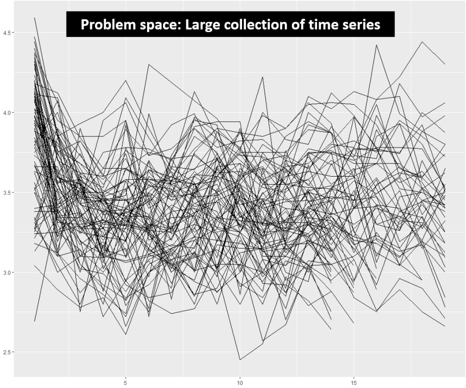
MONASH BUSINESS SCHOOL

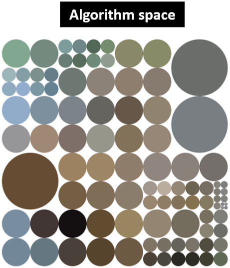
Feature-based Time Series Forecasting

Thiyanga Talagala,
Rob J Hyndman, George Athanasopoulos,
Feng Li, Yanfei Kang

11 July 2019

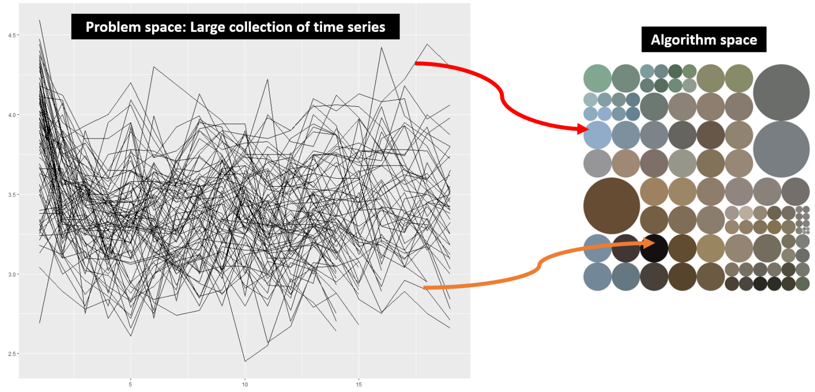
Big picture





- What algorithm is likely to perform best?

Big picture



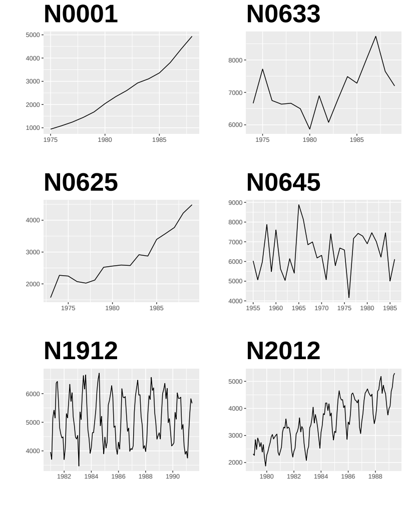
- What algorithm is likely to perform best?
- Algorithm selection problem, John Rice (1976)

Time series features

- Transform a given time series $y = \{y_1, y_2, \cdots, y_n\}$ to a feature vector $F = (f_1(y), f_2(y), \cdots, f_p(y))'\}$.

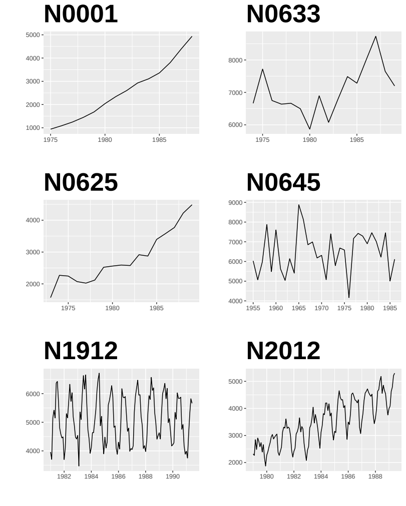
Time series features

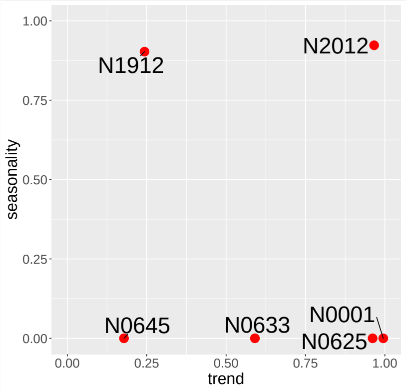
- Transform a given time series $y = \{y_1, y_2, \cdots, y_n\}$ to a feature vector $F = (f_1(y), f_2(y), \cdots, f_p(y))'\}$.



