seer: R package for feature-based forecast model selection

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Large collections of time series

- Forecasting demand for thousands of products across multiple warehouses.

Time series features

Objective

Develop a framework that automates the selection of the most appropriate forecasting method for a given time series by using an array of features computed from the time series.

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  - strength of seasonality
  - lag-1 autocorrelation
  - spectral entropy

Time series features

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

Methodology: FFORMS

FFORMS: Feature-based **FOR**ecast **M**odel **S**election

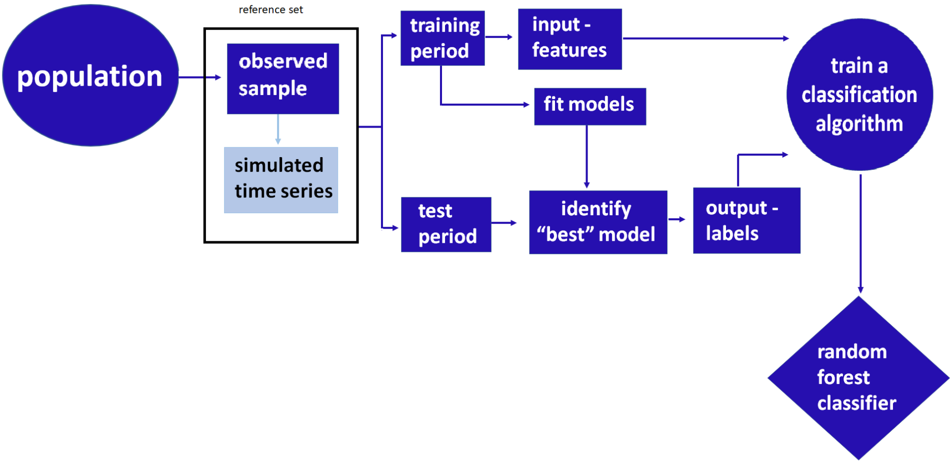
Offline

- A classification algorithm (the meta-learner) is trained.

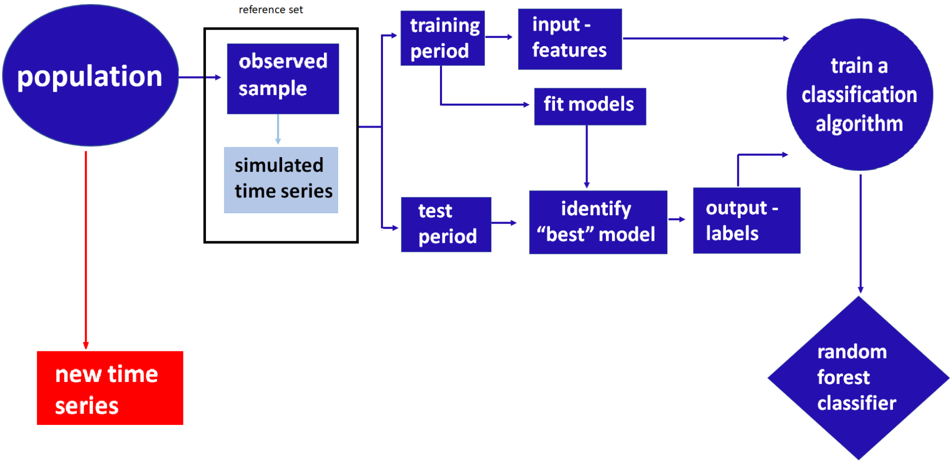
Online

- Calculate the features of a time series and use the pre-trained classifier to identify the best forecasting method.

