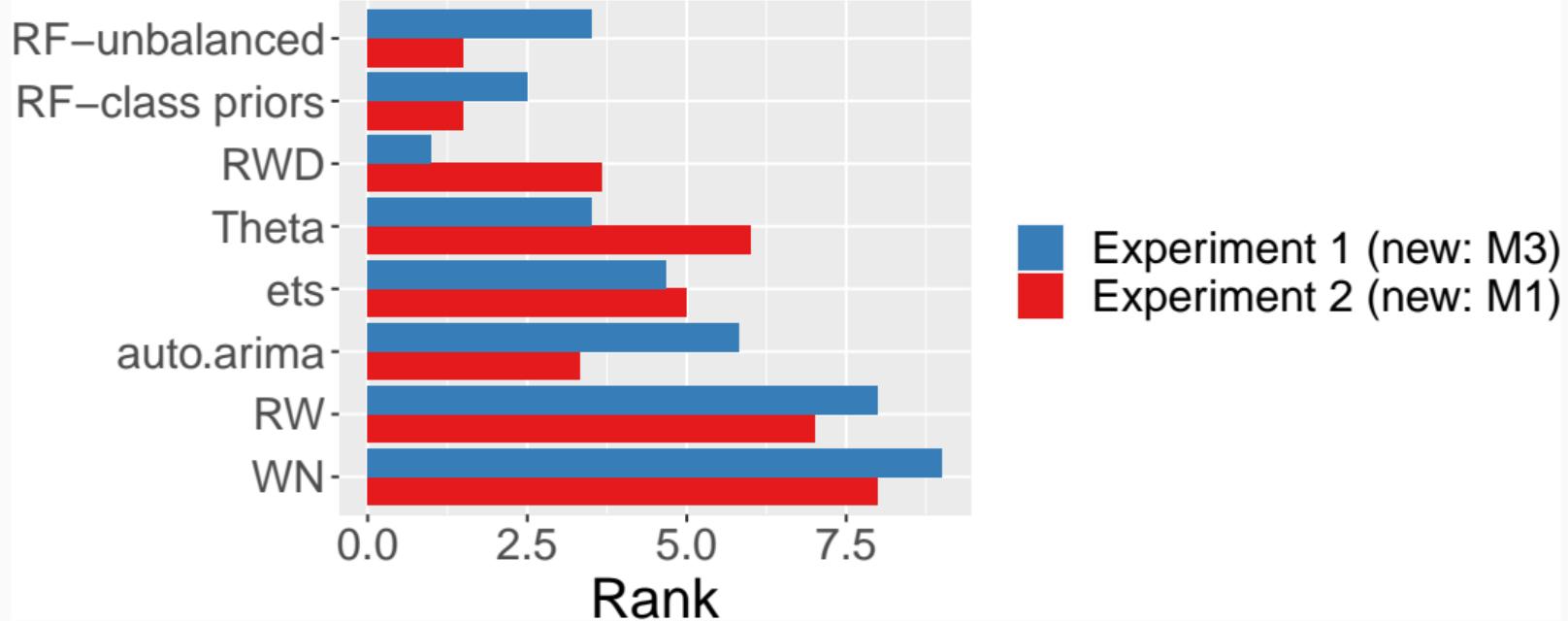
simulated

subset

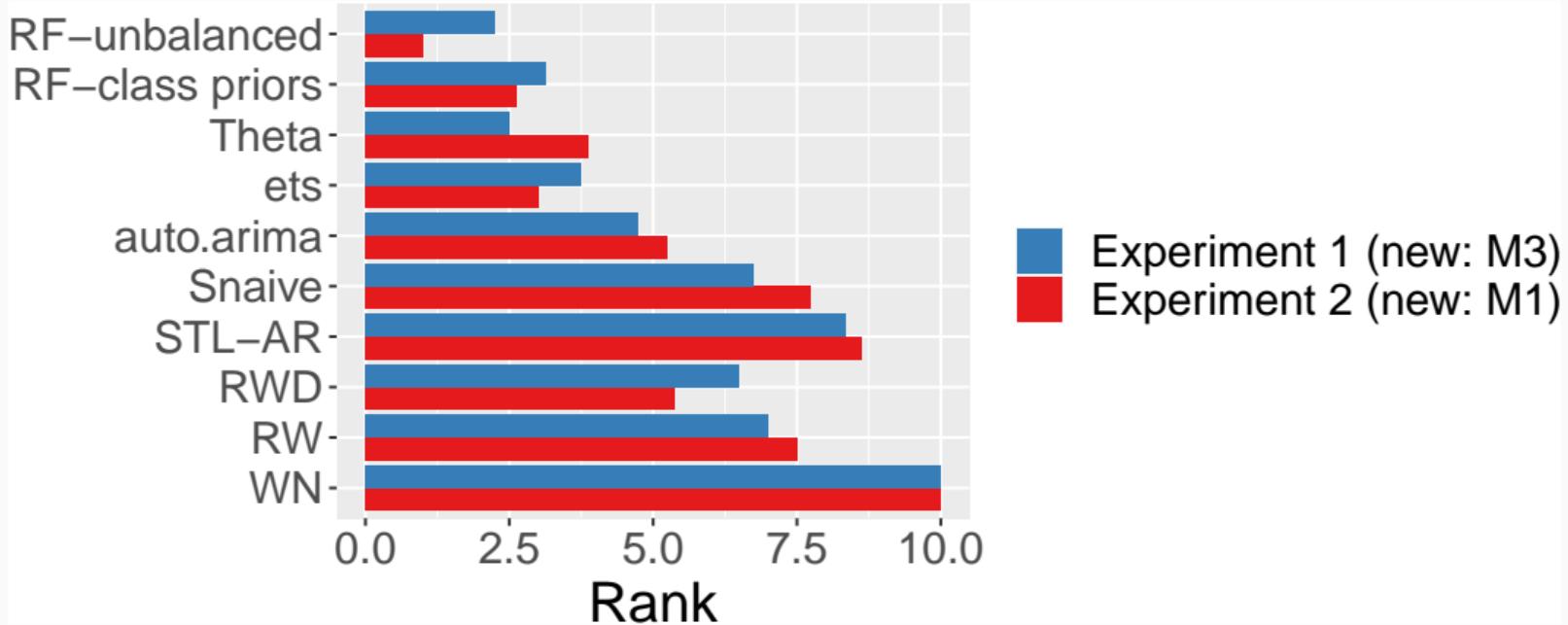
new - M1



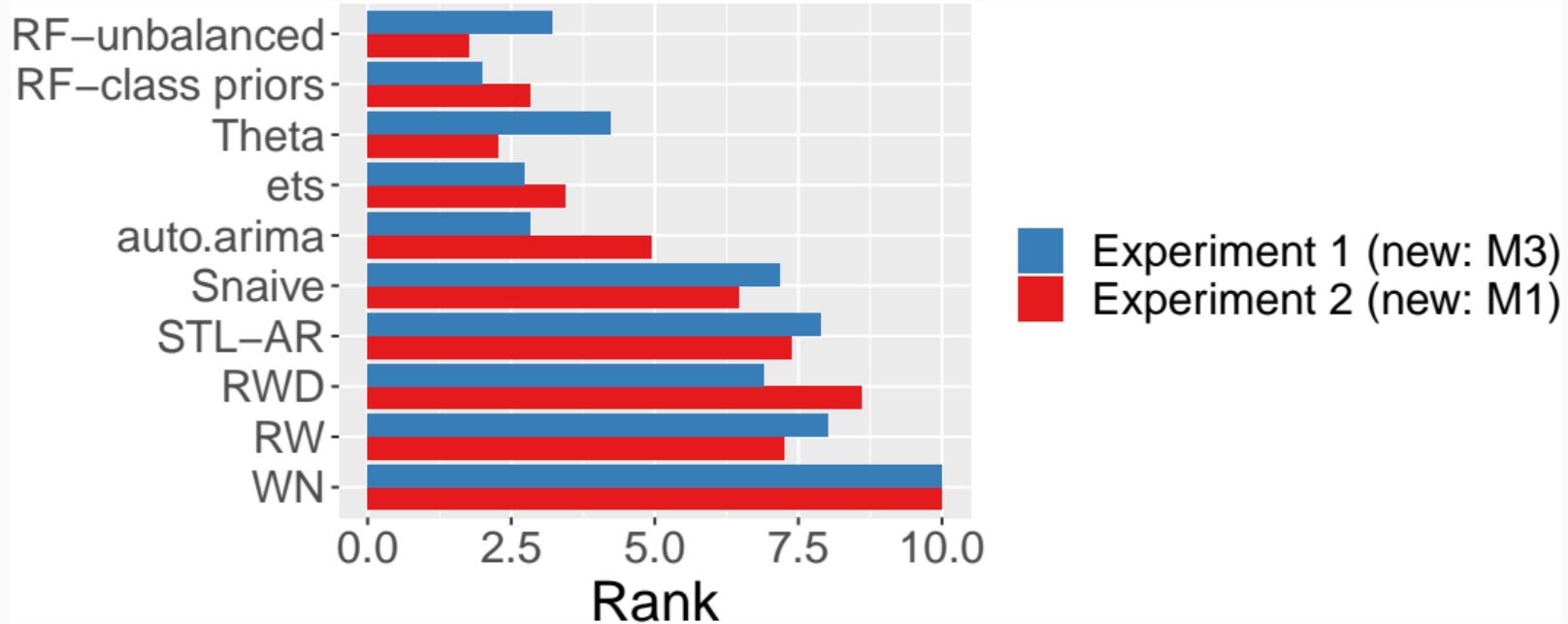
Results: Yearly



Results: Quarterly



Results: Monthly



FFORMA: Feature-based FORecast Model Averaging

