MONASH University

MONASH BUSINESS SCHOOL

# Feature-based Time Series Forecasting

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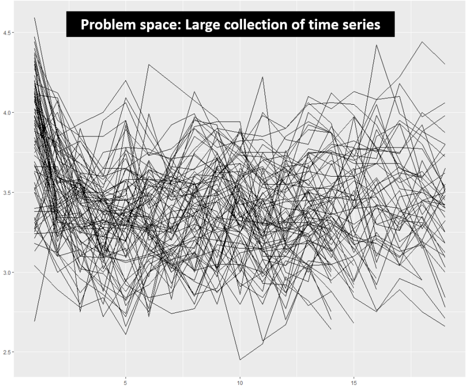
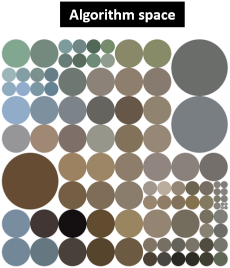
Rob J Hyndman, George Athanasopoulos,
Feng Li, Yanfei Kang

11 July 2019

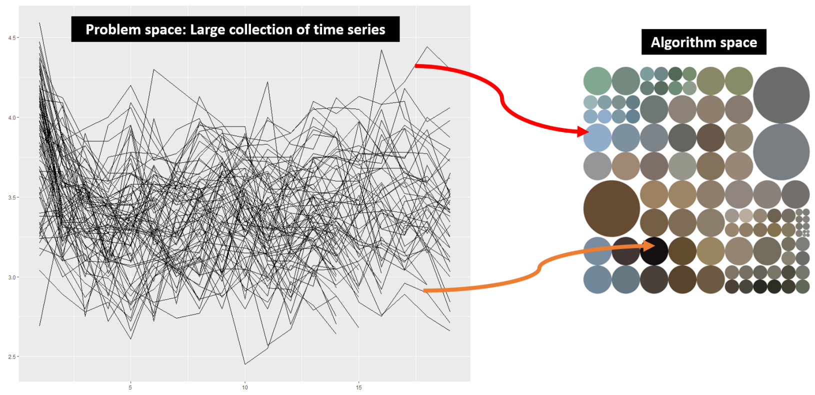
# Big picture




- 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 $F = (f_1(y), f_2(y), \cdots, f_p(y))'$.

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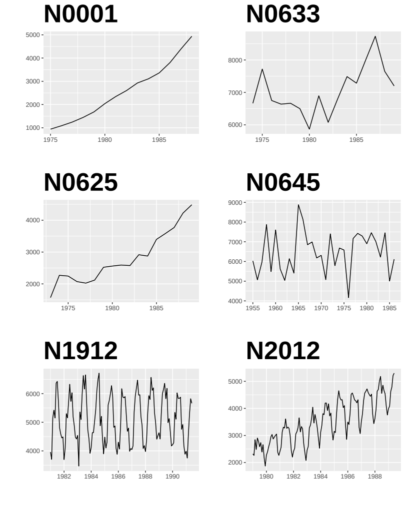

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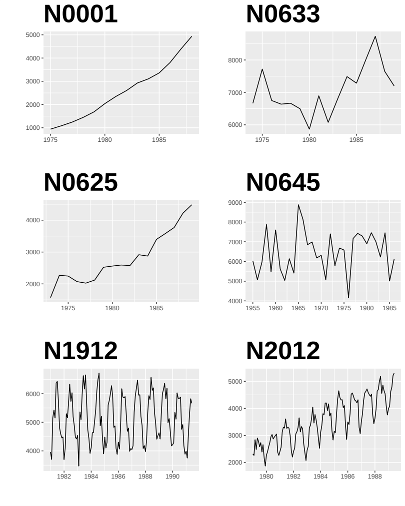
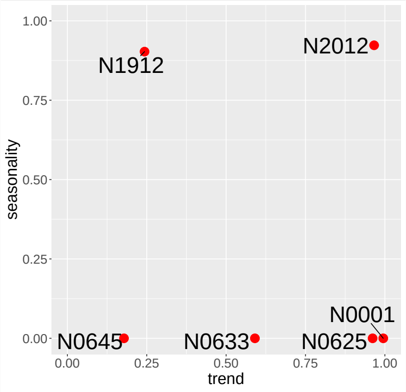
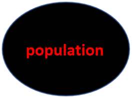