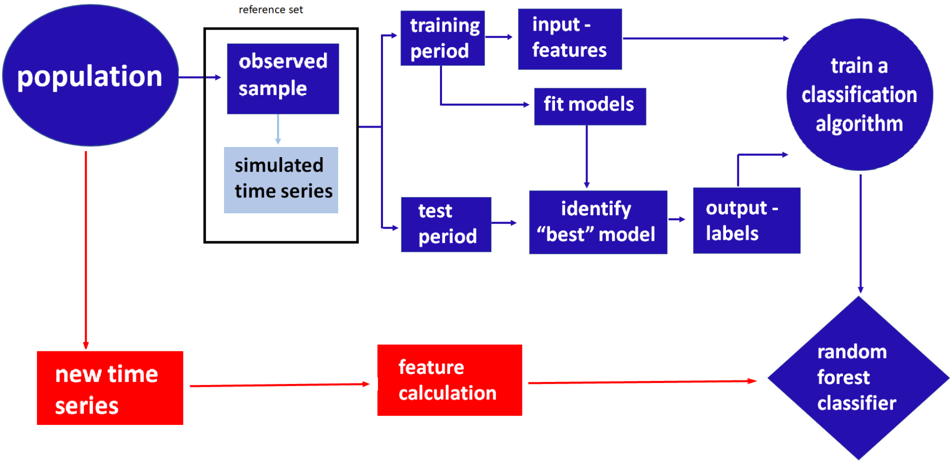
FFORMS: “offline” part of the algorithm



FFORMS: “online” part of the algorithm



FFORMS: "online" part of the algorithm



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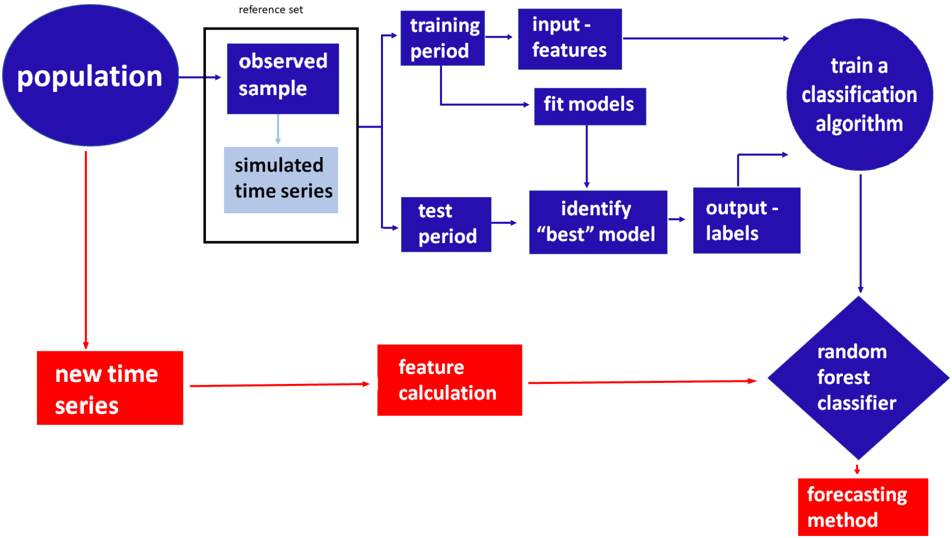

R package: seer

Installation

```r
devtools::install_github("thiyangt/seer")
library(seer)
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Example datasets

observed time series - M1 yearly series (181)

```
library(Mcomp)
yearlym1 <- subset(M1, "yearly")
```

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Example datasets

observed time series - M1 yearly series (181)

```r
library(Mcomp)
yearlym1 <- subset(M1, "yearly")
```

new time series - M3 yearly series (645)

```r
yearlym3 <- subset(M3, "yearly")
```

Input: features

```r
cal_features(yearlym1[1:3], database="M3",
h=6, highfreq=FALSE)
```

```
# A tibble: 3 x 25
  entropy lumpiness stability hurst trend  spikiness linearity curvature
    <dbl>     <dbl>     <dbl> <dbl> <dbl>      <dbl>     <dbl>     <dbl>
1   0.683    0.0400     0.977 0.985 0.985 0.00000132      4.46     0.705
2   0.711    0.0790     0.894 0.988 0.989 0.00000154      4.47     0.613
3   0.716    0.0160     0.858 0.987 0.989 0.00000113      4.60     0.695
# ... with 17 more variables: e_acf1 <dbl>, y_acf1 <dbl>,
#   diff1y_acf1 <dbl>, diff2y_acf1 <dbl>, y_pacf5 <dbl>,
#   diff1y_pacf5 <dbl>, diff2y_pacf5 <dbl>, nonlinearity <dbl>,
#   lmres_acf1 <dbl>, ur_pp <dbl>, ur_kpss <dbl>, N <int>, y_acf5 <dbl>,
#   diff1y_acf5 <dbl>, diff2y_acf5 <dbl>, alpha <dbl>, beta <dbl>
```

Output: labels