Time series features

- Transform a given time series $y = \{y_1, y_2, \cdots, y_n\}$ to a feature vector $F = (f_1(y), f_2(y), \cdots, f_p(y))'\}$.

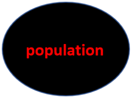




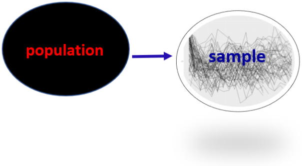
More features

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

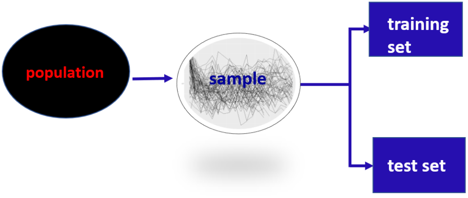
Algorithm selection framework



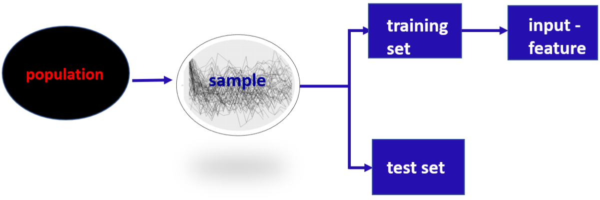
Algorithm selection framework



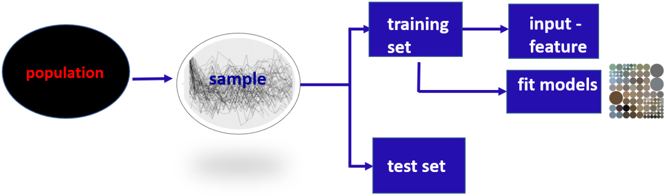
Algorithm selection framework



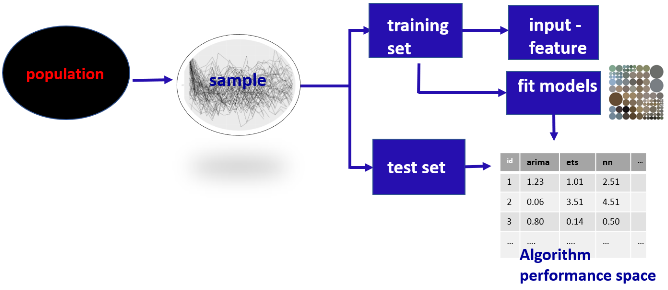
Algorithm selection framework



Algorithm selection framework

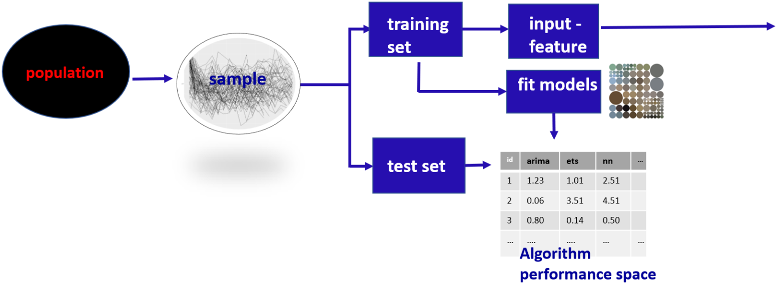


Algorithm selection framework



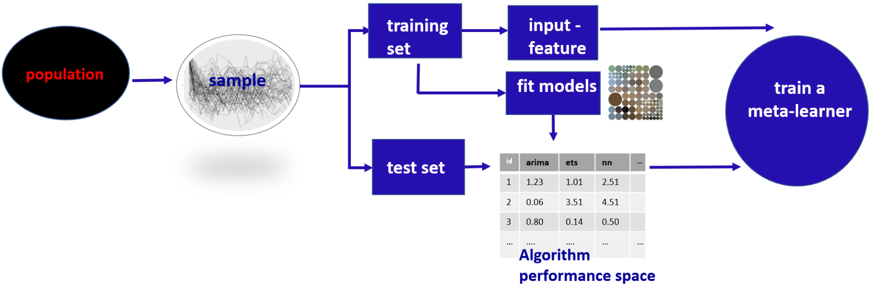
id	arima	ets	nn	...
1	1.23	1.01	2.51	
2	0.06	3.51	4.51	
3	0.80	0.14	0.50	
...	....	....	...	...

Algorithm selection framework

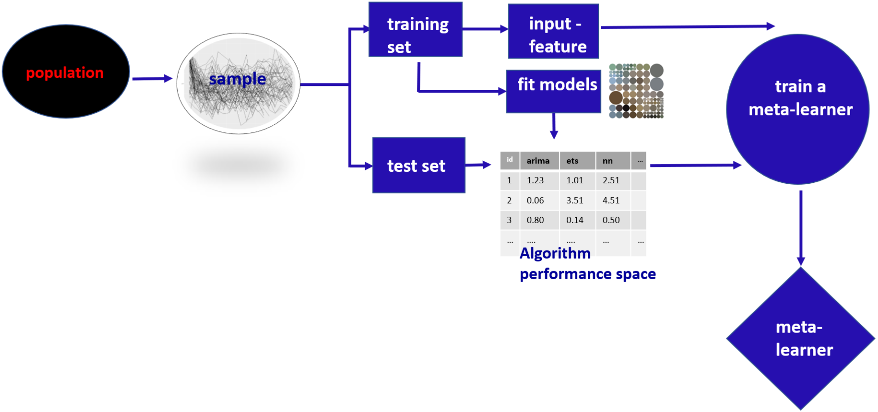


id	arima	ets	nn	...
1	1.23	1.01	2.51	
2	0.06	3.51	4.51	
3	0.80	0.14	0.50	
...	....	....	...	...