# More features

- 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



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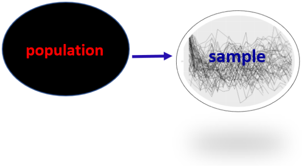

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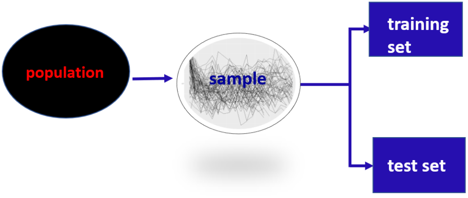

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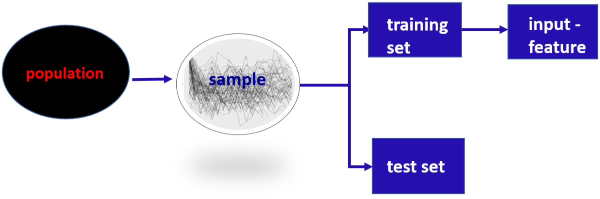

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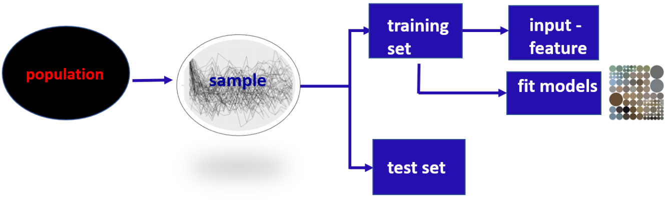

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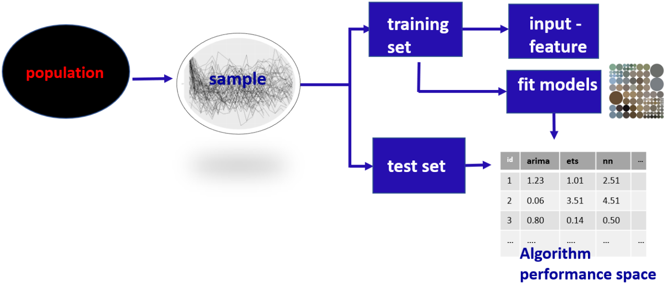


| id | arima | ets | nn | ... |
|---|---|---|---|---|
| 1 | 1.23 | 1.01 | 2.51 | |
| 2 | 0.06 | 3.51 | 4.51 | |
| 3 | 0.80 | 0.14 | 0.50 | |
| ... | .... | .... | ... | ... |

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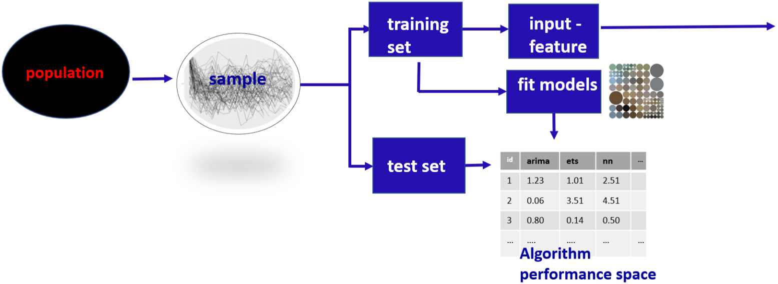


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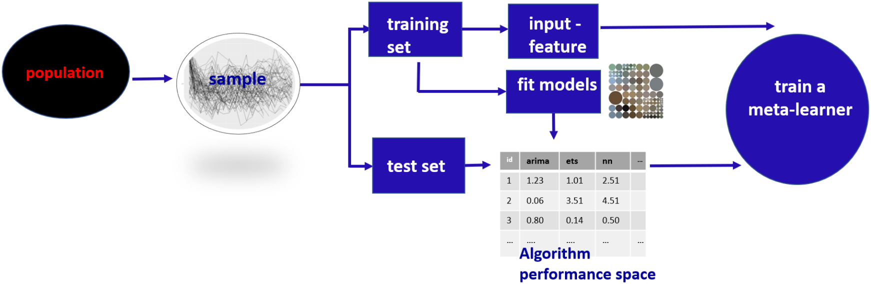

