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Demand Forecasting in Supply Chains: Aggregation and Hierarchical Approaches
Bahman Rostami-Tabar (@Bahman_R_T)
Website www.bahmanrt.com
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Outline

- What is a hierarchical and grouped time series, and why they are essential in forecasting?
- What are common approaches to forecast hierarchical/groupoed time series?
- What is temporal aggregation, what are different TA approaches and how it may affect time series features?
- Given a high frequency time series (e.g. daily), If we want a lower frequency forecast(e.g. weekly), should we first forecast and aggregate them or first aggregate time series and forecast?

Terminilogy

One time series

- Time granularity
- Temporal aggregation / temporal hierarchies

Collection of time series

- Cross-sectional aggregation / hierarchical / grouped

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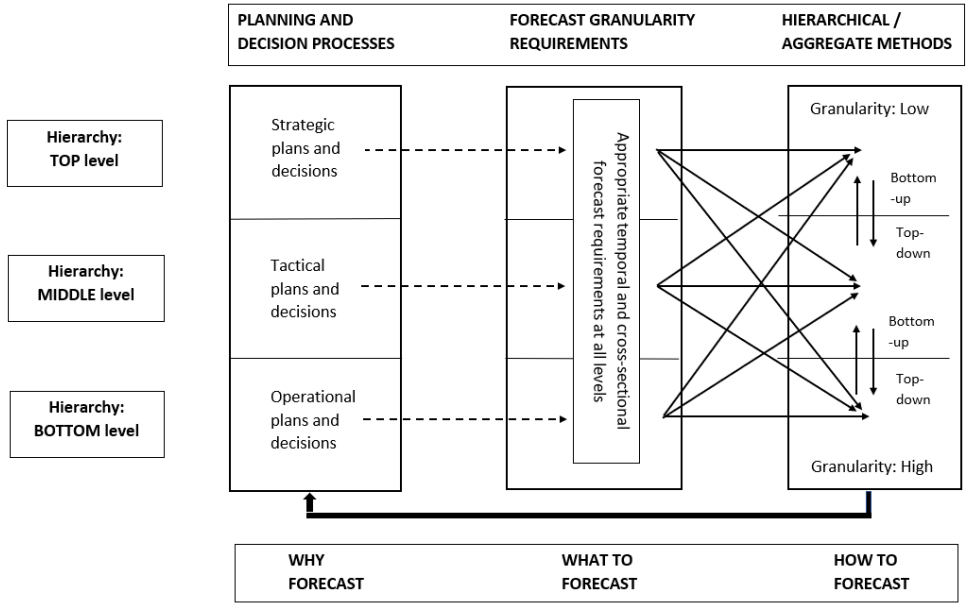
Informing decisions in multiple levels

- Multiple decisions
- Multiple level of forecasting requirements
- Coherency between different levels
- Using information avaialble at multiple levels



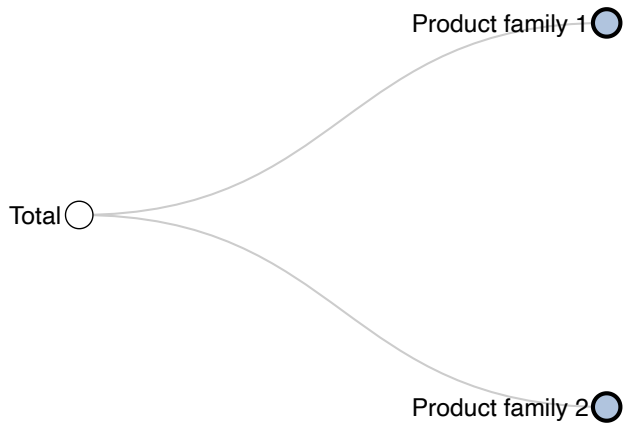
Hierarchical time series

A hierarchical time series is a collection of several time series that are linked together in a hierarchical structure (unique structure).

Grouped time series

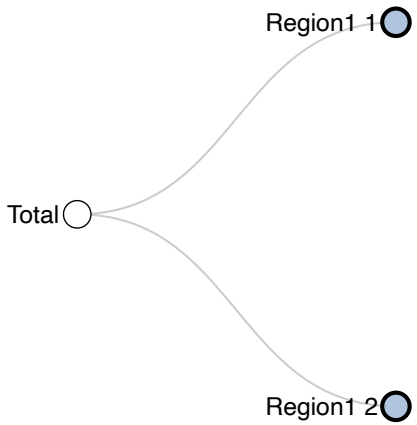
A grouped time series is a collection of time series that can be grouped together in a number of non-hierarchical ways.

Grouped time series

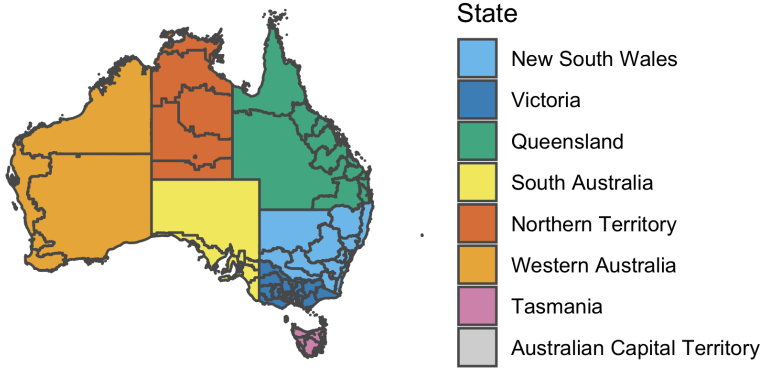


Hierarchical & Grouped time series

Ambulance attendance



Australian tourism regions



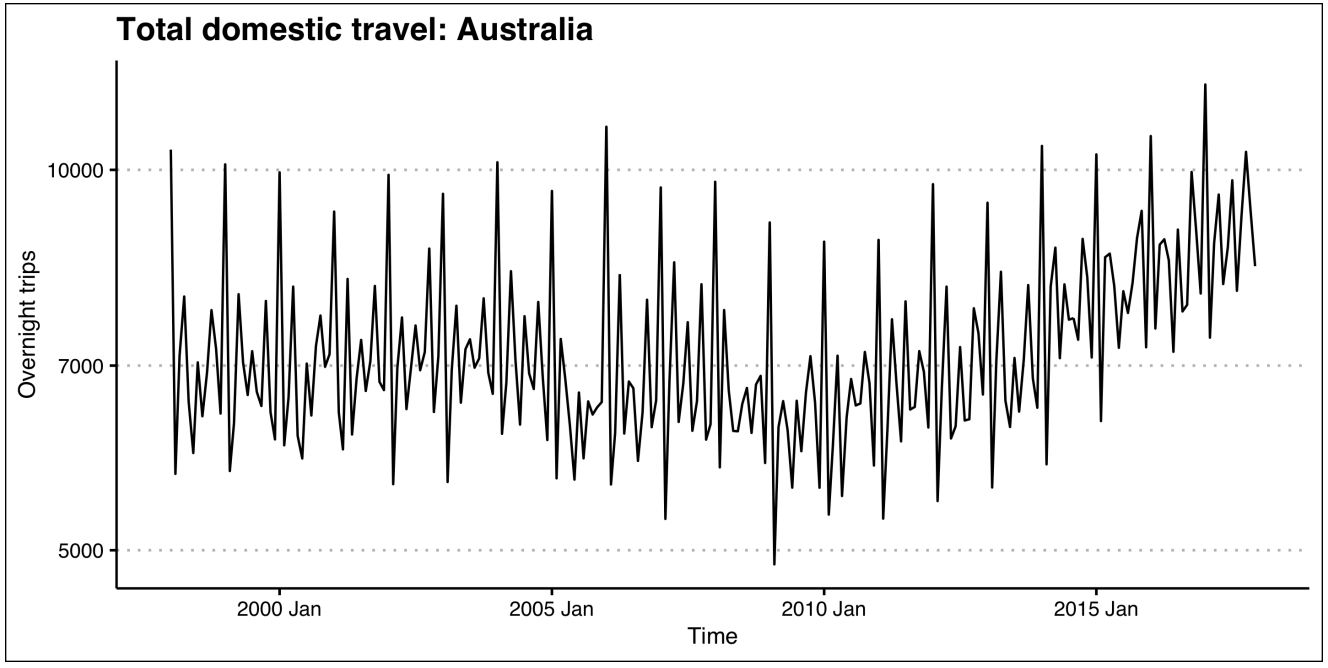
Australian tourism data

- Monthly data on visitor night from 1998 -- 2017
- Geographical hierarchy split by
  - 7 states
  - 27 zones
  - 75 regions

