

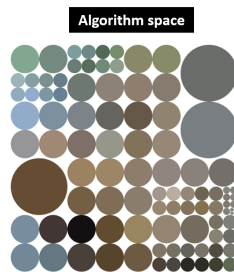
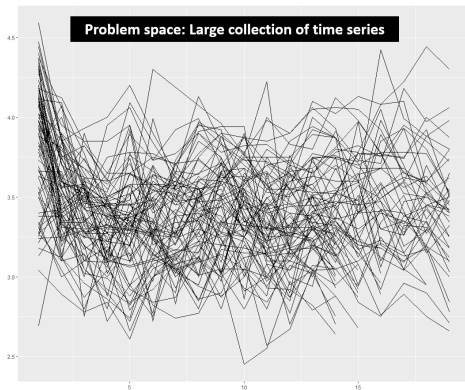


Feature-based Time Series Forecasting

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

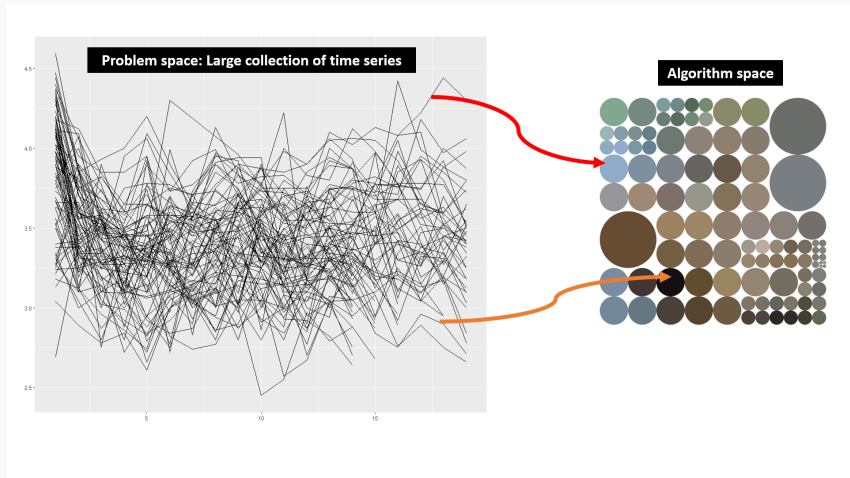
11 July 2019

Big picture



- What algorithm is likely to perform best?

Big picture



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

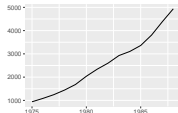
Time series features

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

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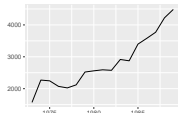
N0001



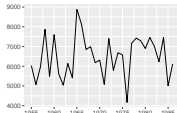
N0633



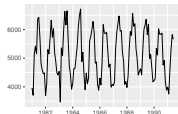
N0625



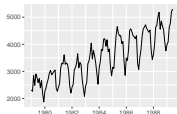
N0645



N1912



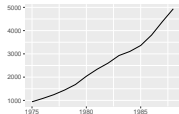
N2012



Time series features

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

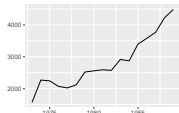
N0001



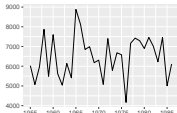
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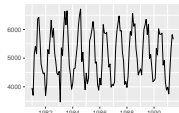
N0625



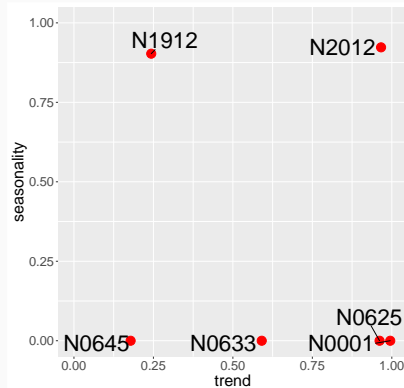
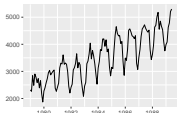
N0645



