MONASH University

MONASH BUSINESS SCHOOL

Peeking inside FFORMS: Feature-based FORecast-Model Selection

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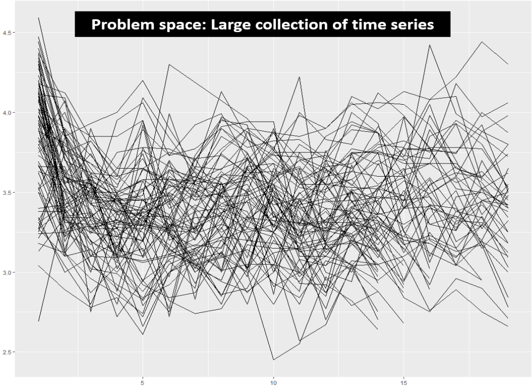
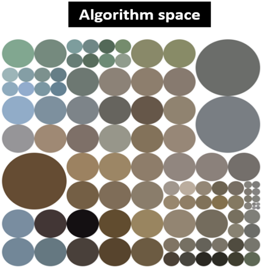
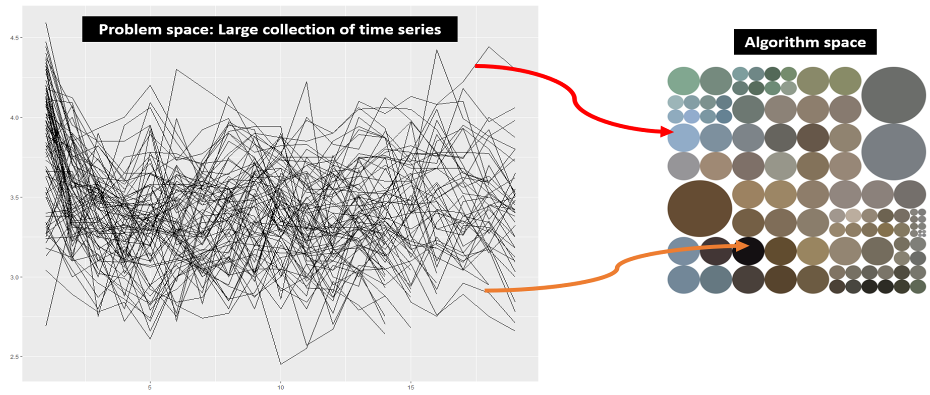
Big picture





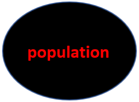
- What algorithm is likely to perform best?

Big picture



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

FFORMS: Feature-based FORecast Model Selection



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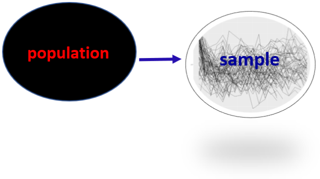

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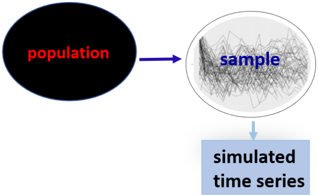

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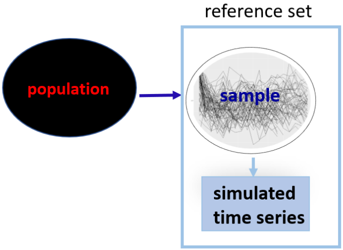

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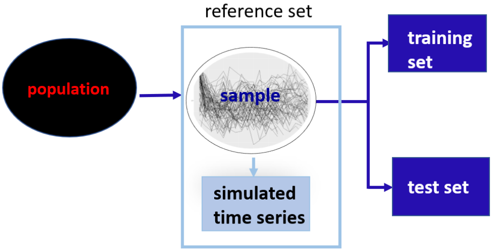