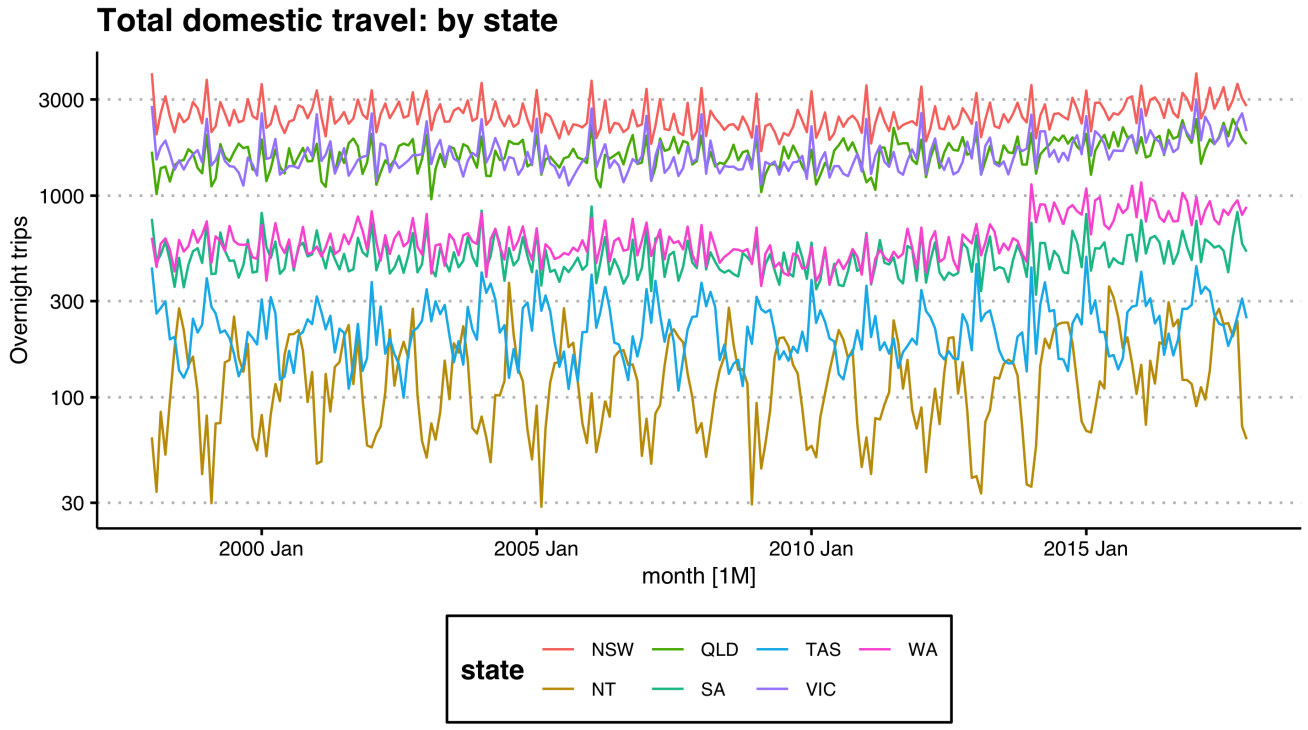
Australian tourism data

```
#> # A tsibble: 18,000 x 5 [1M]
#> # Key:       state, zone, region [75]
#>      month state zone      region visitors
#>      <mth> <chr> <chr>     <chr>     <dbl>
#> 1 1998 Jan NSW   Metro NSW Sydney     926.
#> 2 1998 Feb NSW   Metro NSW Sydney     647.
#> 3 1998 Mar NSW   Metro NSW Sydney     716.
#> 4 1998 Apr NSW   Metro NSW Sydney     621.
#> 5 1998 May NSW   Metro NSW Sydney     598.
#> 6 1998 Jun NSW   Metro NSW Sydney     601.
#> # … with 17,994 more rows
```

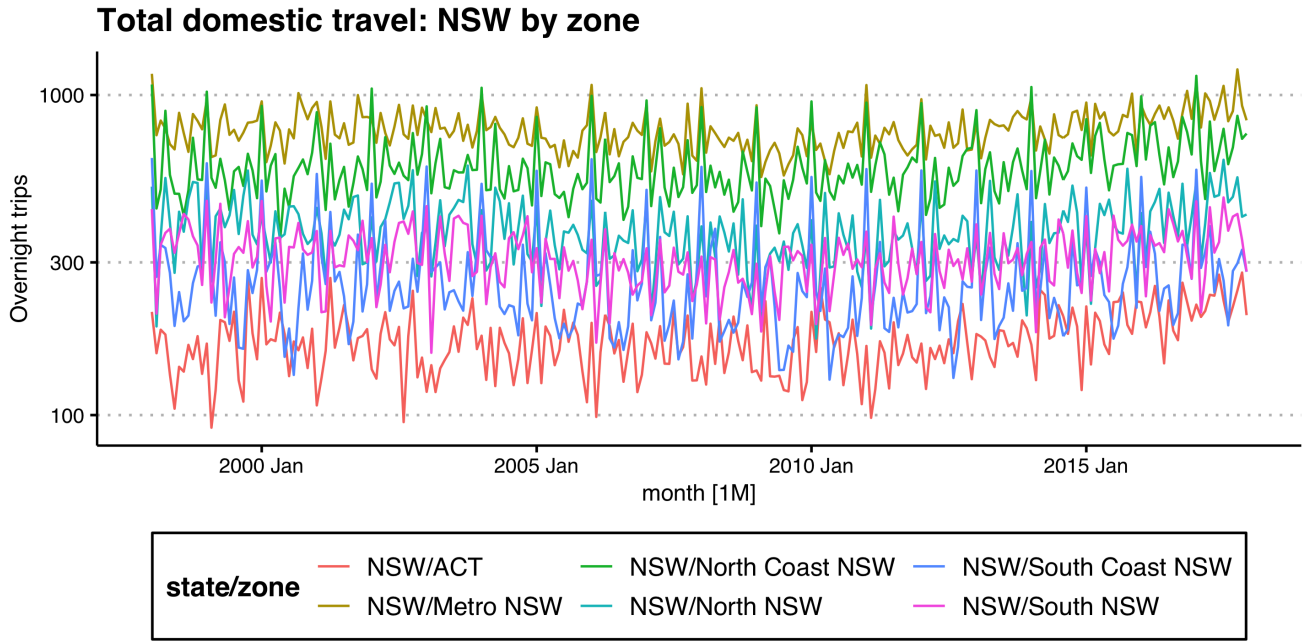
Australian tourism data



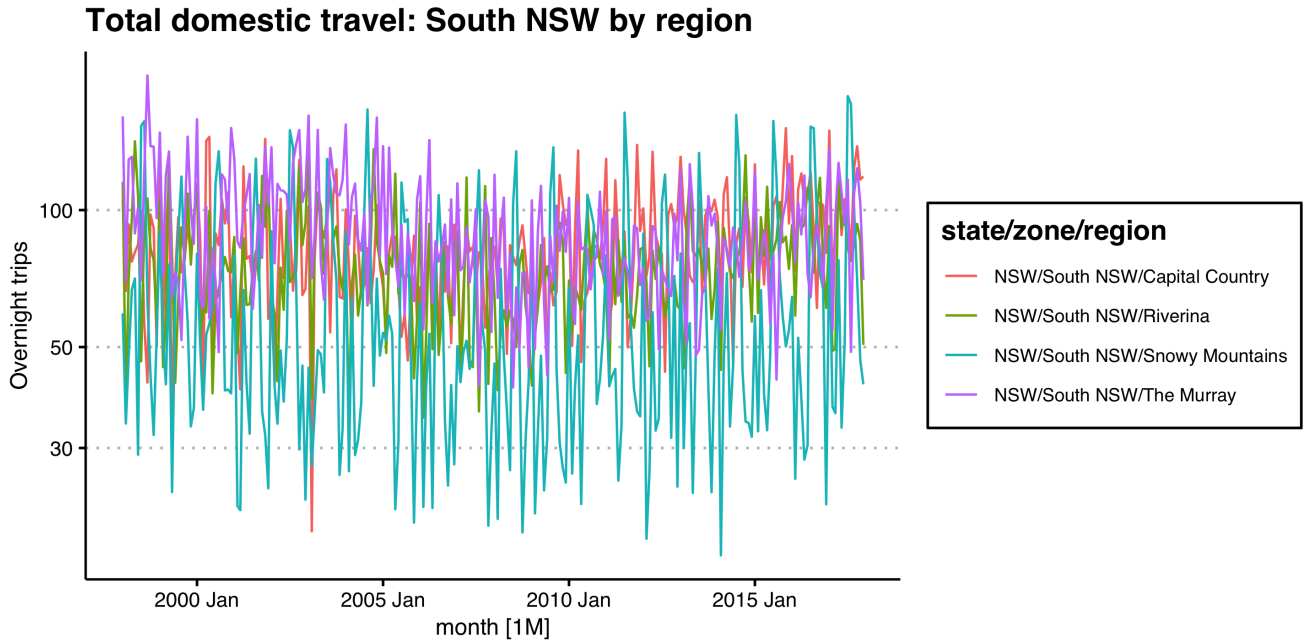
Australian tourism data



Australian tourism data



Australian tourism data



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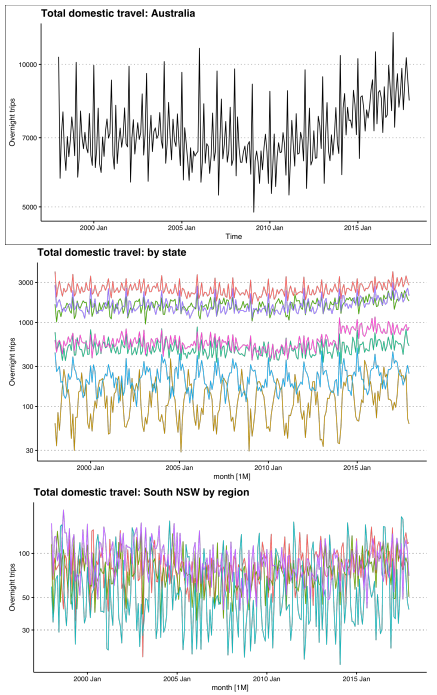
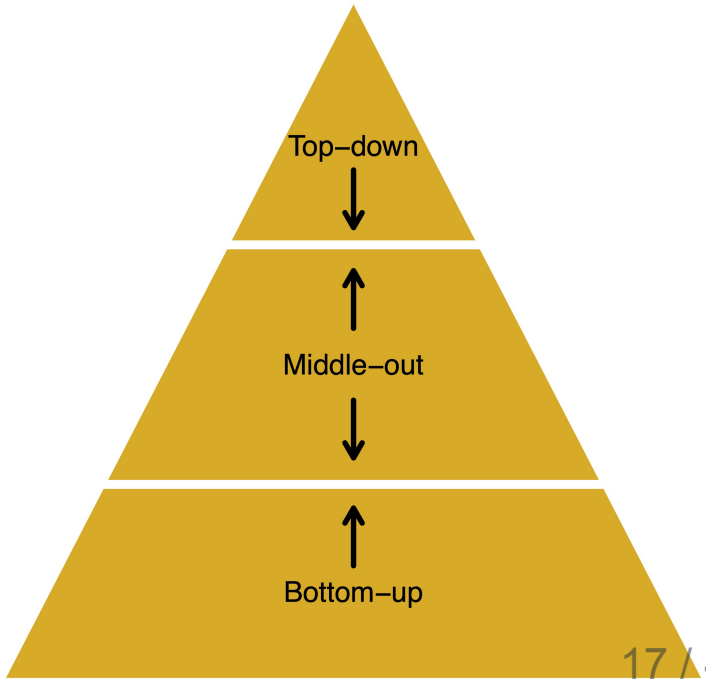
How to forecast hierarchical/grouped series?