N1912



N2012



More features

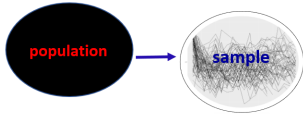
- length
- strength of seasonality
- strength of trend
- linearity
- curvature
- spikiness
- stability
- lumpiness
- spectral entropy
- Hurst exponent
- nonlinearity
- unit root test statistics
- parameter estimates of Holt's linear trend method
- parameter estimates of Holt-Winters' additive method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

Algorithm selection framework

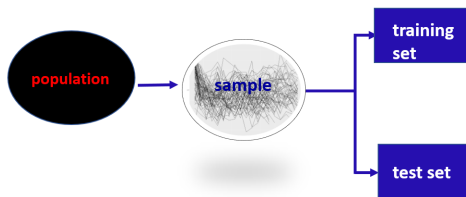


population

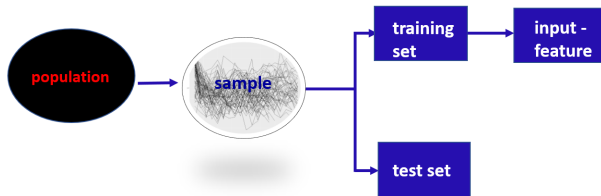
Algorithm selection framework



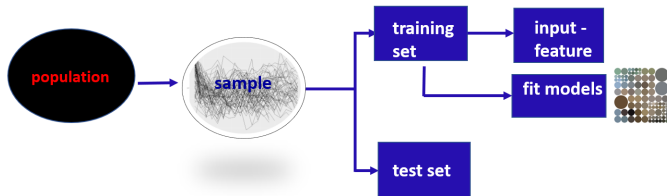
Algorithm selection framework



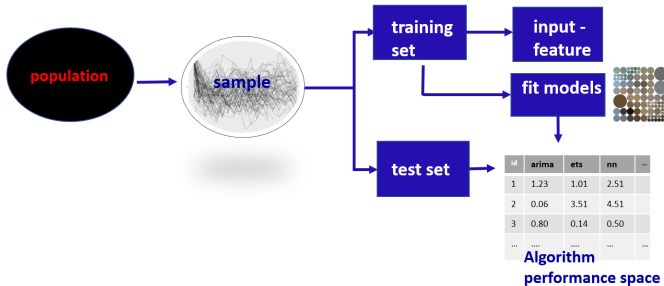
Algorithm selection framework



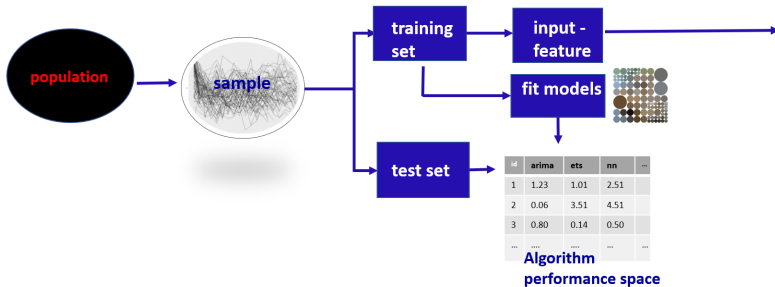