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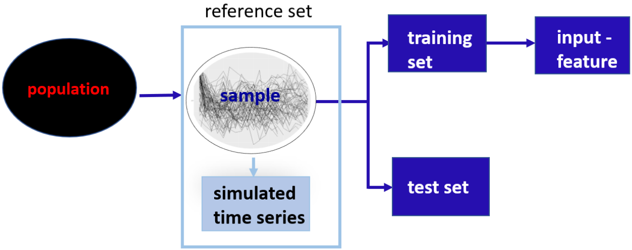

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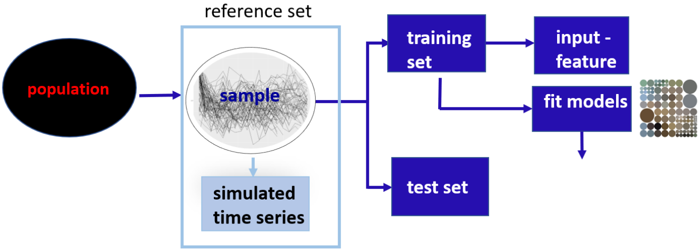

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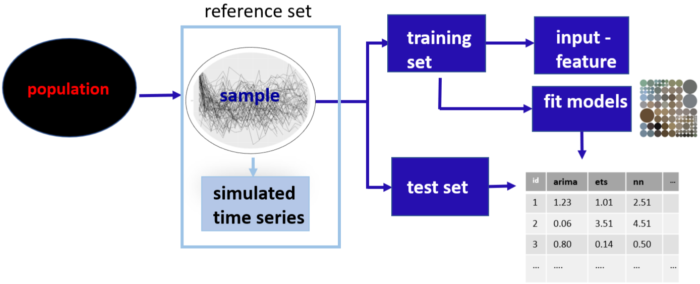

id	arima	ets	nn	...
1	1.23	1.01	2.51	
2	0.06	3.51	4.51	
3	0.80	0.14	0.50	
...	....	....	...	...

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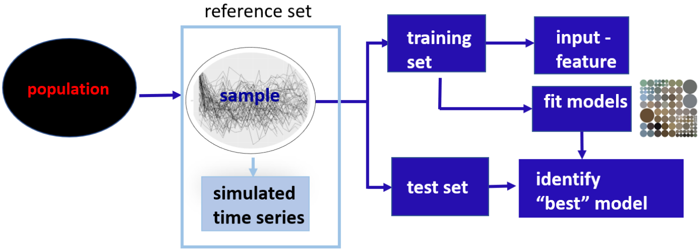

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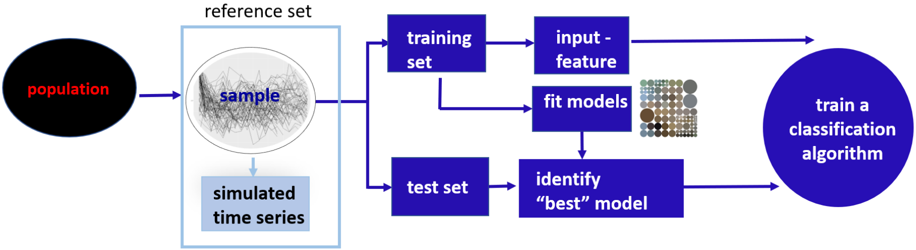

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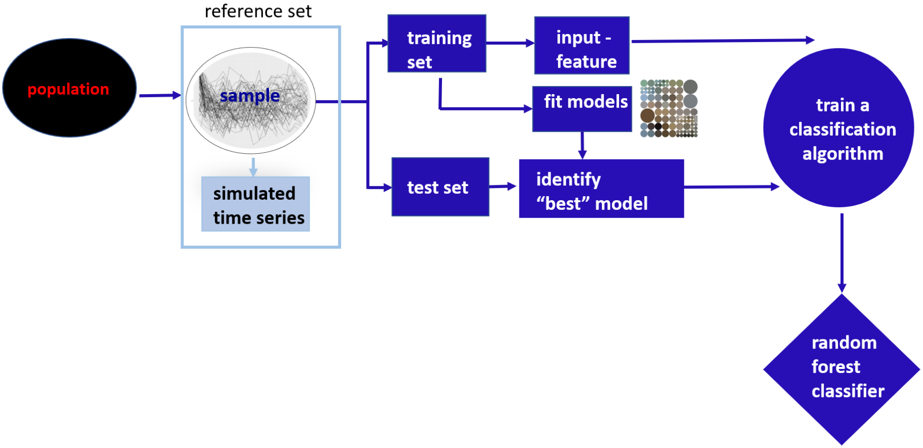