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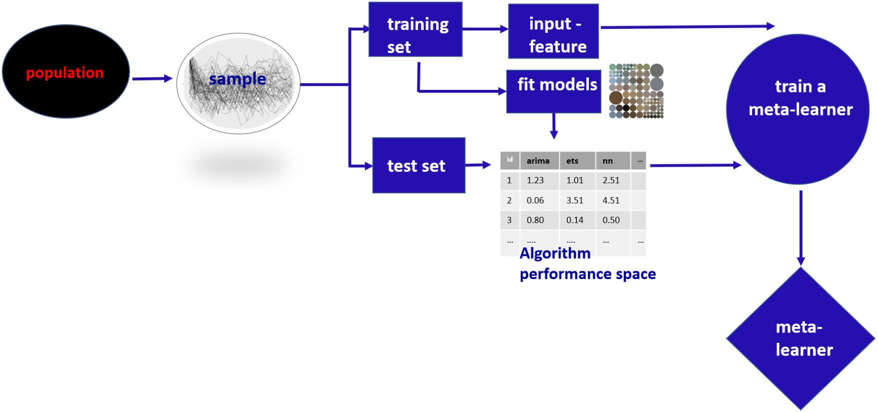

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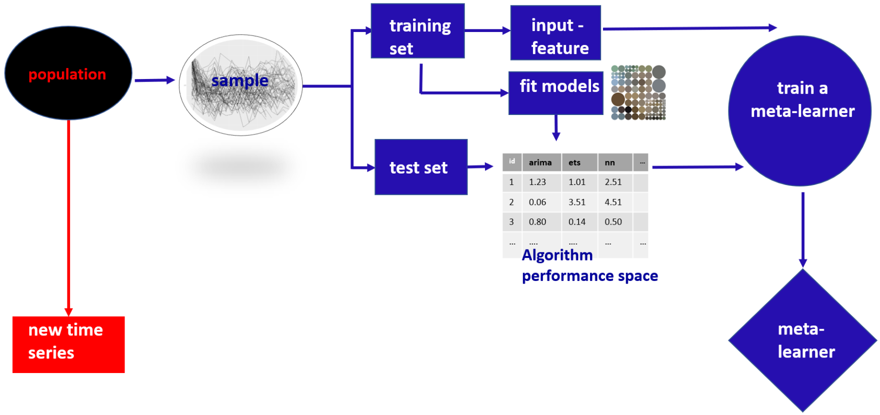

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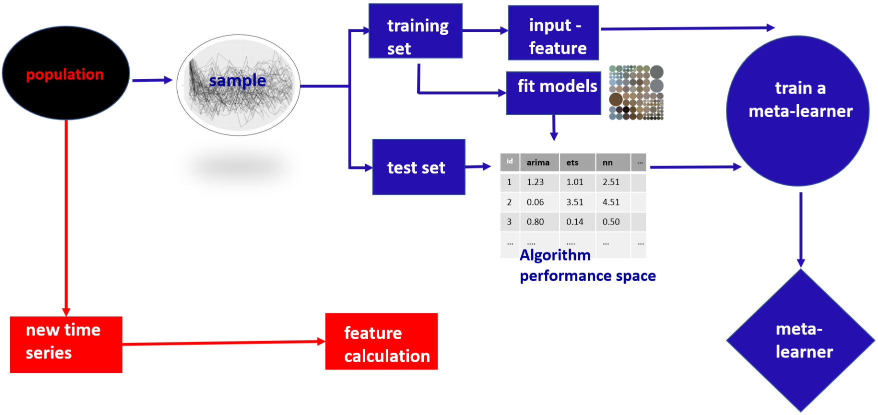