Algorithm selection framework



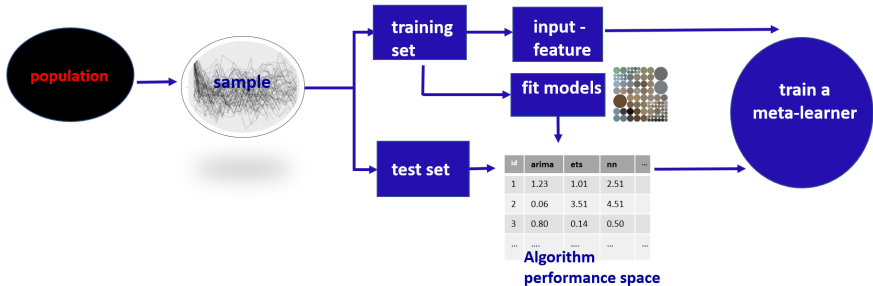
Algorithm selection framework



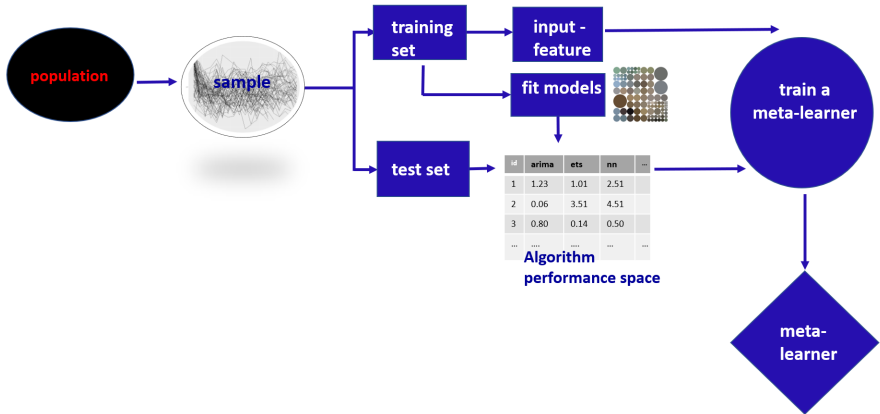
Algorithm selection framework



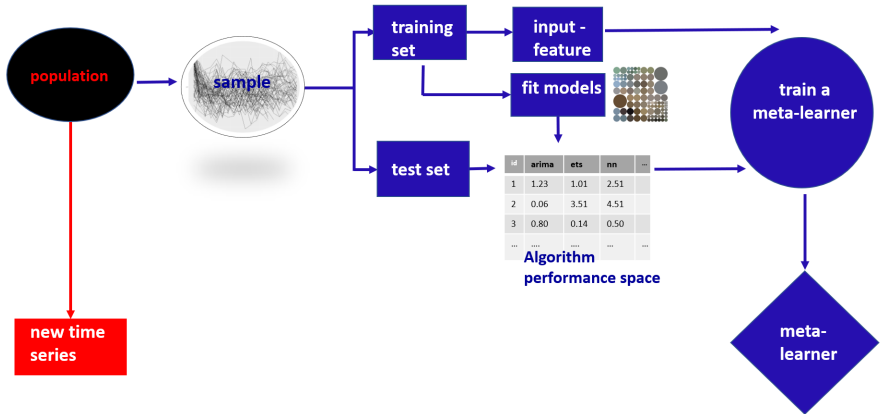
Algorithm selection framework



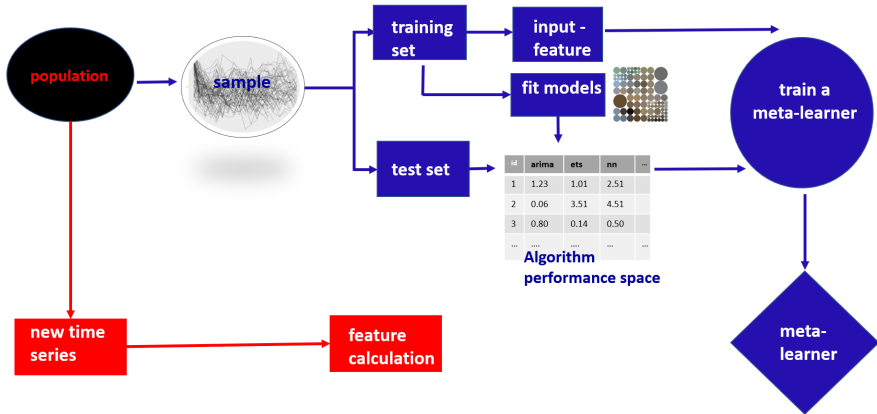
Algorithm selection framework



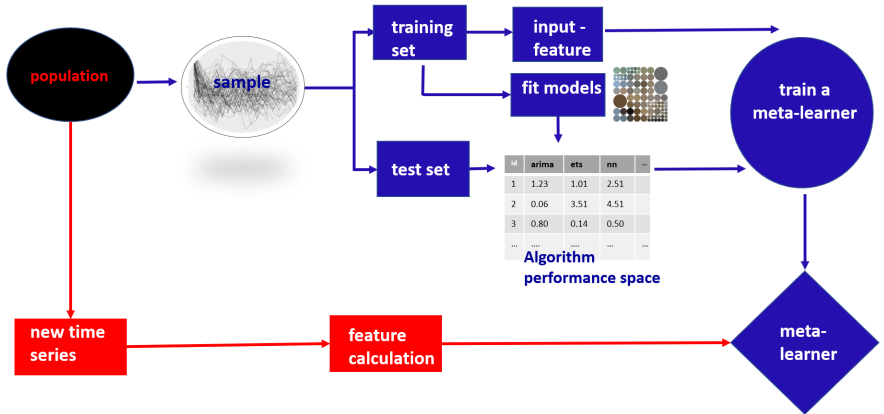
Algorithm selection framework



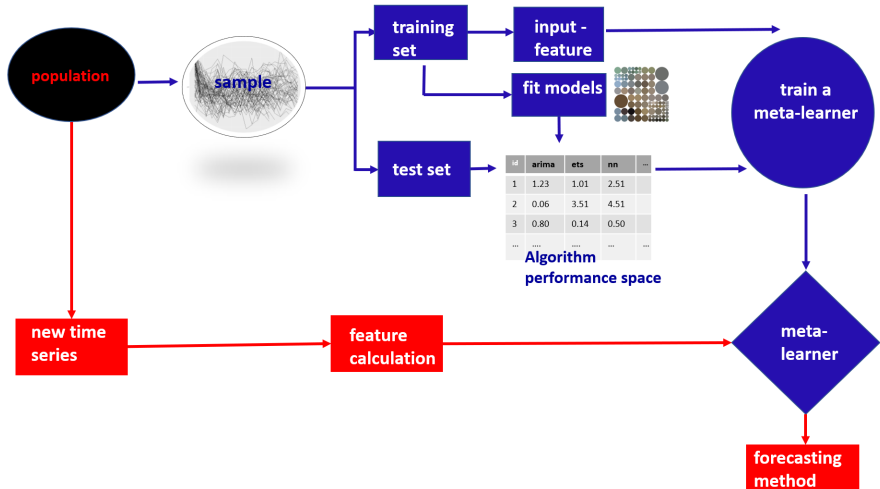
Algorithm selection framework



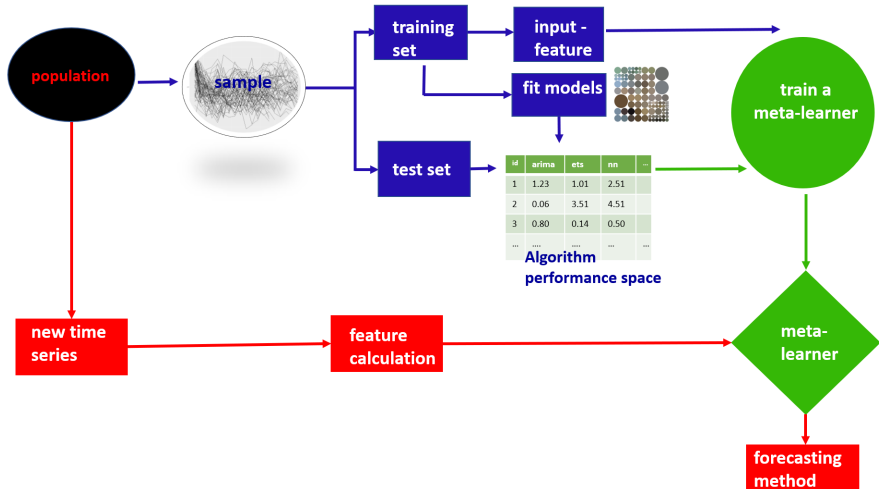
Algorithm selection framework



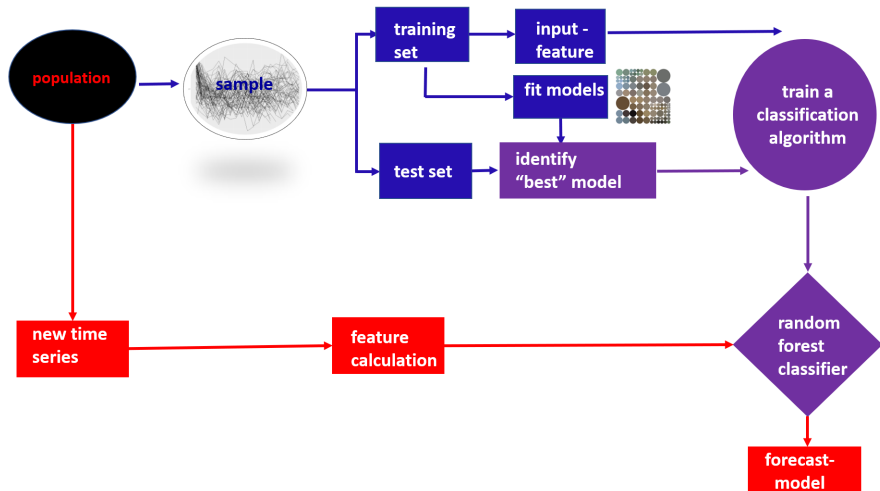
Algorithm selection framework



Algorithm selection framework

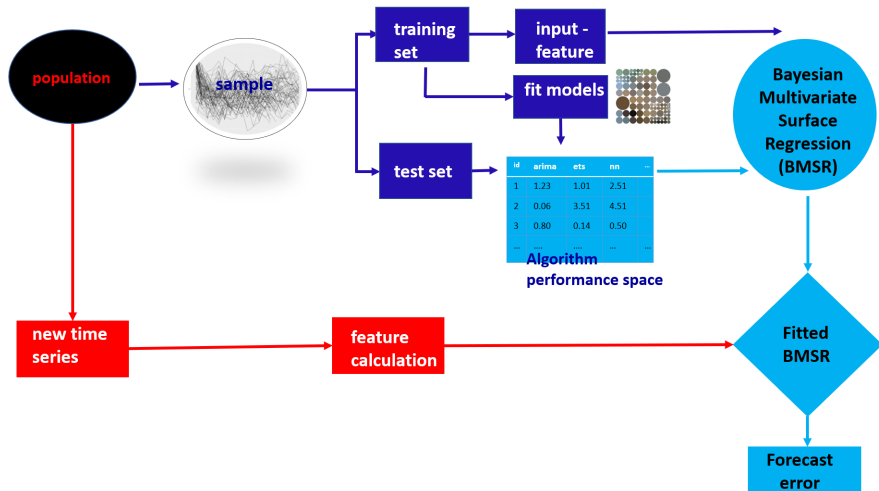


FFORMS: Feature-based FOREcast Model Selection



■ two algorithms: **FFORMS**, FFORMPP

FFORMPP: Feature-based FOREcast Model Performance Prediction



■ two algorithms: **FFORMS**, **FFORMPP**

Installation

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





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Example dataset

observed time series - M1 yearly series (181)

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



Installation

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Example dataset

observed time series - M1 yearly series (181)

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

Input: features

```
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

```
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 11.819470  
YAF3  5.713867  7.704409  7.78949  6.225463  6.700766
```

```
$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

```
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

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

Predictions

```
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

```
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	...	arma
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



- 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

Installation

```
devtools::install_github("thiayangt/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

```
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/thiyanagt/seer

- **fformpp**: FFORMPP

github.com/thiyanagt/fformpp

Papers and Slides

thiyanaga.netlify.com/talk/user19-talk/

email: thiyanaga.talagala@monash.edu