Algorithm selection framework

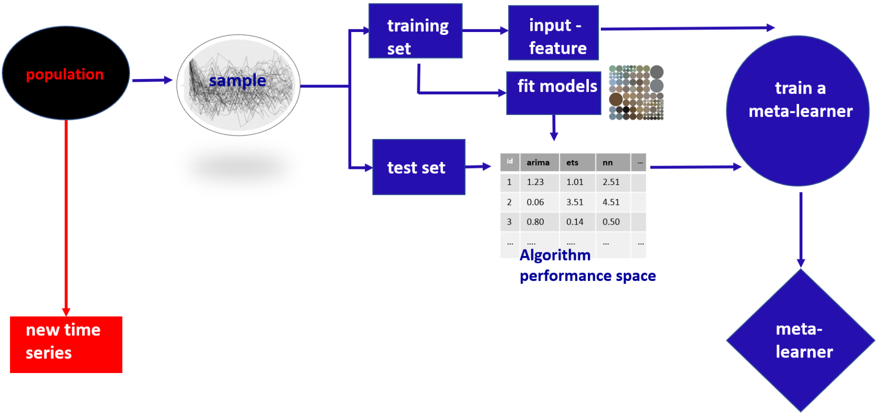


Algorithm selection framework

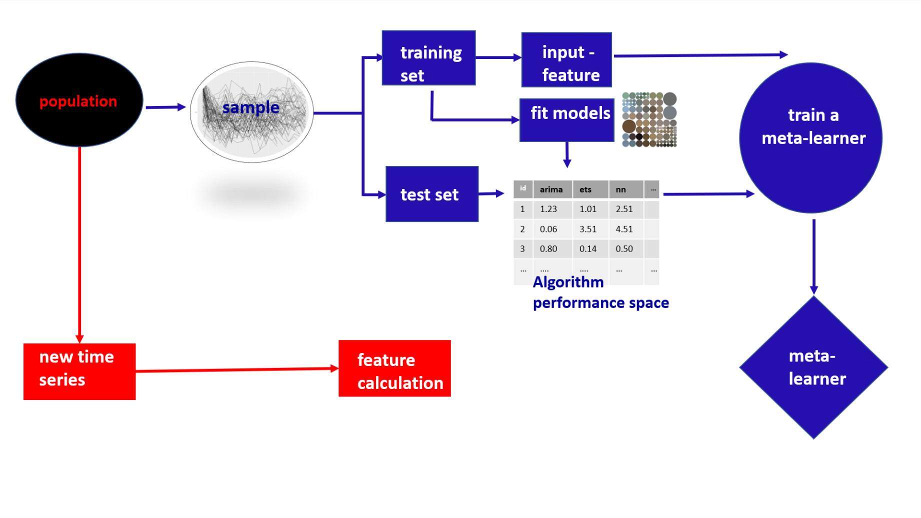


id	arima	ets	nn	...
1	1.23	1.01	2.51	
2	0.06	3.51	4.51	
3	0.80	0.14	0.50	
...	....	....	...	...