Hierarchical series



Hierarchical forecasting approaches



Optimal reconceiliation

- This approach involves first generating independent base forecast for each series in the hierarchy.
- As these base forecasts are independently generated they will not be “aggregate consistent” (i.e., they will not add up according to the hierarchical structure).
- The optimal combination approach optimally combines the independent base forecasts and generates a set of revised forecasts that are as close as possible to the univariate forecasts but also aggregate consistently with the hierarchical structure.
- Unlike any other existing method, this approach uses all the information available within a hierarchy.

Research gaps

- There is a need to examine empirically the validity of these theoretical developments in supply chains
- Very little research has examined the association between characteristics of time series and the performance of approaches
- The potential benefit of incorporating exogenous variables in a hierarchy structure still needs to be examined
- Using probabilistic forecasting in hierarchies instead of point forecast in supply chains
- The theoretical developments in this area do not support the count nature of time series
- Investigating the benefit beyond forecast accuracy

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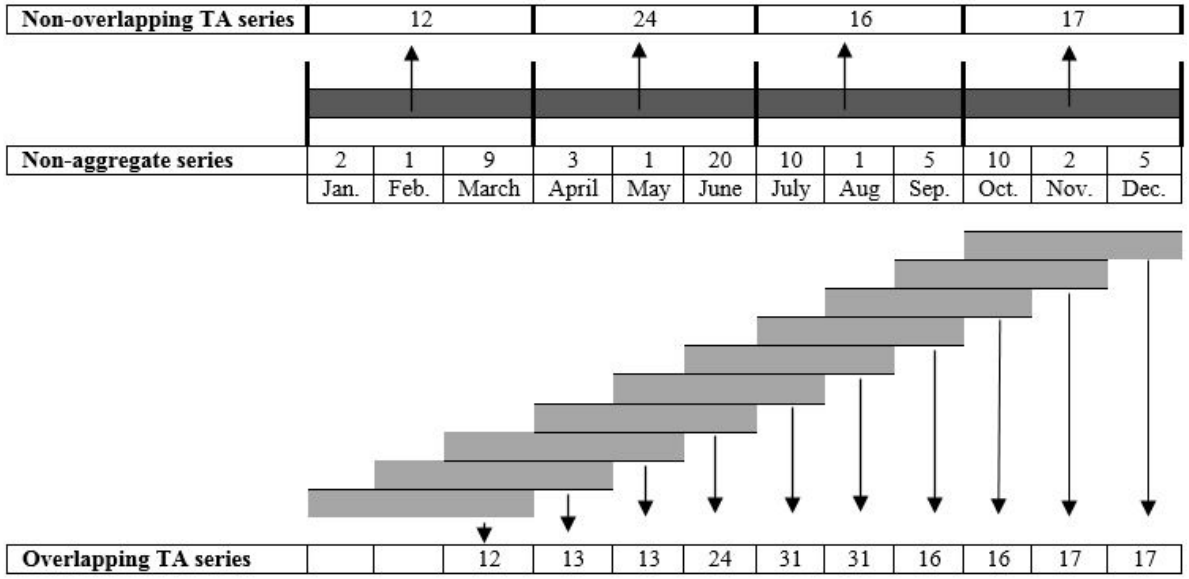
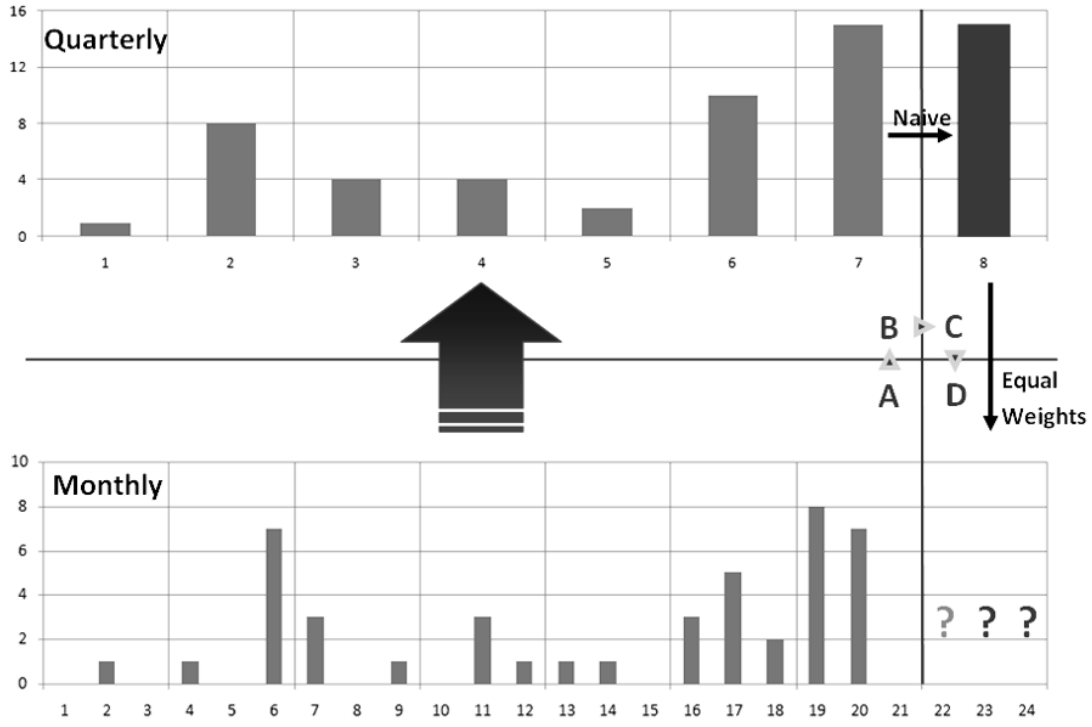
Temporal aggregation approaches