```
fcast_accuracy(yearlym1[1:3],
  models=c("arima","ets","rw","rwd","theta","nn"),
  database="M3", cal_MASE, h=6)
```

```
$accuracy
         arima       ets       rw       rwd     theta        nn
YAF2 10.527612 10.319029 13.52428 10.527612 12.088375 11.794209
YAF3  5.713867  7.704409  7.78949  5.225965  6.225463  6.700765
YAF4  8.633590  8.091416 11.55633  8.440105  9.952742 10.784679

$ARIMA
                     YAF2                      YAF3
"ARIMA(0,1,0) with drift" "ARIMA(0,1,1) with drift"
                     YAF4
"ARIMA(0,1,2) with drift"

$ETS
        YAF2         YAF3         YAF4
"ETS(A,A,N)" "ETS(M,A,N)" "ETS(M,A,N)"
```

Reference set

```r
accuracy_m1 <- fcast_accuracy(tslist=yearlym1,
models= c("arima","ets","rw","rwd", "theta", "nn"),
database ="M1", cal_MASE)

features_m1 <- cal_features(yearlym1, database="M1", highfreq = FALSE)

reference_set <- prepare_trainingset(accuracy_set = accuracy_m1,
feature_set = features_m1)
head(reference_set$trainingset, 1)
```

```
# A tibble: 1 x 26
  entropy lumpiness stability hurst trend  spikiness linearity curvature
    <dbl>     <dbl>     <dbl> <dbl> <dbl>      <dbl>     <dbl>     <dbl>
1   0.683    0.0400     0.977 0.985 0.985 0.00000132      4.46     0.705
# ... with 18 more variables: e_acf1 <dbl>, y_acf1 <dbl>,
#   diff1y_acf1 <dbl>, diff2y_acf1 <dbl>, y_pacf5 <dbl>,
#   diff1y_pacf5 <dbl>, diff2y_pacf5 <dbl>, nonlinearity <dbl>,
#   lmres_acf1 <dbl>, ur_pp <dbl>, ur_kpss <dbl>, N <int>, y_acf5 <dbl>,
#   diff1y_acf5 <dbl>, diff2y_acf5 <dbl>, alpha <dbl>, beta <dbl>,
#   classlabels <chr>
```

FFORMS classifier

```
ym3_features <- cal_features(yearlym3,
                database="M3", highfreq = FALSE)

fforms <- build_rf(training_set = ref_set$trainingset,
          testset=ym3_features,  rf_type="rcp",
            ntree=100, seed=7, import=FALSE)

fforms$predictions %>% head(10)
```

```
##         1         2         3         4         5         6         7
## ETS-trend       rwd       rwd       rwd       rwd       rwd       rwd
##         8         9        10        11        12        13        14
##       rwd       rwd       rwd       rwd ETS-trend       rwd       rwd
##        15        16        17        18        19        20
##        nn       rwd       rwd       rwd       rwd     ARIMA
## 10 Levels: ARIMA ARMA/AR/MA ETS-dampedtrend ... wn
```

Generate point foecasts and 95% prediction intervals

```r
rf_forecast(fforms$predictions[1:2],
tslist=yearlym3[1:2], database="M3",
function_name="cal_MASE", h=6, accuracy=TRUE)
```

```
## $mean
##          [,1]     [,2]     [,3]     [,4]     [,5]     [,6]
## [1,] 5486.429 6035.865 6585.301 7134.737 7684.173 8233.609
## [2,] 4402.227 4574.454 4746.681 4918.908 5091.135 5263.362
##
## $lower
##          [,1]     [,2]     [,3]     [,4]     [,5]      [,6]
## [1,] 4984.162 4893.098 4629.135 4199.745 3606.858 2848.8735
## [2,] 2890.401 2366.671 1959.916 1608.186 1288.666  990.2221
##
## $upper
##          [,1]     [,2]     [,3]      [,4]      [,5]      [,6]
## [1,] 5988.696 7178.632 8541.467 10069.729 11761.488 13618.344
## [2,] 5914.053 6782.236 7533.445  8229.629  8893.603  9536.501
##
## $accuracy
## [1] 1.5636089 0.6123443
```

Augmenting the observed sample with simutated time series