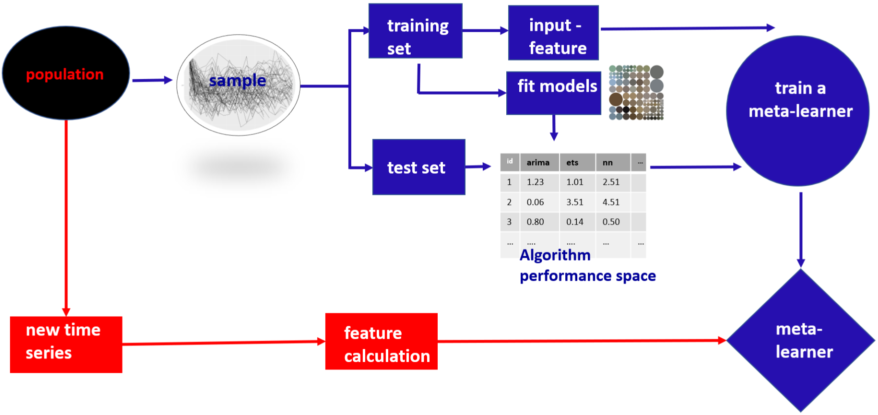
Algorithm selection framework



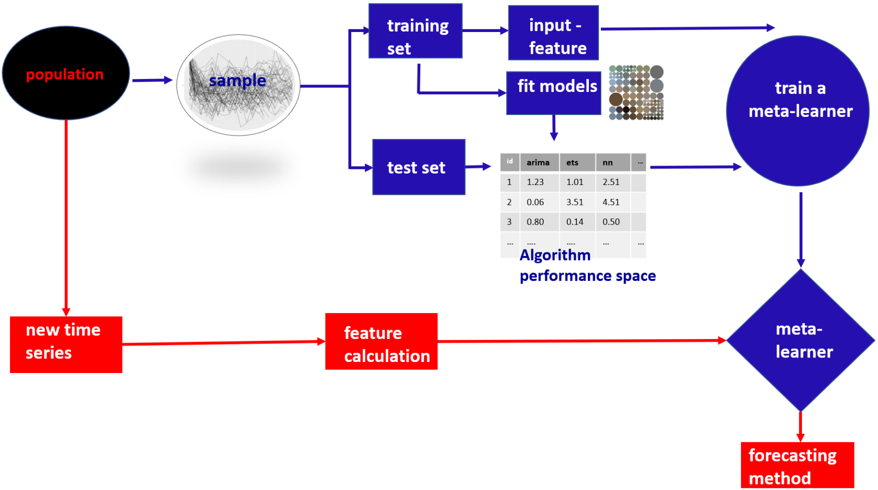
Algorithm selection framework



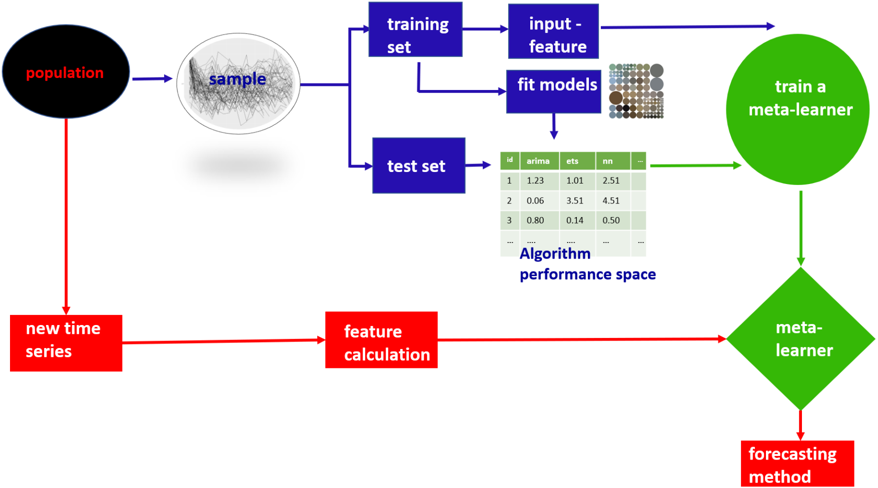
Algorithm selection framework