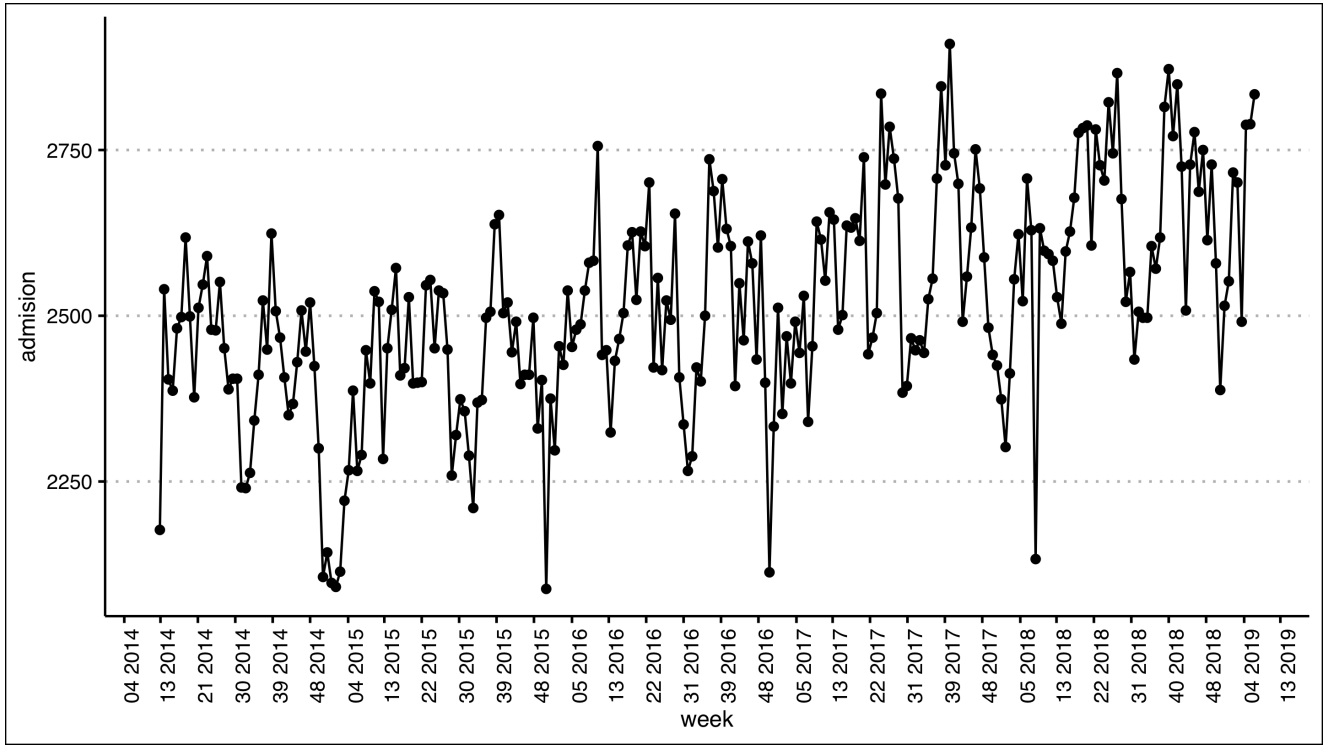
Using TA (non-overlapping) to forecast



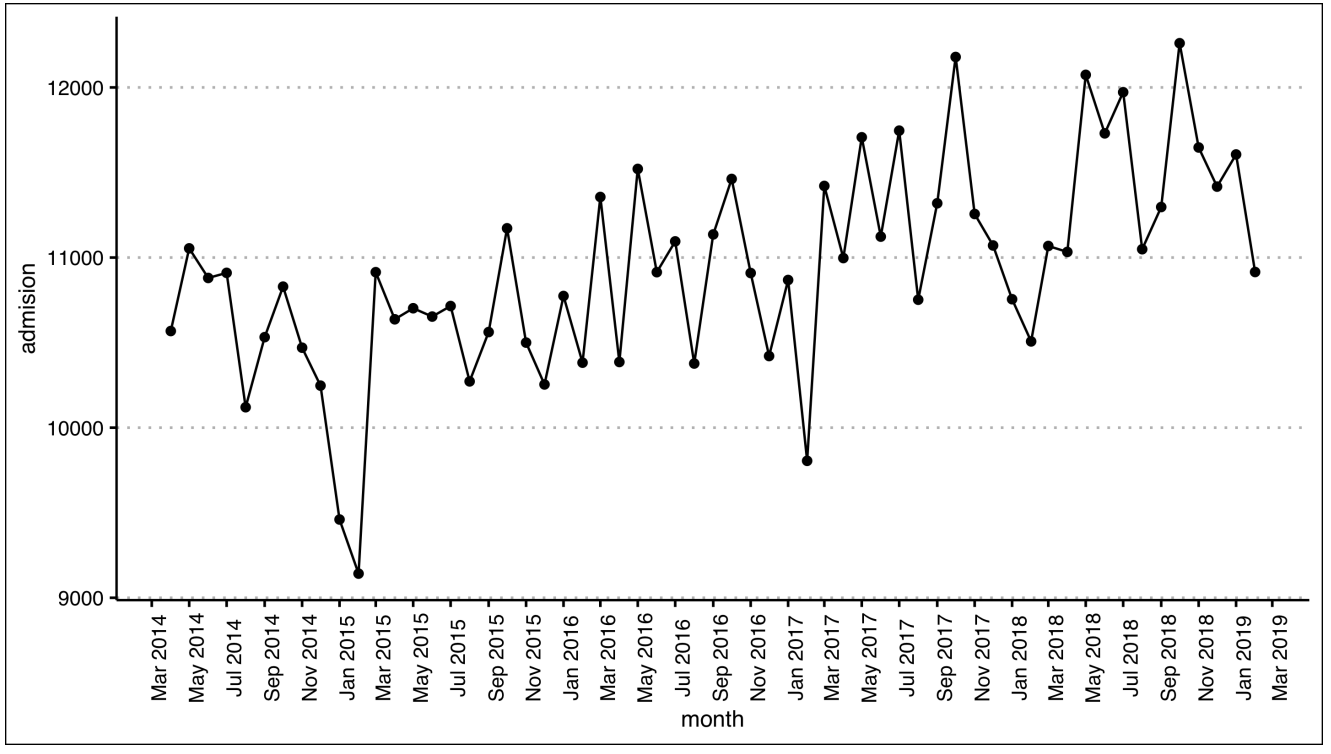
Hourly time series: ambulance attendance

Daily time series: ambulance attendance

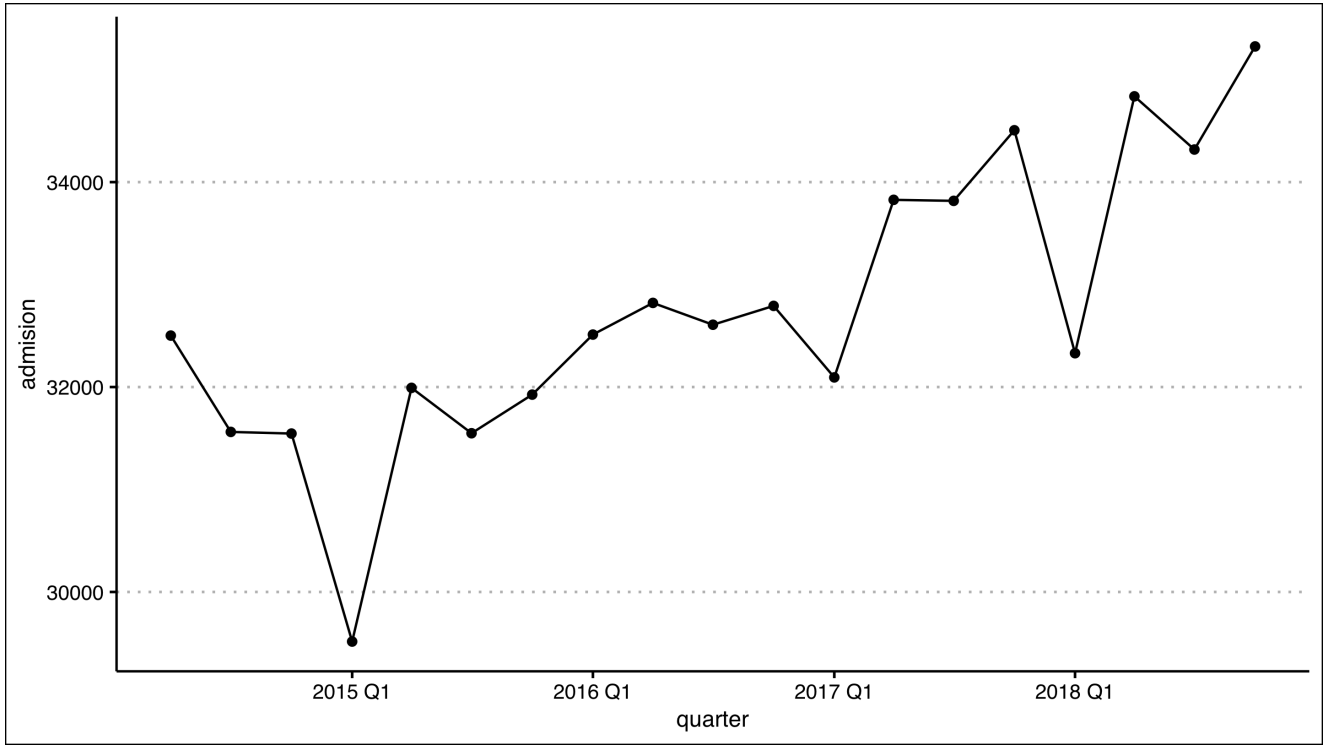
Weekly time series: ambulance attendance



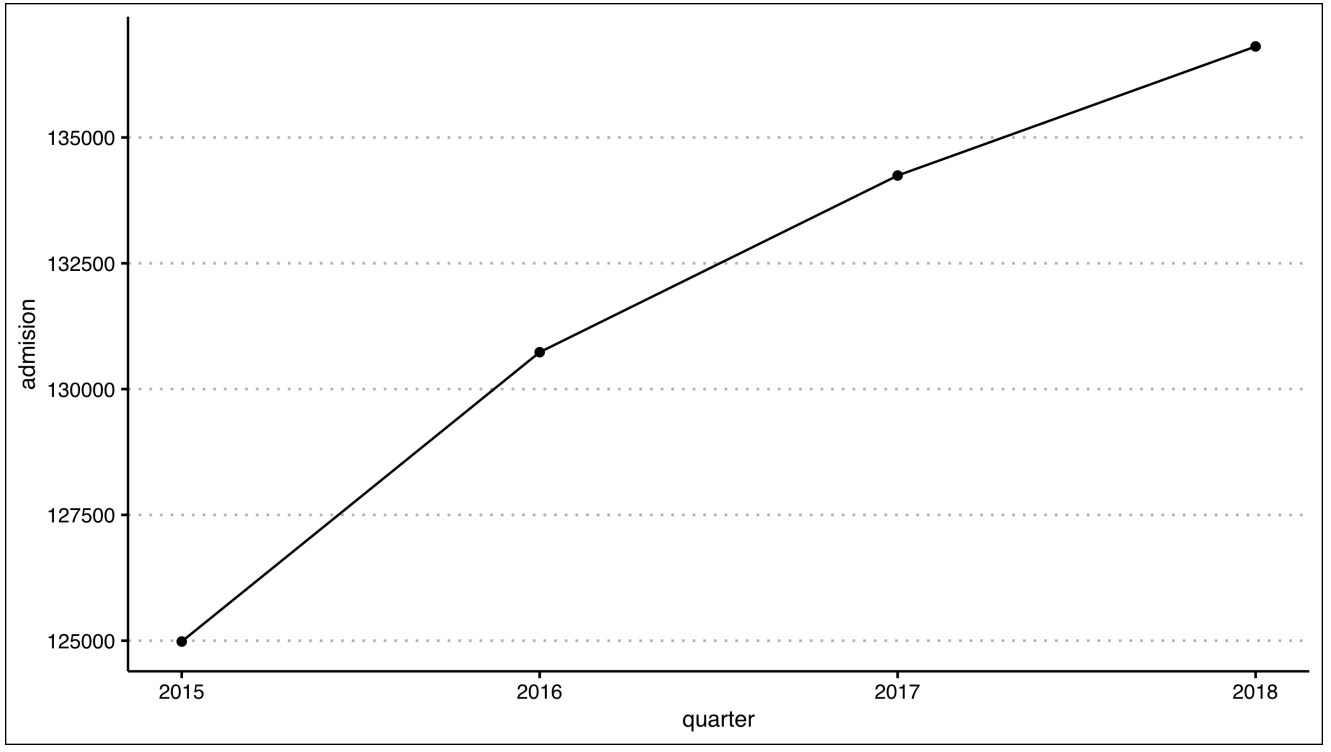
Monthly time series: ambulance attendance