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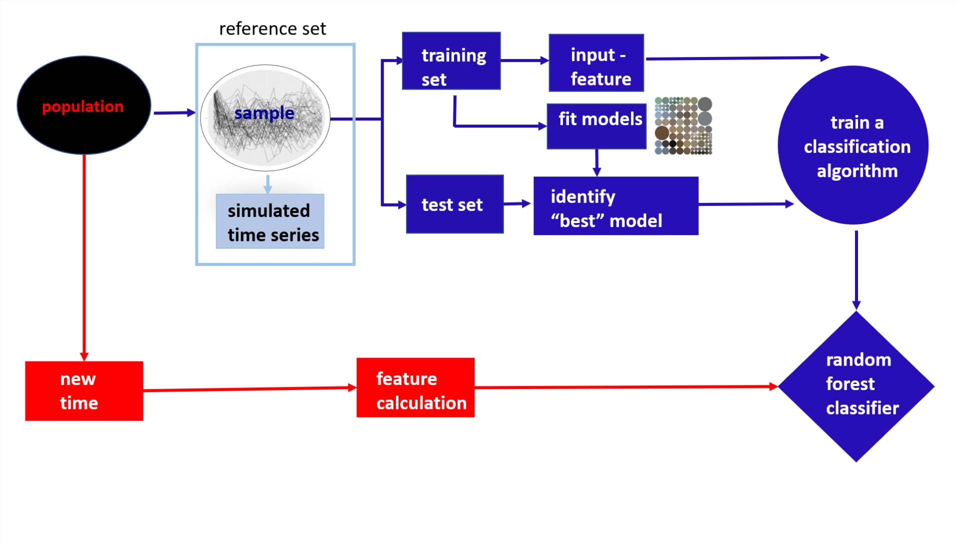

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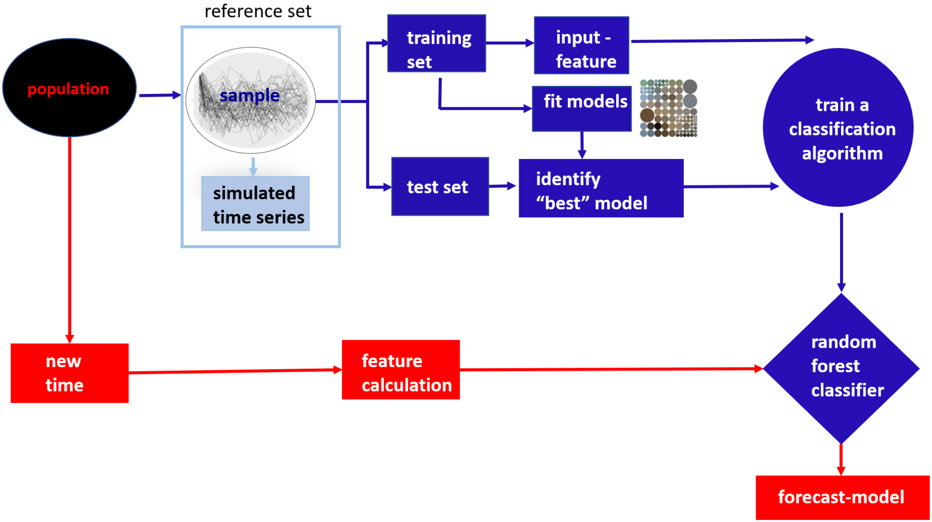

Forecast-models included

- White noise process
- ARMA/AR/MA
- ARIMA
- SARIMA
- Random walk with drift
- Random walk
- Seasonal naive
- TBATS
- neural network forecasts
- Theta method
- STL-AR
- ETS-without trend and seasonal
- ETS-trend
- ETS-damped trend
- ETS-trend and seasonal
- ETS-damped trend and seasonal
- ETS-seasonal
- MSTL-ETS
- MSTL-ARIMA

Time series 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.