Algorithm selection framework

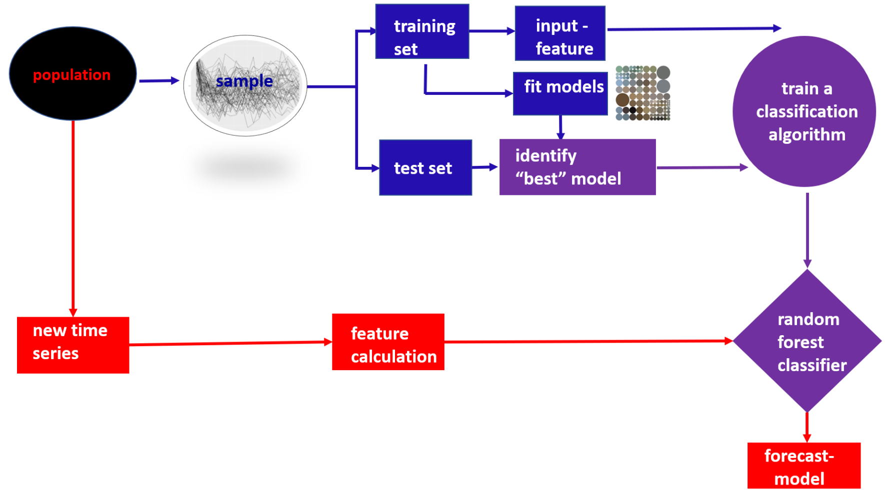


Algorithm selection framework



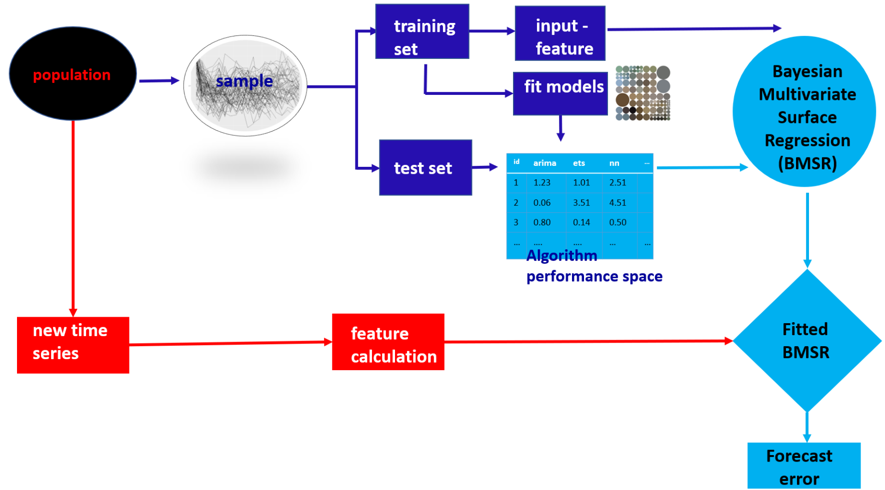
id	arima	ets	nn	...
1	1.23	1.01	2.51	
2	0.06	3.51	4.51	
3	0.80	0.14	0.50	
...	....	....	...	...