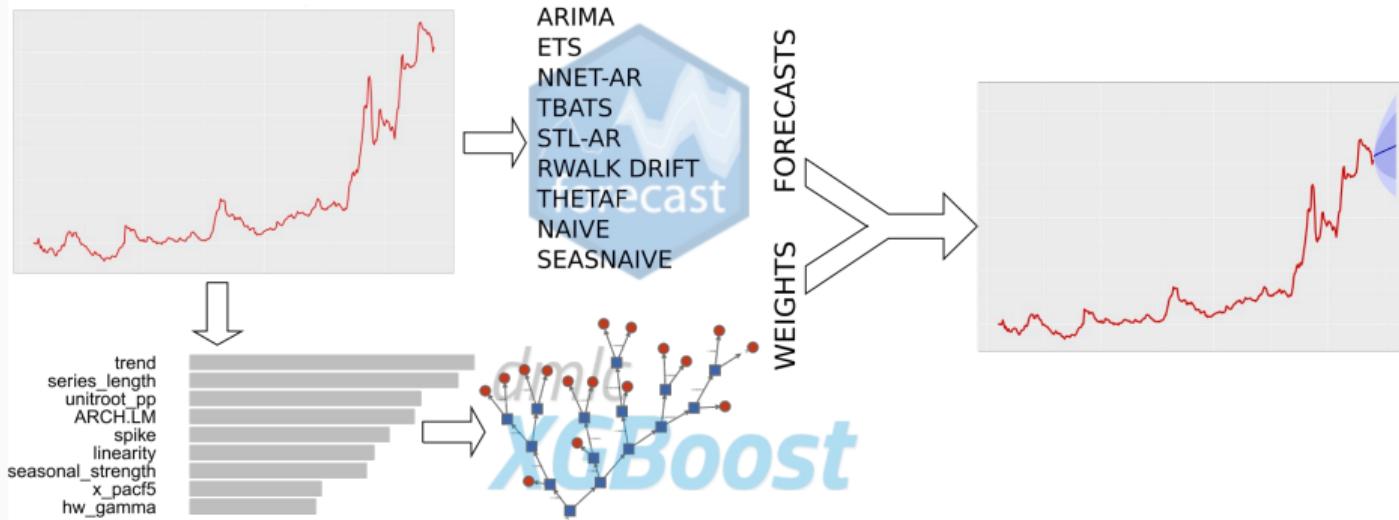
- Like FFORMS but using gradient boosted trees (xgboost) rather than random forest.
- Trained on temporal holdout version of M4 dataset, where size of test sets equal to required forecast horizons