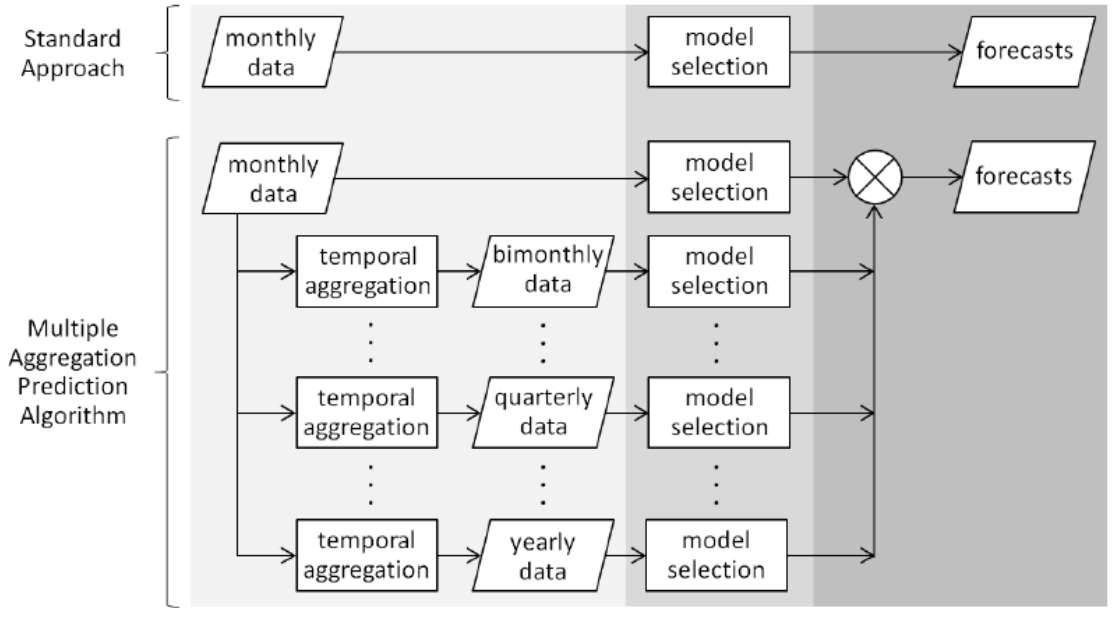
Quarterly time series: ambulance attendance



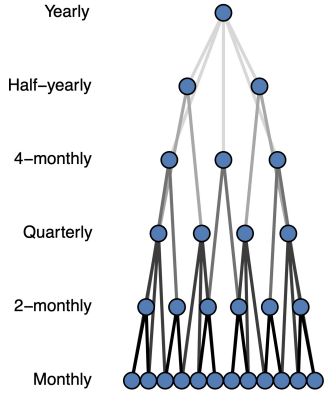
Yearly time series: ambulance attendance

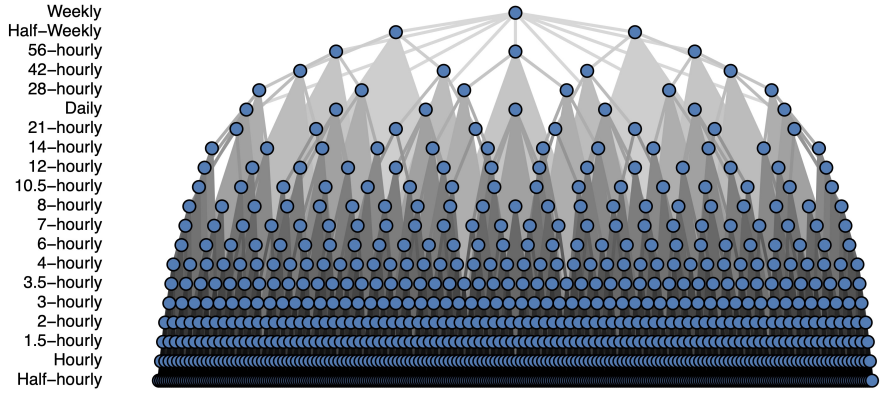


Using information in multiple levels: MAPA



Using information in multiple levels: temporal hierarchies





Research gaps

- We are still unclear when overlapping, non-overlapping or BU should be used
- Investigate the association between time series features and the performance of each approach
- Investigate TA on high frequency time series (e.g. hourly)
- Linking forecast to utility measures
- TA research has been built on the non-overlapping aggregation assumption, the characteristics of time series when aggregated with an overlapping approach have not been fully identified yet
- Using probabilistic forecast rather than only point forecast