FFORMS: Feature-based FORecast Model Selection



- two algorithms: FFORMS, FFORMPP

FFORMPP: Feature-based FORecast Model Performance Prediction



- two algorithms: FFORMS, FFORMPP

seer R package

Installation

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

seer R package

Installation

```
devtools::install_github("thiyangt/seer")
library(seer)
```

Example dataset

observed time series - M1 yearly series (181)

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

seer R package

Installation

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

Example dataset

observed time series - M1 yearly series (181)

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

Input: features

```r
cal_features(yearlym1[1:3], database="M1",
h=6, highfreq=FALSE)
```

```
# A tibble: 2 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   1.32e-6      4.46     0.705
2   0.711    0.0790     0.894 0.988 0.989   1.54e-6      4.47     0.613
# ... 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: class labels

```
seer::fcast_accuracy(tslist=yearlym1[1:2],
                models= c("arima","ets","rw", "theta", "nn"),
                database ="M1", cal_MASE, h=6,
                length_out = 1,
                fcast_save = TRUE)
```

```
$accuracy
         arima       ets       rw      theta         nn
YAF2 10.527612 10.319029 13.52428 12.088375 11.718207
YAF3  5.713867  7.704409  7.78949  6.225463  6.688268

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

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

$forecasts
$forecasts$arima
         YAF2     YAF3
[1,] 579581.0 390955.9
[2,] 605761.9 407325.1
[3,] 631942.9 423694.4
[4,] 658123.8 440063.6
[5,] 684304.8 456432.8
[6,] 710485.7 472802.0
```

Training set

```r
prepare_trainingset(accuracy_set = accuracy_m1,
feature_set = features_m1)$trainingset
```

```
# A tibble: 2 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   1.32e-6      4.46     0.705
2   0.711    0.0790     0.894 0.988 0.989   1.54e-6      4.47     0.613
# ... 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

```r
rf <- build_rf(training_set = training_set,
               testset= M3yearly_features,
               rf_type="ru", ntree=100, seed=1,
              import=FALSE, mtry = 8)
```

Predictions

```r
head(rf$predictions)
```

```
##         1         2         3         4         5         6
## ETS-trend       rwd       rwd       rwd       rwd       rwd
## 10 Levels: ARIMA ARMA/AR/MA ETS-dampedtrend ... wn
```

FFORMS classifier

```r
rf$randomforest
```

```
## randomForest(formula = classlabels ~ ., data = training_set,
##     importance = import, ntree = ntree, mtry = mtry)
```

Pre-trained classifiers

Load FFORMS classifier for hourly series

```
data("hourly_fforms")
```

Pre-trained classifiers

Load FFORMS classifier for hourly series

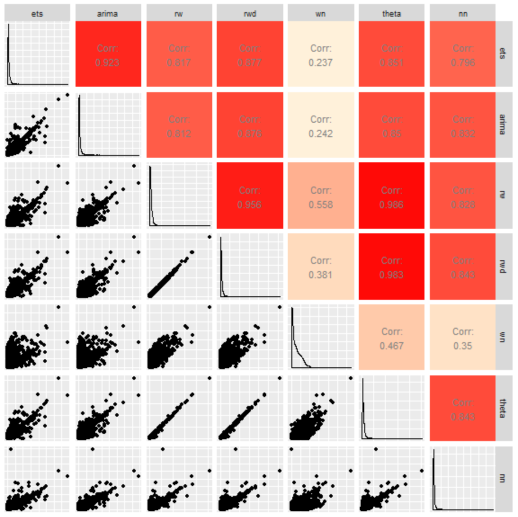
```
data("hourly_fforms")
```

Forecast hourly time series in the M4-competition

```
fcast.models <- predict(hourly_fforms, features_M4H)
head(fcast.models)
```

```
##      1      2      3      4      5      6
## tbats     nn  stlar  stlar     nn     nn
## Levels: mstlarima mstlets nn rw rwd snaive stlar tba
```