```r
lapply(yearlym1[1], sim_arimabased, Nsim=2)
```

```
## $YAF2
## $YAF2[[1]]
## Time Series:
## Start = 1972
## End = 1993
## Frequency = 1
##  [1]   3600.00  36303.86  77620.17  87135.29 118331.78  77243.15  88067.05
##  [8]  88870.48  59481.51  12189.03  65357.58  65908.67 122893.84  74796.77
## [15]  70353.15 100206.74 128145.90 123266.24 165428.09 234896.98 212138.11
## [22] 230546.28
##
## $YAF2[[2]]
## Time Series:
## Start = 1972
## End = 1993
## Frequency = 1
##  [1]   3600.000  -9347.681  49345.161  38947.540  33268.905  53802.044
##  [7] 101405.223 120836.658 141418.247 166030.391 171539.163 165193.914
## [13] 197562.762 205935.526 262298.229 300168.377 352400.806 391134.490
## [19] 403593.677 447238.169 455087.438 492134.771
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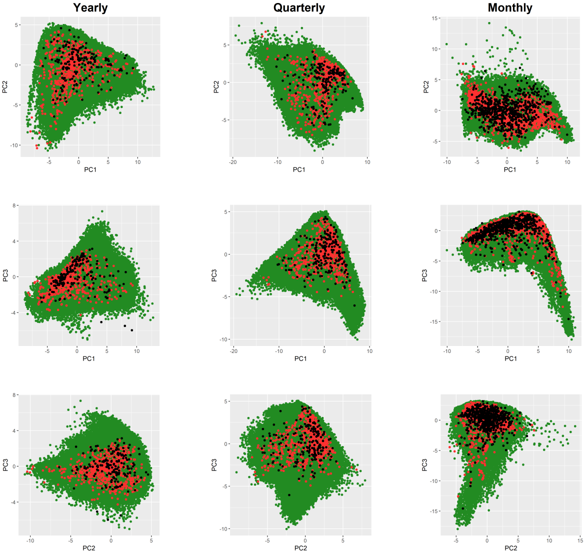
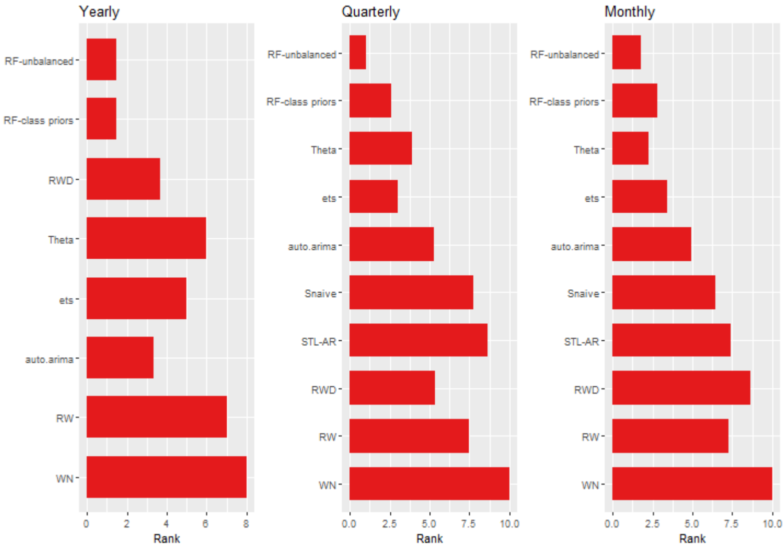
other methods:

```r
lapply(yearlym1[1], sim_etsbased, Nsim=2)
lapply(yearlym1[1], sim_mstlbased, Nsim=2)
```

observed - M1 | simulated | new - M3



Results



Yearly
RF-unbalanced
RF-class priors
RWD
Theta
ets
auto.arima
RW
WN
0
2
4
6
8
Rank
Quarterly
RF-unbalanced
RF-class priors
Theta
ets
auto.arima
Snaive
STL-AR
RWD
RW
WN
0.0
2.5
5.0
7.5
10.0
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- FFORMS algorithm uses the knowledge of the past performance of candidate forecast models on a collection of time series in order to identify the best forecasting method for a new series.
- For real-time forecasting, our framework involves only the calculation of features, the selection of a forecast method based on the FFORMS random forest classifier, and the calculation of the forecasts from the chosen model.
- We have also introduced a simple set of time series features that are useful in identifying the "best" forecast method for a given time series.

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available at: https://github.com/thiyangt/seer

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paper: https://robjhyndman.com/publications/fforms/

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