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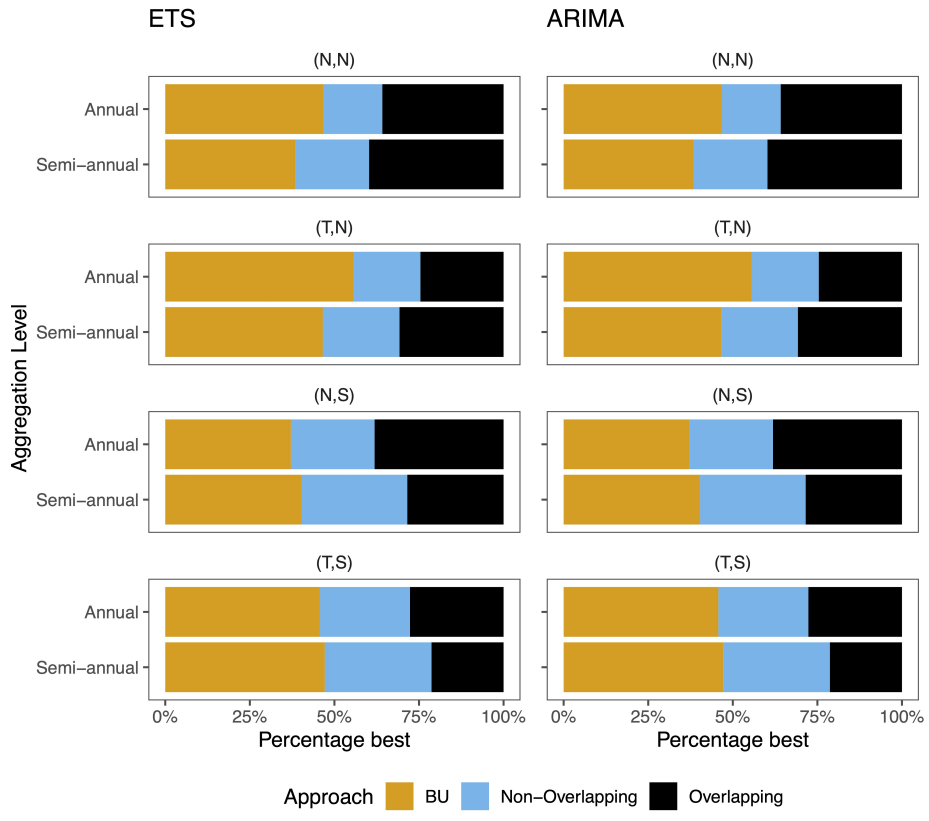
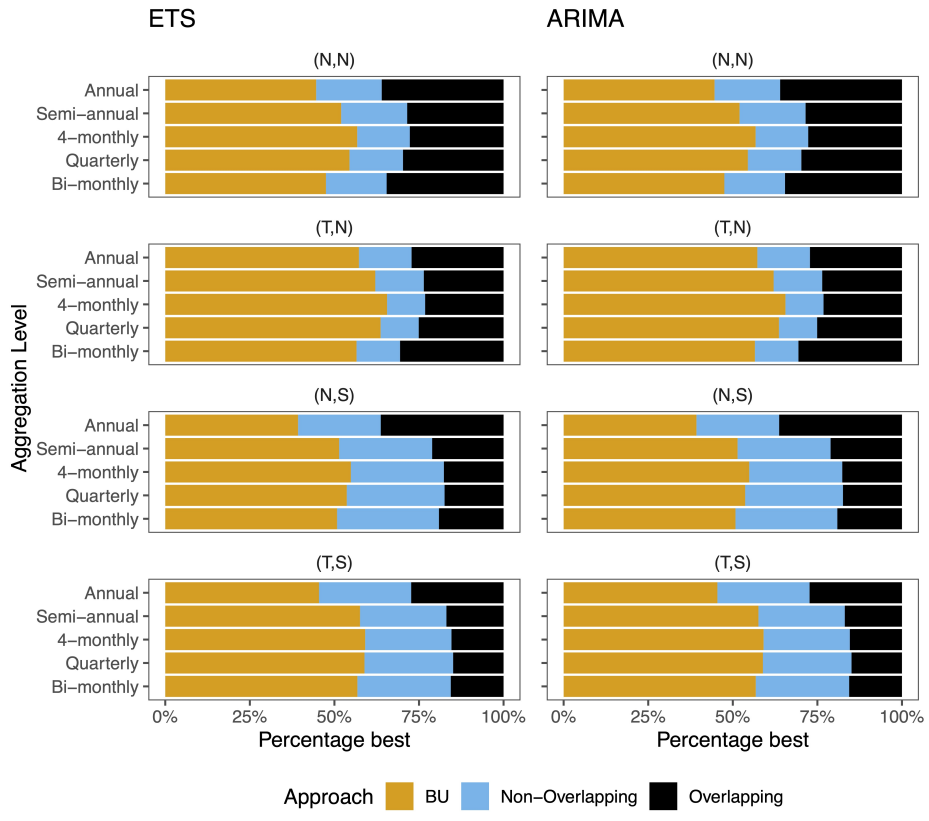
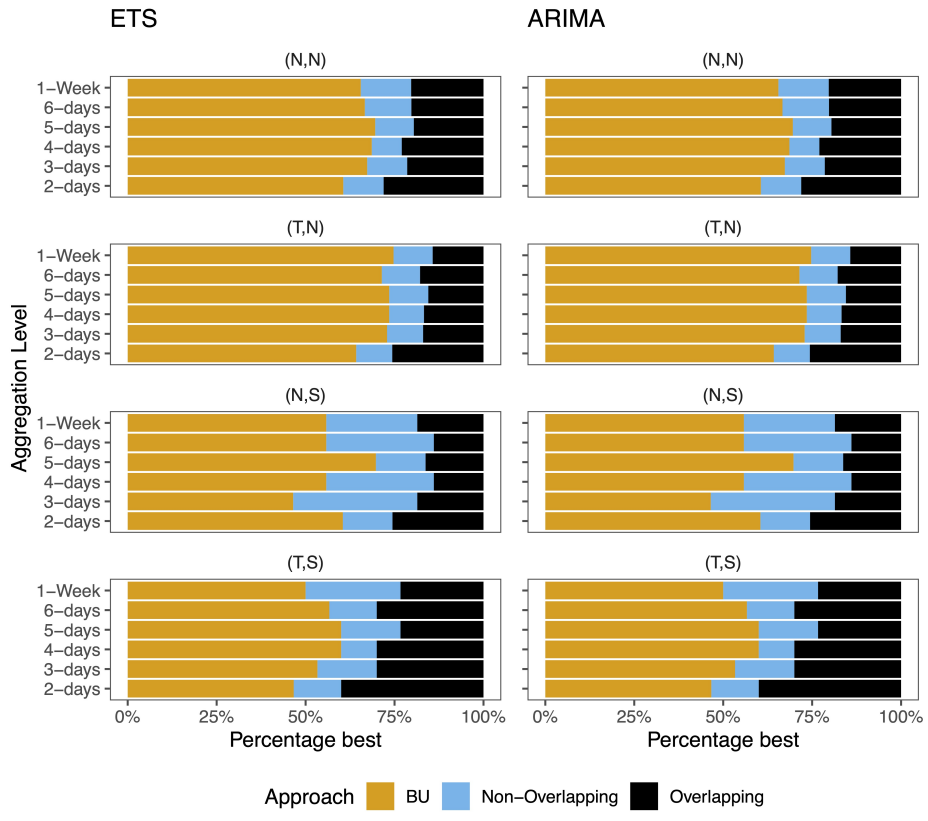
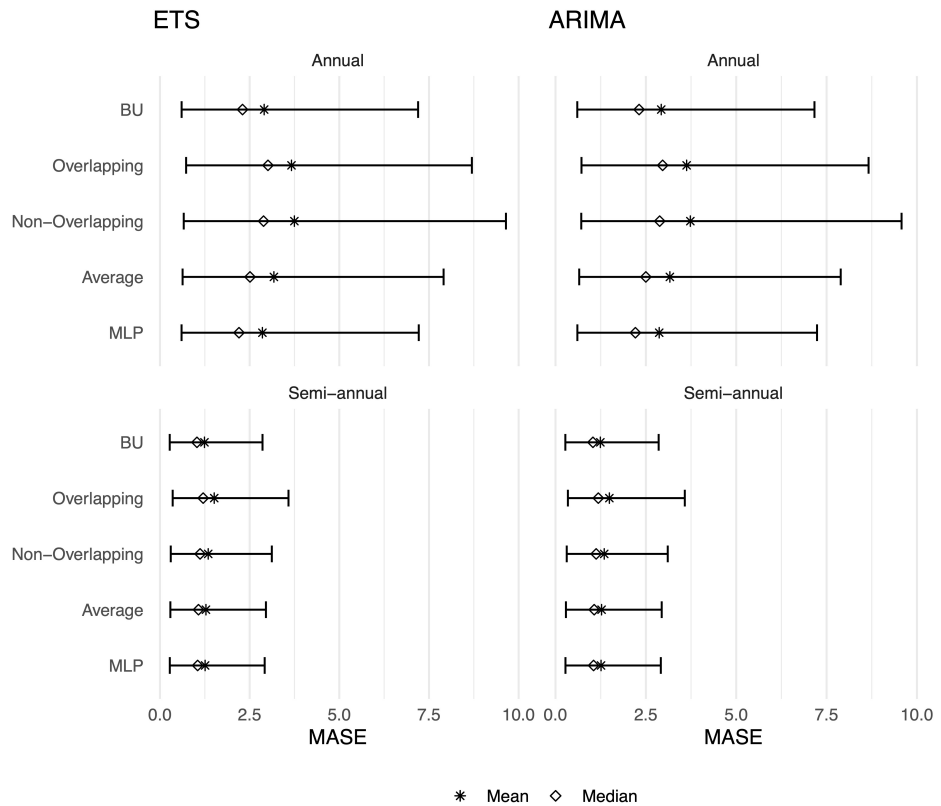
Experiment setup

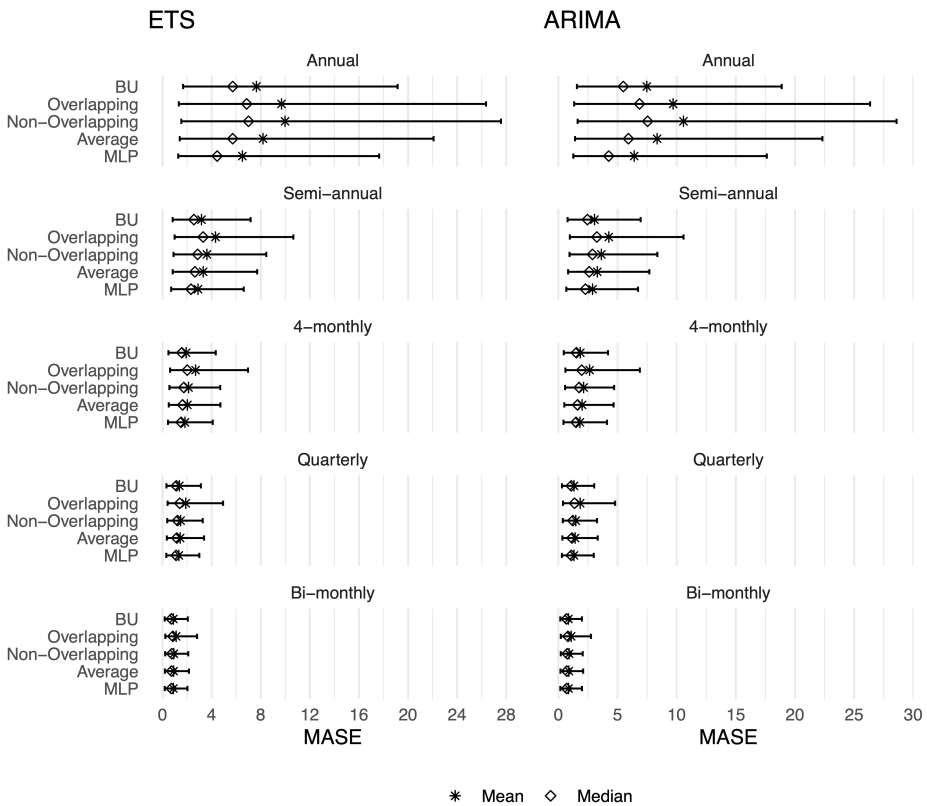
- M4 competition data time series
  - 24,000 Quarterly
  - 48,000 monthly
  - 4,227 daily
- Time series features
  - 42 features
  - use `tsfeatures::tsfeatures()` or `feasts::features()` in R
- Forecasting methods: ARIMA and Exponential Smoothing State Space (ETS)
- Accuracy measure: Mean Absolute Scaled Error (MASE)
- Forecasting for lower frequency time using higher frequency time granularity (e.g. using monthly series to forecast bi-monthly, quarterly, yearly forecast)