Results: M4 Competition data

	Yearly	Quarterly	Monthly	Weekly	Daily	Hourly
FFORMS	3.17	1.20	0.98	2.31	3.57	0.84
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

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- Can we trust ML-algorithms if we don’t know how it works?

Peeking inside FFORMS!!!

- Which features are the most important?
- Where they get important?
- How they get important?
- When and how these features linked with the prediction outcome?
- When and how strongly each feature interact with other features?

Global explanation of feature contribution

Overall role of features in the choice of different forecast-model selection.

- contribution to predictive accuracy
  - Permutation-based variable importance
  - Mean decrease in Gini coefficient
- causality: change in the value of Y for a increase or decrease in the value of x
  - Partial dependence plots (Jerome H. Friedman, 2001)
  - Individual Conditional Expectation (ICE) curves (Goldstein et al., 2015; Zhao and Hastie, 2017)

Partial dependence plots and ICE curves

x1	x2	x3
11	4	5
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x1	x2	x3	$\hat{f}^i(\text{x1})$	$\overline{f}(\text{x1})$
11	4	5	$\hat{f}^1(11)$	$\frac{\sum \hat{f}^i(11)}{2}$
11	6	7	$\hat{f}^2(11)$	
12	4	5	$\hat{f}^1(12)$	$\frac{\sum \hat{f}^i(12)}{2}$
12	6	7	$\hat{f}^2(12)$	

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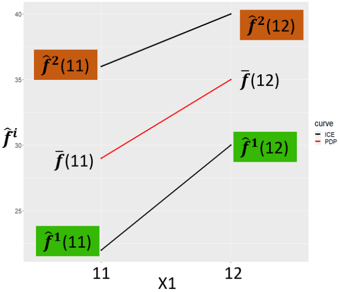

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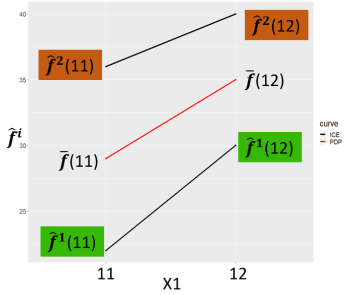
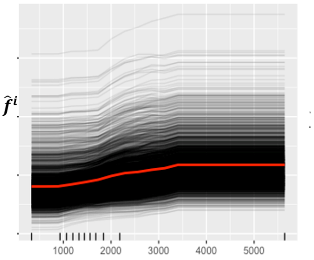


More than 2 observations and more than 2 levels

PDP



Partial dependence curve and ICE curves

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11	6	7	$\hat{f}^2(11)$	
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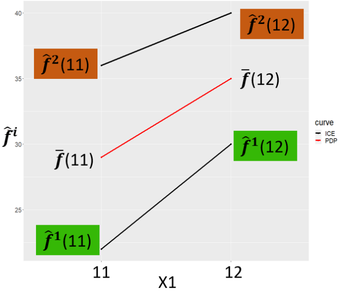