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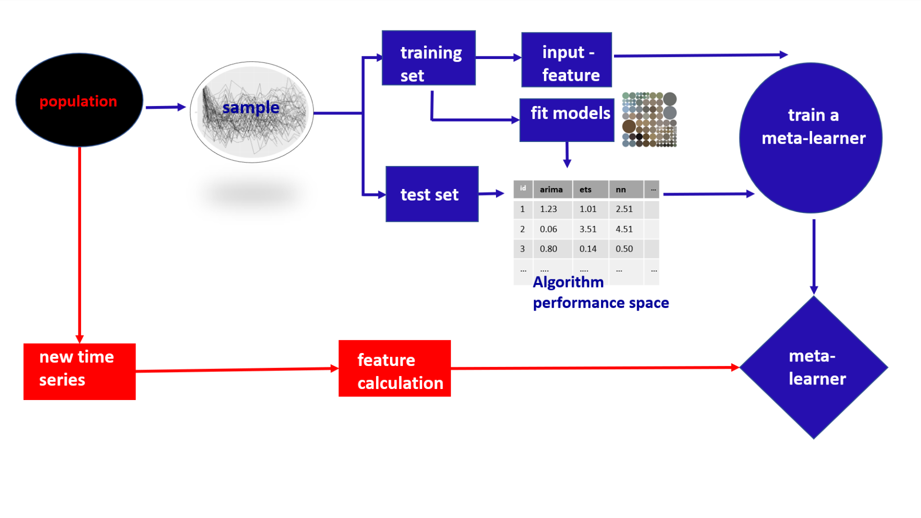

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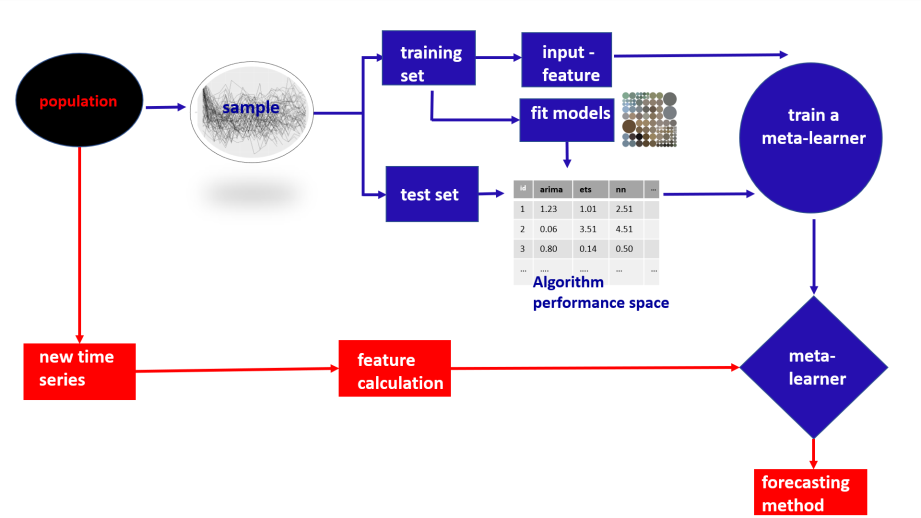

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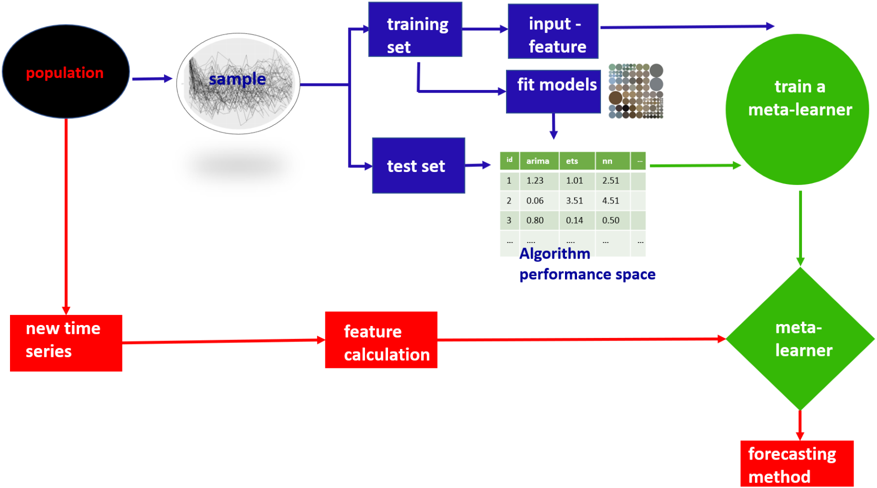