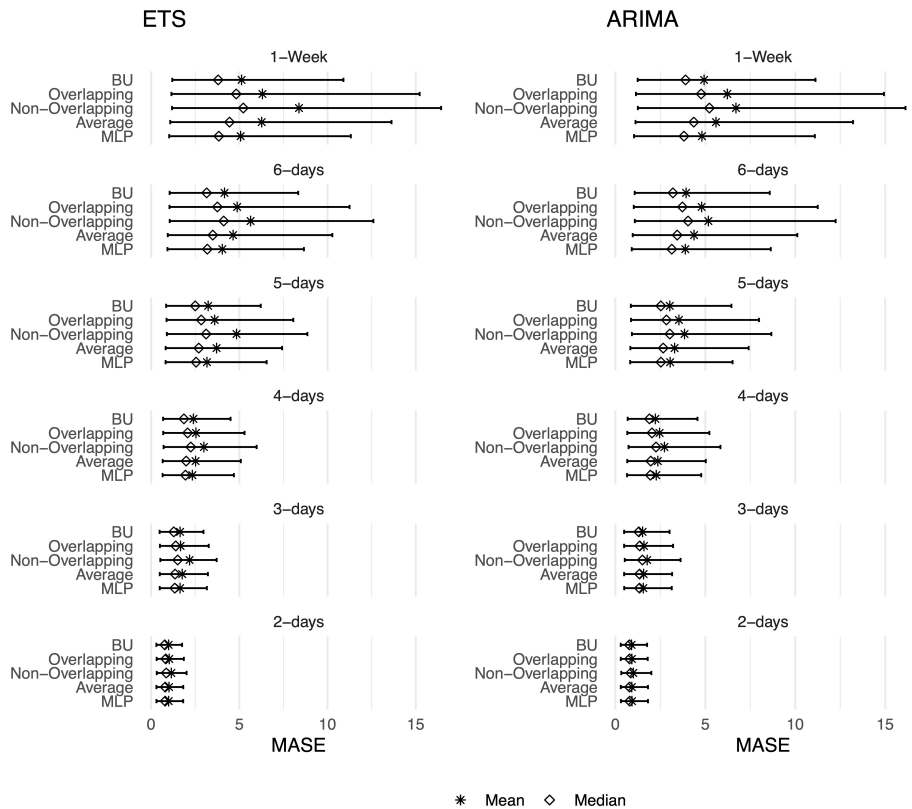

ETS
ARIMA
(N,N)
(T,N)
(N,S)
(T,S)
Annual
Semi−annual
Aggregation Level
0%
25%
50%
75%
100%
Percentage best
Approach
BU
Non−Overlapping
Overlapping


ETS
ARIMA
(N,N)
(T,N)
(N,S)
(T,S)
Annual
Semi−annual
4−monthly
Quarterly
Bi−monthly
Aggregation Level
0%
25%
50%
75%
100%
Percentage best
Approach
BU
Non−Overlapping
Overlapping

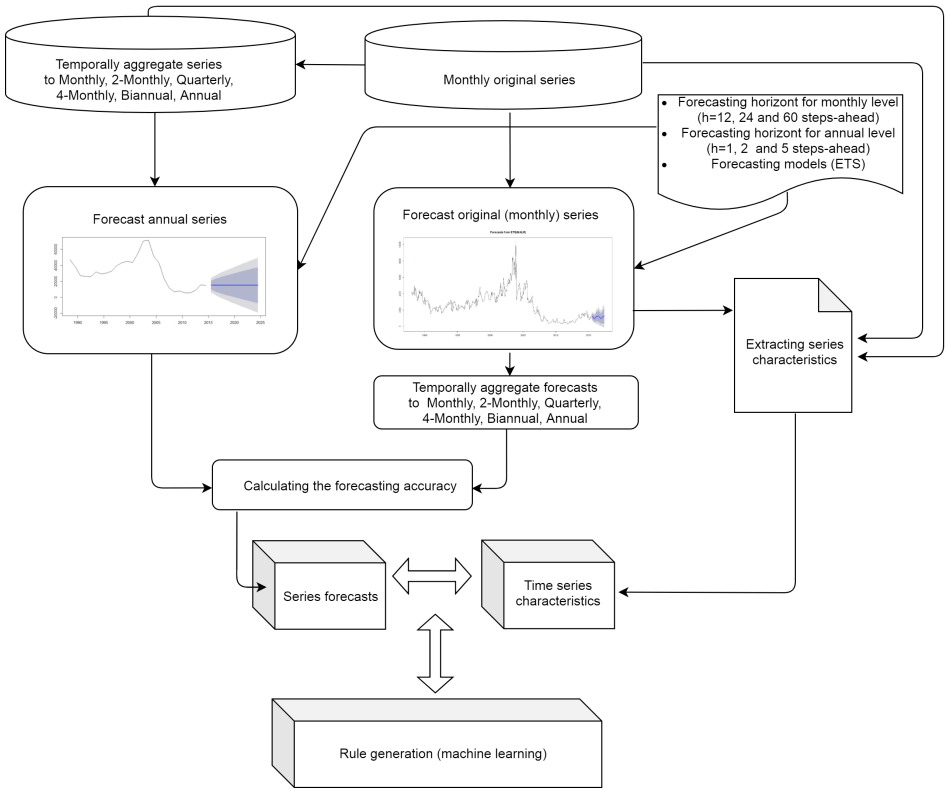

ETS
ARIMA
(N,N)
(T,N)
(N,S)
(T,S)
1–Week
6–days
5–days
4–days
3–days
2–days
Aggregation Level
0%
25%
50%
75%
100%
Percentage best
Approach
BU
Non–Overlapping
Overlapping


ETS
ARIMA
Annual
Annual
BU
Overlapping
Non−Overlapping
Average
MLP
Semi−annual
Semi−annual
BU
Overlapping
Non−Overlapping
Average
MLP
0.0
2.5
5.0
7.5
10.0
0.0
2.5
5.0
7.5
10.0
MASE
MASE
Mean
Median

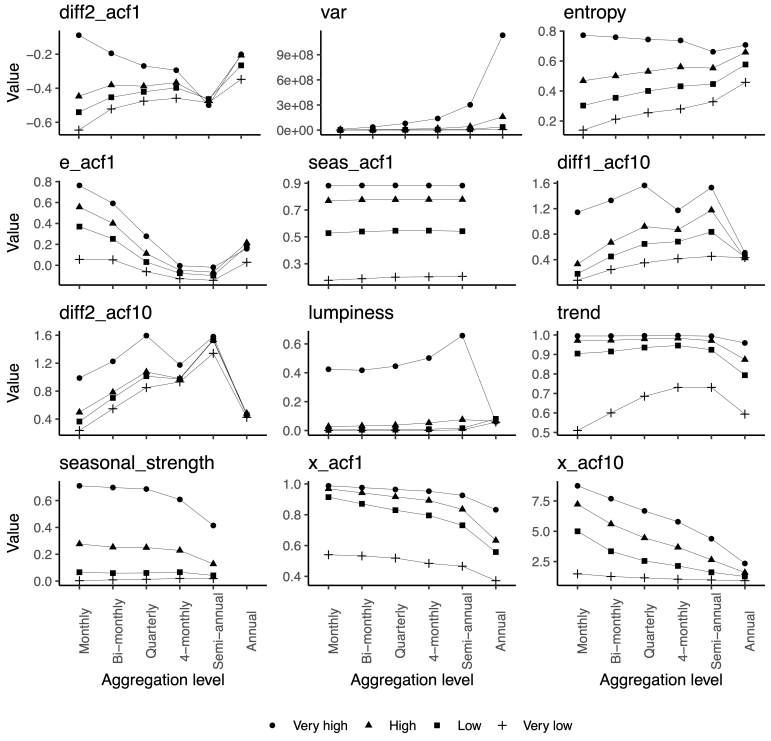

ETS
ARIMA
Annual
Semi−annual
4−monthly
Quarterly
Bi−monthly
BU
Overlapping
Non−Overlapping
Average
MLP
0 4 8 12 16 20 24 28
0 5 10 15 20 25 30
MASE
Mean
Median


ETS
ARIMA
1–Week
6–days
5–days
4–days
3–days
2–days
BU
Overlapping
Non–Overlapping
Average
MLP
0
5
10
15
MASE
Mean
Median