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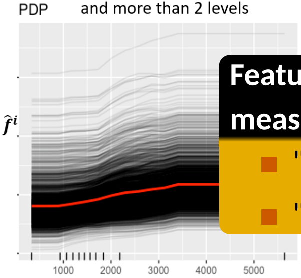
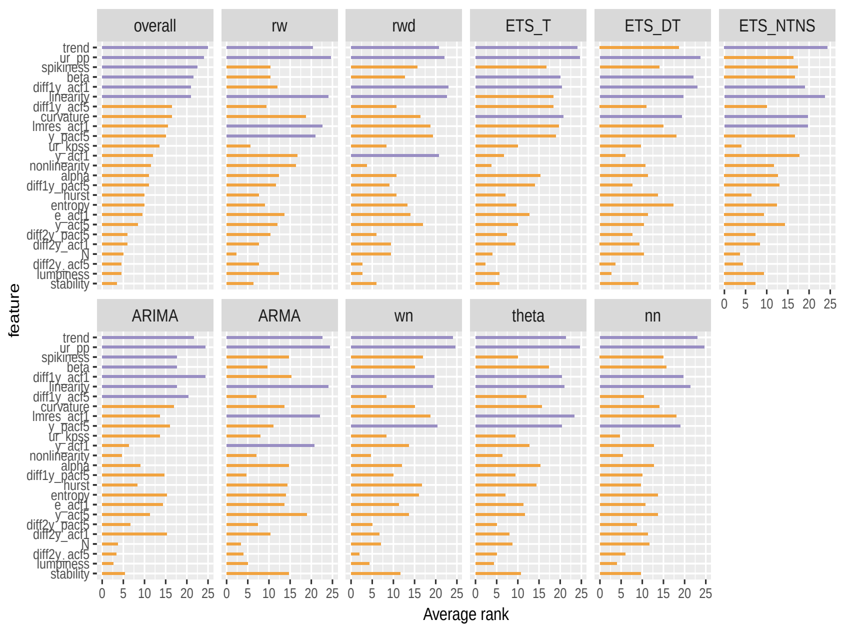


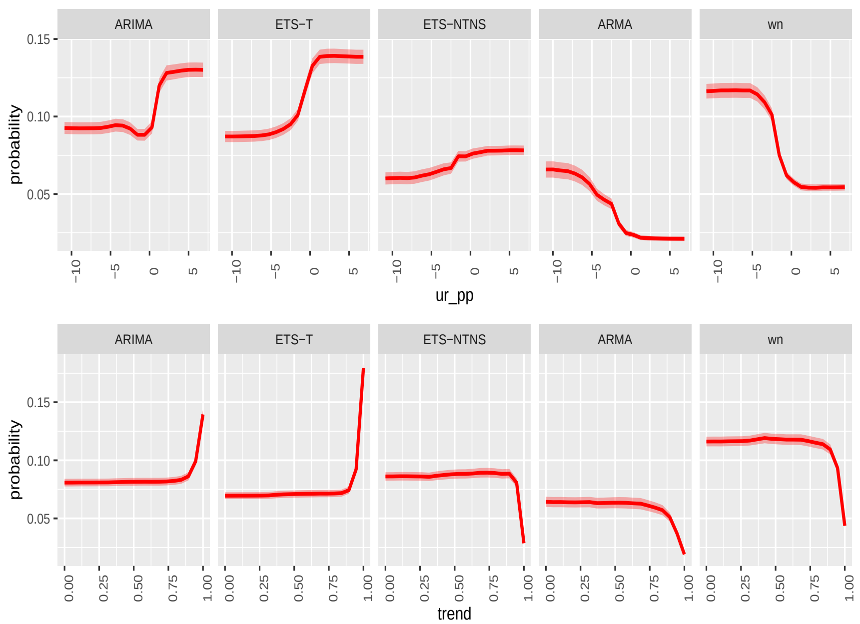
Feature importance measures:

- "flatness" of PD curve
- "flatness" of ICE curves

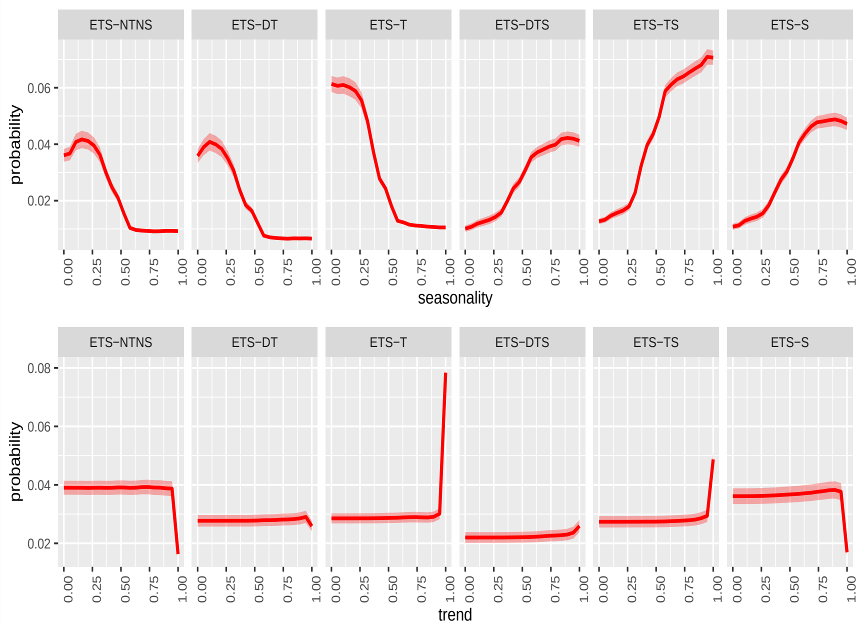
Feature importance plot for yearly data



Partial dependency plots for yearly data

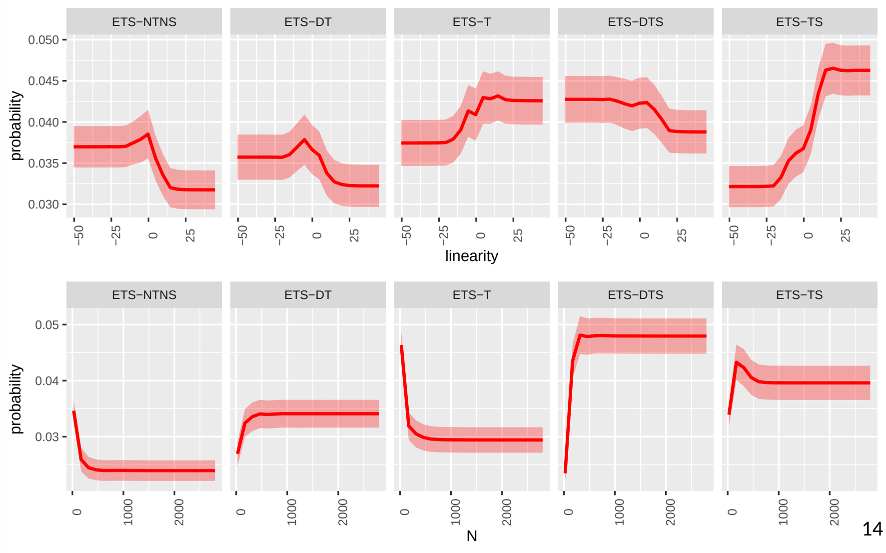


Partial dependency plots for quarterly data



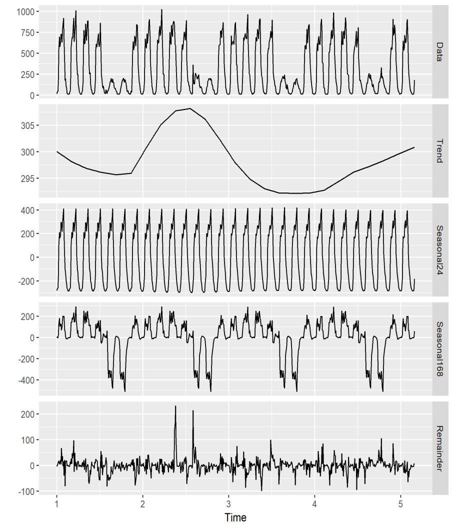
Partial dependency plots for monthly data

linearity: estimated value of β_1 based on $T_t = \beta_0 + \beta_1\phi_1(t) + \beta_2\phi_2(t) + \varepsilon_t$