Yearly: Correlation between MASE values across different forecast-models



FFORMPP: Feature-based FORecast Model Performance Prediction

id	seasonality	...	entropy	trend	rw	rwd	....	arima
1	0.89		0.21	0.82	1.02	0.89		0.78
2	0.20		0.82	0.10	1.10	2.81		2.87
N	0.50		0.40	0.30	0.87	0.89		0.99

X-features Y-MASE

- Efficient Bayesian Multivariate Surface Regression (Feng Li & Mattias Villani, 2013)
  - handles interactions and nonlinear relationships
  - allows the knot locations to move freely in the feature space

fformpp R package

Installation

```
devtools::install_github("thiyangt/fformpp")
library(fformpp)
```

Train a model

```
fit_fformpp(feamat=features_mat, accmat=forecast.error,
            sknots=2, aknots=2,
            fix.s=0, fix.a=0, fix.shrinkage=1:5,
            fix.covariance=0,
            fix.coefficients=0, n.iter=100,
            knot.moving.algorithm="Random-Walk",
            ptype=c("identity", "identity", "identity"),
            prior.knots=100)
```

FFORMPP: online phase

```r
predict.m1 <- predict(fformpp.model, features.m1.df,
        c("ets", "arima", "rw", "rwd", "wn", "theta", "nn"),
        log=FALSE, final.estimate=median)
head(predict.m1)
```

```
##            ets    arima       rw      rwd        wn    theta       nn
## [1,] 5.015336 5.065616 5.149868 4.293450 16.681046 4.316341 4.554838
## [2,] 1.990880 1.831033 1.830689 2.010443  7.845106 1.434183 2.864783
## [3,] 3.825084 3.284397 3.893353 3.876207 12.867128 3.279123 2.885896
## [4,] 2.169089 3.162256 2.178721 2.481028  3.126736 2.216428 1.832553
## [5,] 5.199962 3.970234 4.630903 4.174412 15.631346 4.101041 5.765485
## [6,] 4.295996 4.494820 5.135292 3.523215 16.085372 4.021210 3.916389
```

Results: M4 Competition data

	Yearly	Quarterly	Monthly	Weekly	Daily	Hourly
FFORMS_individual	3.17	1.20	0.98	2.31	3.57	0.84
FFORMPP_combination	3.07	1.13	0.89	2.46	3.62	0.96
auto.arima	3.40	1.17	0.93	2.55	-	-
ets	3.44	1.16	0.95	-	-	-
theta	3.37	1.24	0.97	2.64	3.33	1.59
rwd	3.07	1.33	1.18	2.68	3.25	11.45
rw	3.97	1.48	1.21	2.78	3.27	11.60
nn	4.06	1.55	1.14	4.04	3.90	1.09
stlar	-	2.02	1.33	3.15	4.49	1.49
snaive	-	1.66	1.26	2.78	24.46	2.86
tbats	-	1.19	1.05	2.49	3.27	1.30
wn	13.42	6.50	4.11	49.91	38.07	11.68
mstlarima	-	-	-	-	3.84	1.12
mstlets	-	-	-	-	3.73	1.23
combination (mean)	4.09	1.58	1.16	6.96	7.94	3.93
M4-1st	2.98	1.12	0.88	2.36	3.45	0.89
M4-2nd	3.06	1.11	0.89	2.11	3.34	0.81
M4-3rd	3.13	1.23	0.95	2.16	2.64	0.87

Thank you

R packages and papers

R packages

- **seer**: FFORMS

  github.com/thiyangt/seer
- **fformpp**: FFORMPP

  github.com/thiyangt/fformpp

Papers

Available from **robjhyndman.com**

Slides: **https://thiyanga.netlify.com/talk/user19-talk/**

email: thiyanga.talagala@monash.edu