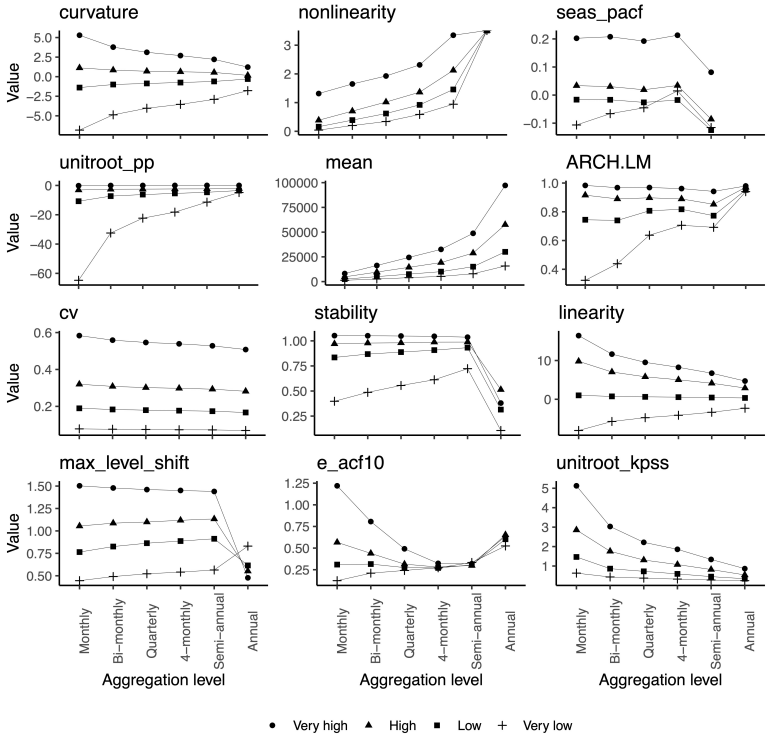
Experiment design

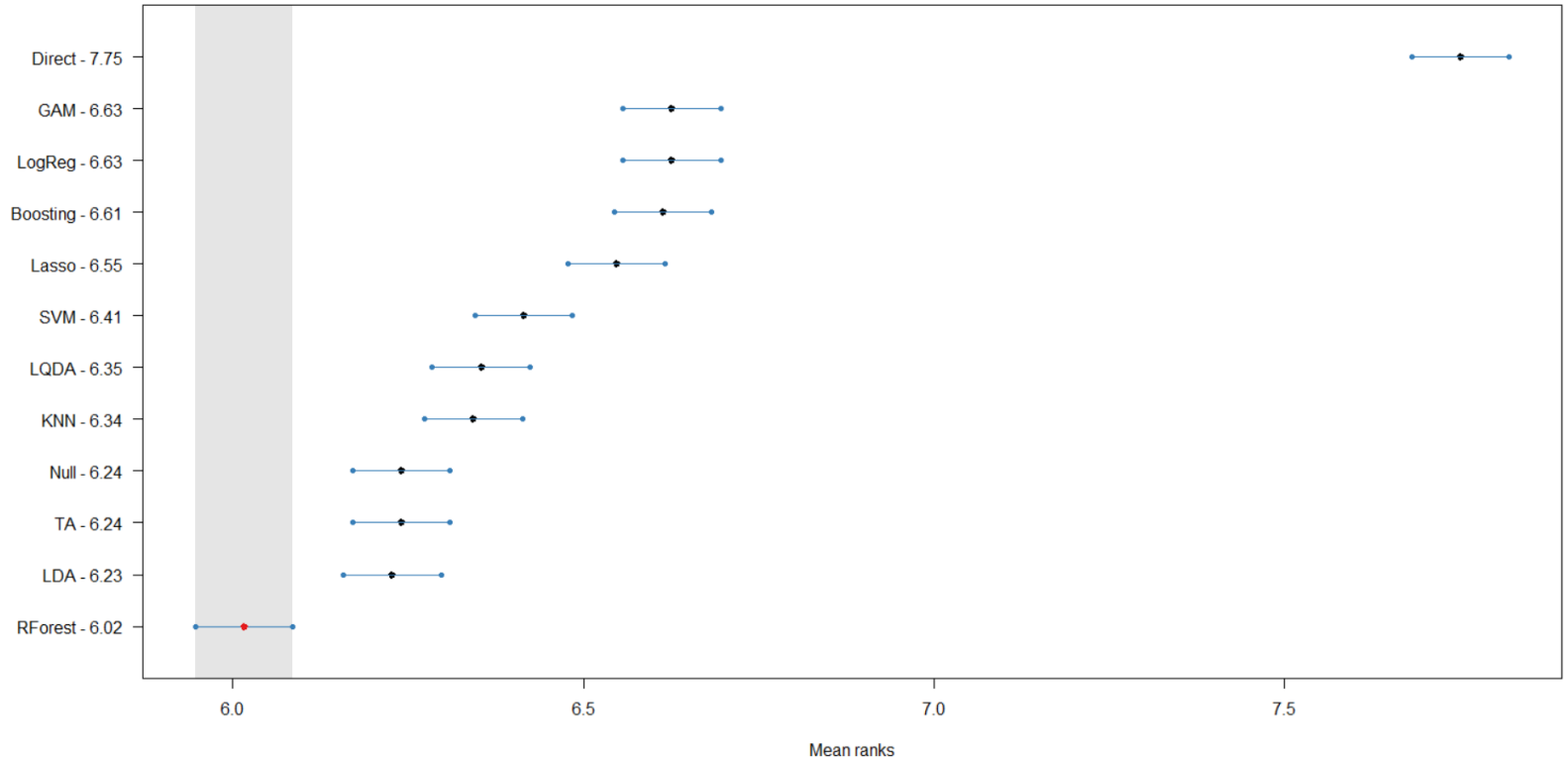


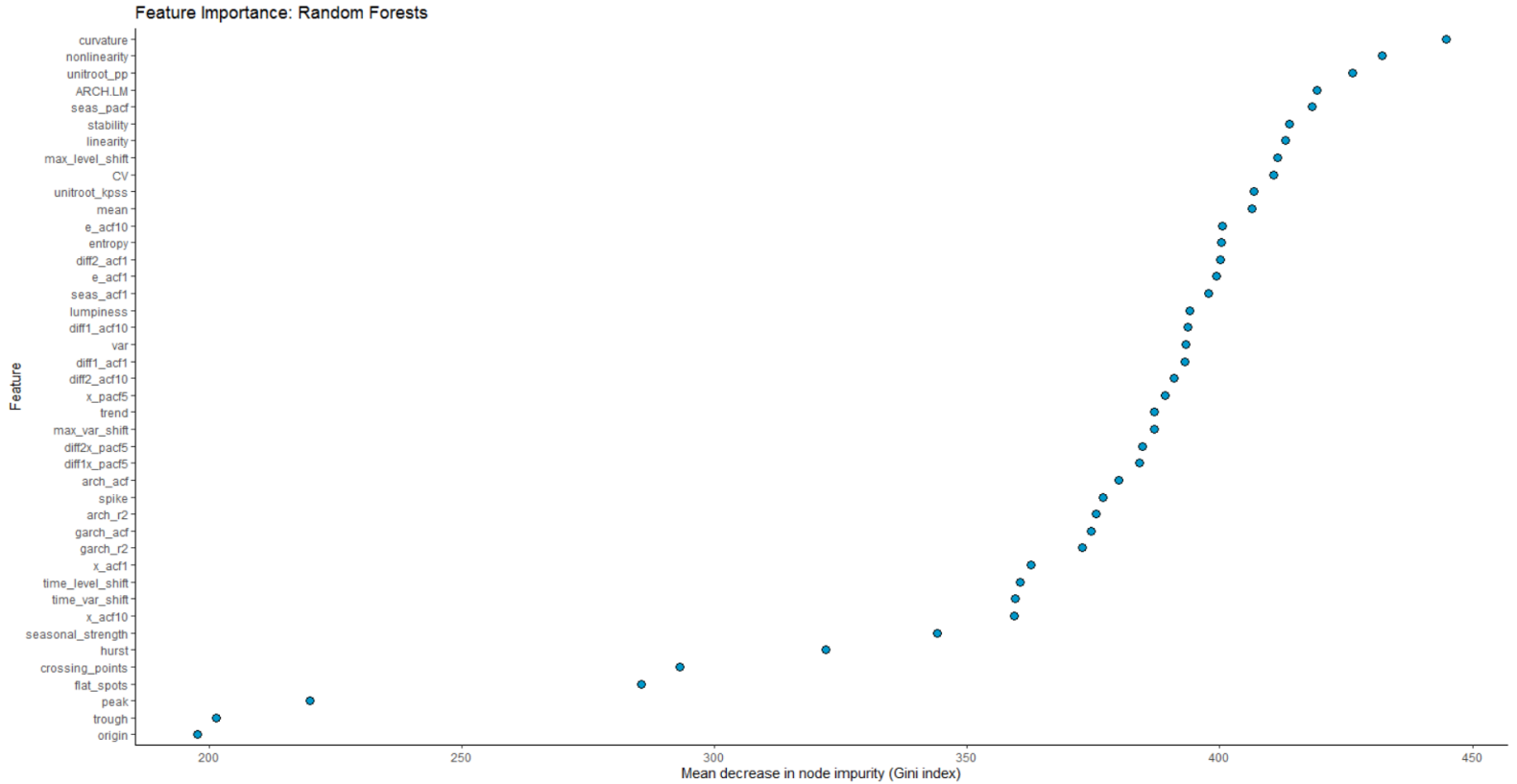
How time series features change with TA



How time series features change with TA




Direct - 7.75
GAM - 6.63
LogReg - 6.63
Boosting - 6.61
Lasso - 6.55
SVM - 6.41
LQDA - 6.35
KNN - 6.34
Null - 6.24
TA - 6.24
LDA - 6.23
RForest - 6.02
6.0
6.5
7.0
7.5
Mean ranks


Feature Importance: Random Forests
curvature
nonlinearity
unitroot_pp
ARCH.LM
seas_pacf
stability
linearity
max_level_shift
CV
unitroot_kpss
mean
e_acf10
entropy
diff2_acf1
e_acf1
seas_acf1
lumpiness
diff1_acf10
var
diff1_acf1
diff2_acf10
x_pacf5
trend
max_var_shift
diff2x_pacf5
diff1x_pacf5
arch_acf
spike
arch_r2
garch_acf
garch_r2
x_acf1
time_level_shift
time_var_shift
x_acf10
seasonal_strength
hurst
crossing_points
flat_spots
peak
trough
origin
Feature
200
250
300
350
400
450
Mean decrease in node impurity (Gini index)

Wroks in progress

- Rostami-Tabar B. Hyndman J. R. (2022), hierarchical count time series forecasting in emergency medicine
- Rostami-Tabar B., Goltsos T. Wang, S. (2022), Overlapping and non-overlapping temporal aggregation: to combine or not to combine
- Rostami-Tabar, D. Mercetic (2022), Temporal aggregation and time series features

Published recently

- Mircetic, D., et al. (2021), "Forecasting hierarchical time series in supply chains: an empirical investigation." International Journal of Production Research, 1-20.
- Babai. M.Z., Boylan, J., Rostami-Tabar, B. (2022), "Demand Forecasting in Supply Chains: A Review of Aggregation and Hierarchical Approaches", International Journal of Production Research, Accepted (to appear).

References for hierarchical forecasting

- Forecasting: Principles and Practice, Chapter 11 Forecasting hierarchical and grouped time series
- ISF2021 Talk, Professor Rob J Hyndman, Ten years of forecast reconciliation

References for temporal aggregation forecasting

- An aggregate–disaggregate intermittent demand approach (ADIDA) to forecasting: an empirical proposition and analysis. Journal of the Operational Research Society.
- Improving forecasting via multiple temporal aggregation. International Journal of Forecasting.
- Demand forecasting by temporal aggregation, Naval Research Logistics
- Forecasting with temporal hierarchies, European Journal of Operational Research

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