Hourly series

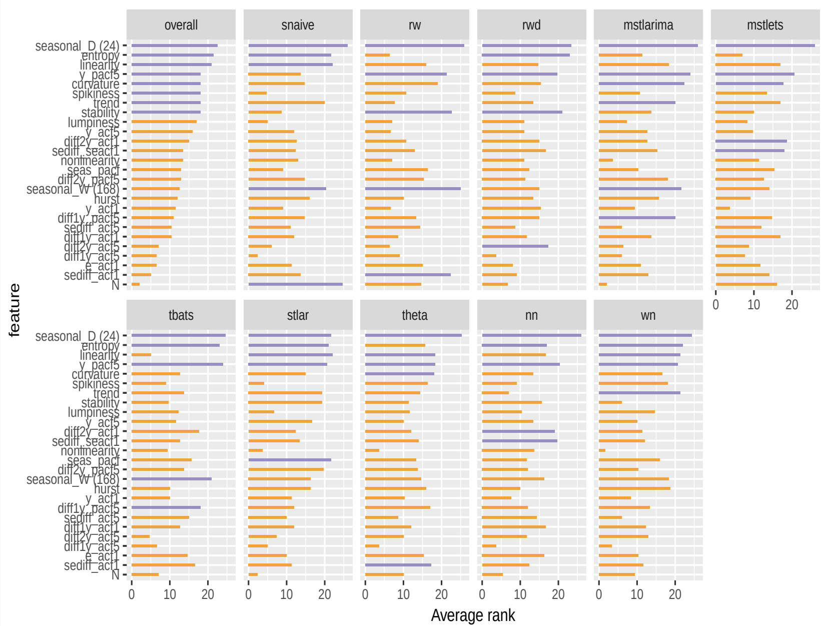
- multiple seasonality



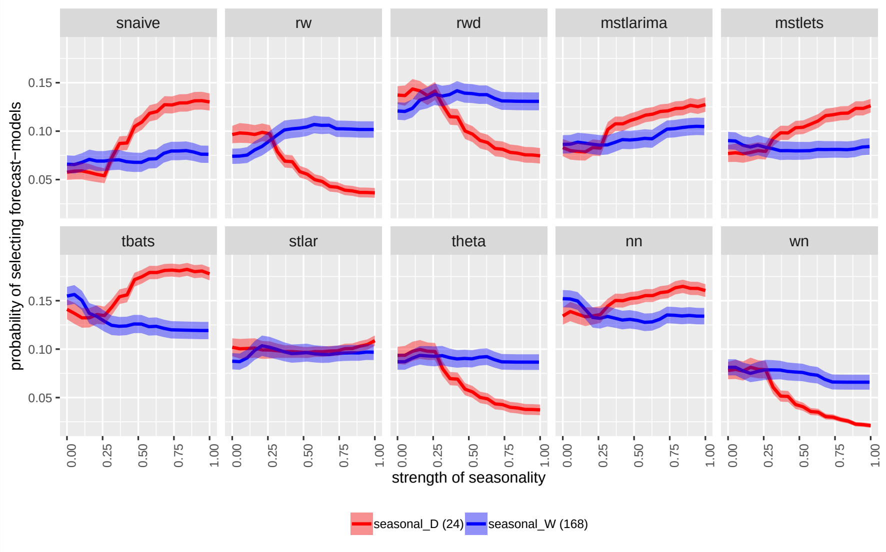
Hourly data

- daily - 24
- weekly - 168

Feature importance plot for hourly data

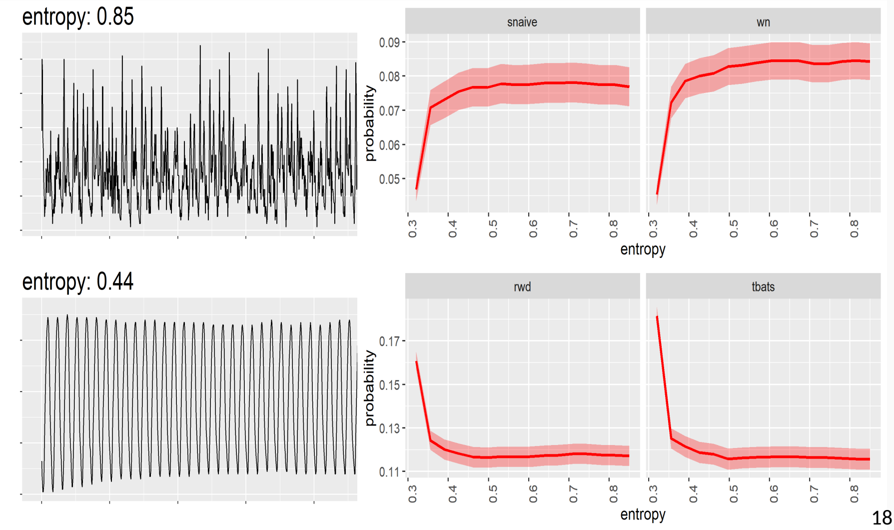


Partial dependency plots for hourly data: Seasonality



Partial dependency plots for hourly data: entropy

- forecastability of a time series



Interaction effect

- Friedman's H-statistic

fraction of variance of two-variable partial dependency not captured by sum of the respective individual partial dependencies.

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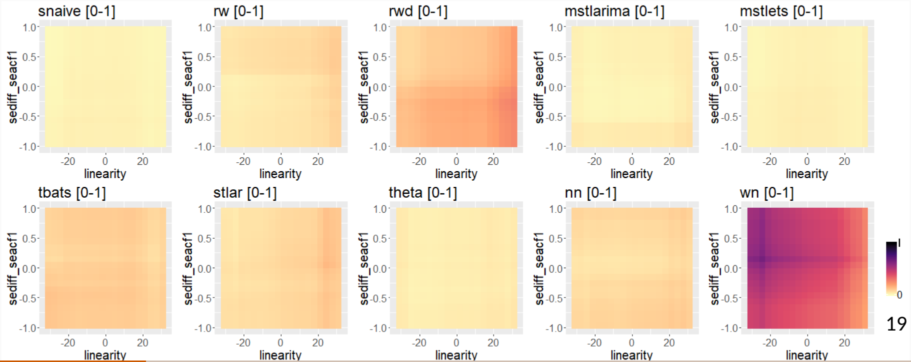