- Optimization criterion: forecast accuracy not classification accuracy.
- Probability of each model being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



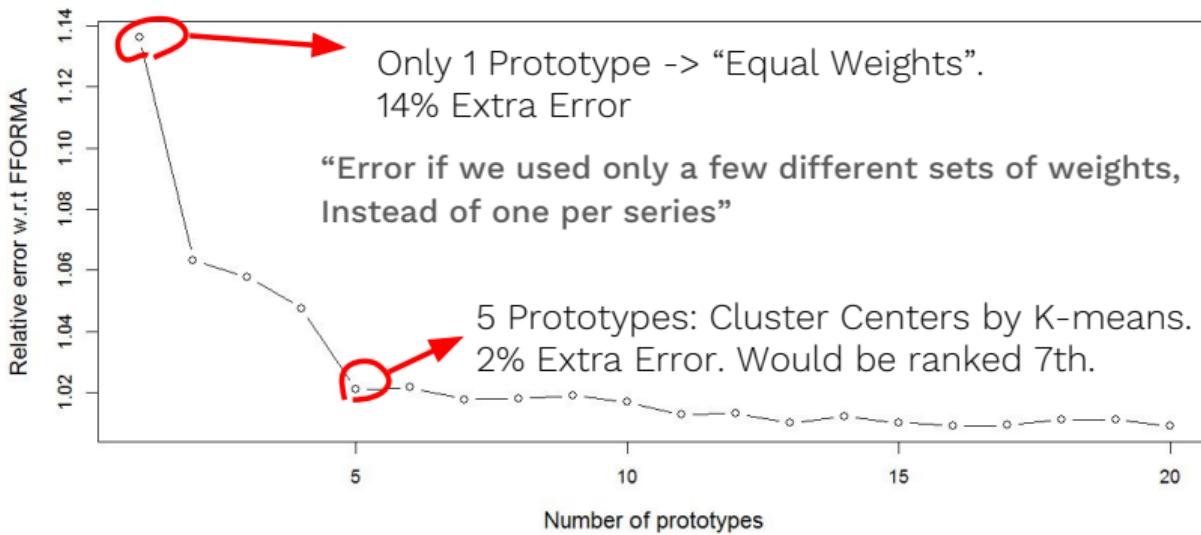
M4 competition results (based on average OWA)