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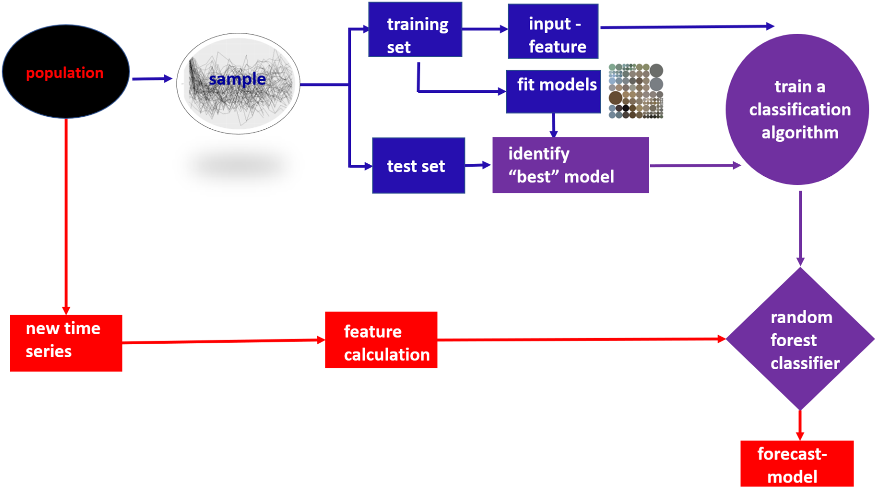
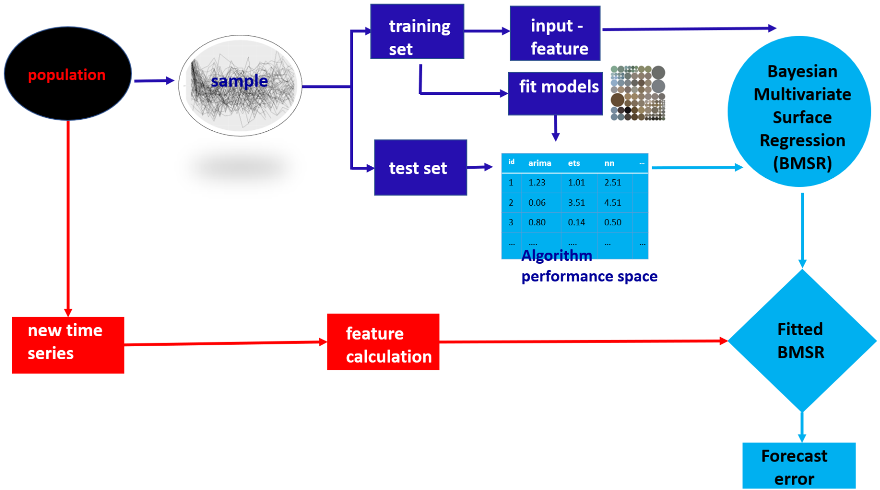
# FFORMS: Feature-based FORecast Model Selection




- two algorithms: FFORMS, FFORMPP

# FFORMPP: Feature-based FORecast Model Performance Prediction




- two algorithms: FFORMS, FFORMPP

# seer R package

## Installation

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

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## Example dataset

**observed time series - M1 yearly series (181)**

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

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## Example dataset

**observed time series - M1 yearly series (181)**

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

# Input: features

```r
cal_features(yearlym1[1:2], 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

```r
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 11.78891
YAF3  5.713867  7.704409  7.78949  6.225463  6.70074

$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
```

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```

**MASE**

$$q_t = \frac{e_t}{\frac{1}{n-1}\sum_{i=2}^{n}|Y_i - Y_{i-1}|}$$

$$MASE = mean(|q_t|)$$

# 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

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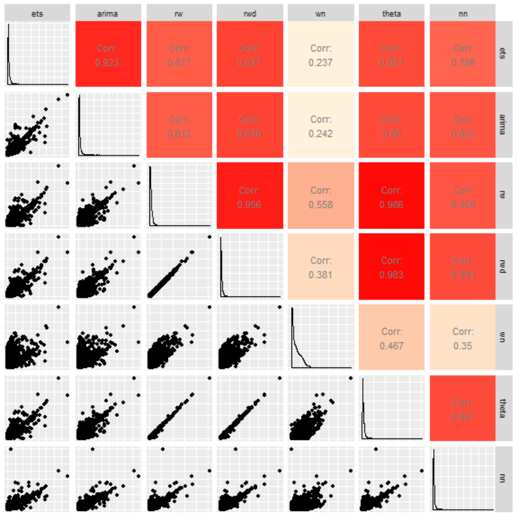
```

**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 and Slides**

**thiyanga.netlify.com/talk/user19-talk/**

email: **thiyanga.talagala@monash.edu**