Hourly: interaction between linearity and seasonal lag at seasonally-differenced series



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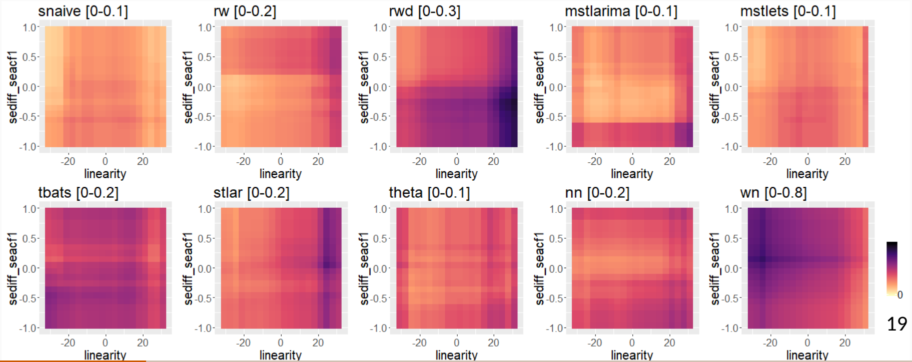

Discussion

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- Global perspective of feature contribution: the overall role of features in the choice of different forecast-models
- The displayed relationships of partial dependency plots consistent with the domain knowledge expectations.
- What next? Local perspective of feature contribution: zoom into local regions of the data to identify which features contribute most to classify a specific instance.