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

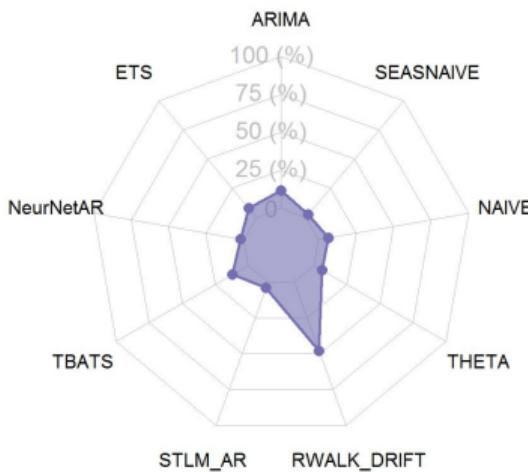
Weights of Prototype I



FFORMA: Feature-based FORecast Model Averaging

“Mostly RandomWalk Drift”. 20000 Series in M4

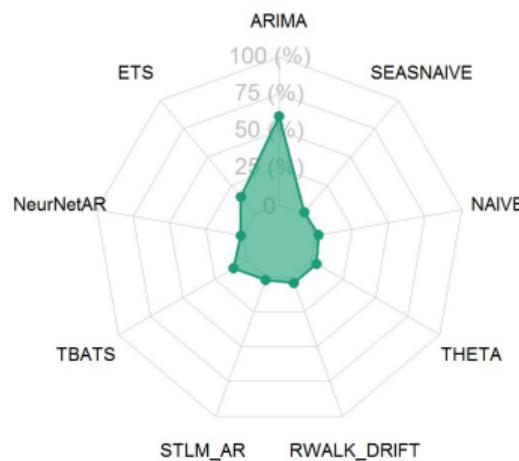
Weights of Prototype II



FFORMA: Feature-based FORecast Model Averaging

“Mostly ARIMA”. 16000 Series in M4

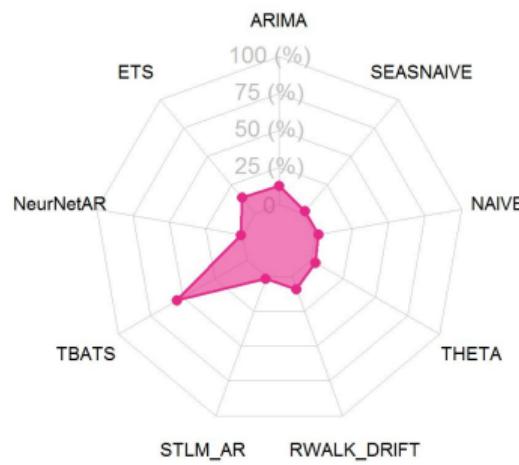
Weights of Prototype III



FFORMA: Feature-based FORecast Model Averaging

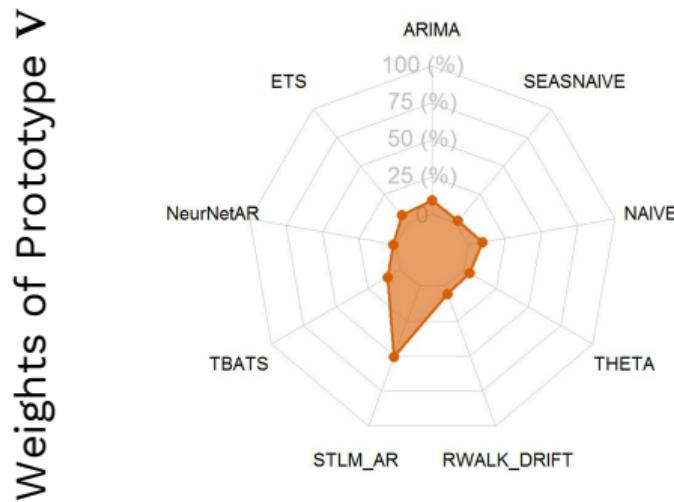
“Mostly TBATS”. 13000 Series in M4

Weights of Prototype IV



FFORMA: Feature-based FORecast Model Averaging

“Mostly STLM-AR”. 8000 Series in M4



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