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Data Schemas for Forecasting (with examples in R)

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What data structures do we need to use in order to handle forecast data efficiently?

Forecast evaluation framework

Our aim:
to find appropriate **data structures** that can be used as a base for implementing a general forecast evaluation framework.

The framework should allow these capabilities:

1) forecast data storage and exchange,
2) exploratory analysis of forecasts and time series
3) measuring forecasting performance.

Requirements:
the **data structures** should be simple, but cross-platform, flexible, and sufficient to implement the above capabilities.

Setup

1) We have a set of time series, the set can contain from 1 to millions of series.

2) For each series we want to store and update actuals and (numeric) forecasts

3) We want to store and update out-of-sample forecasts, made with alternative methods at different origins with different horizons. Calculating forecasts may take relatively long time.

4) We may want to store not only point forecasts, but prediction intervals, density forecasts and any additional information

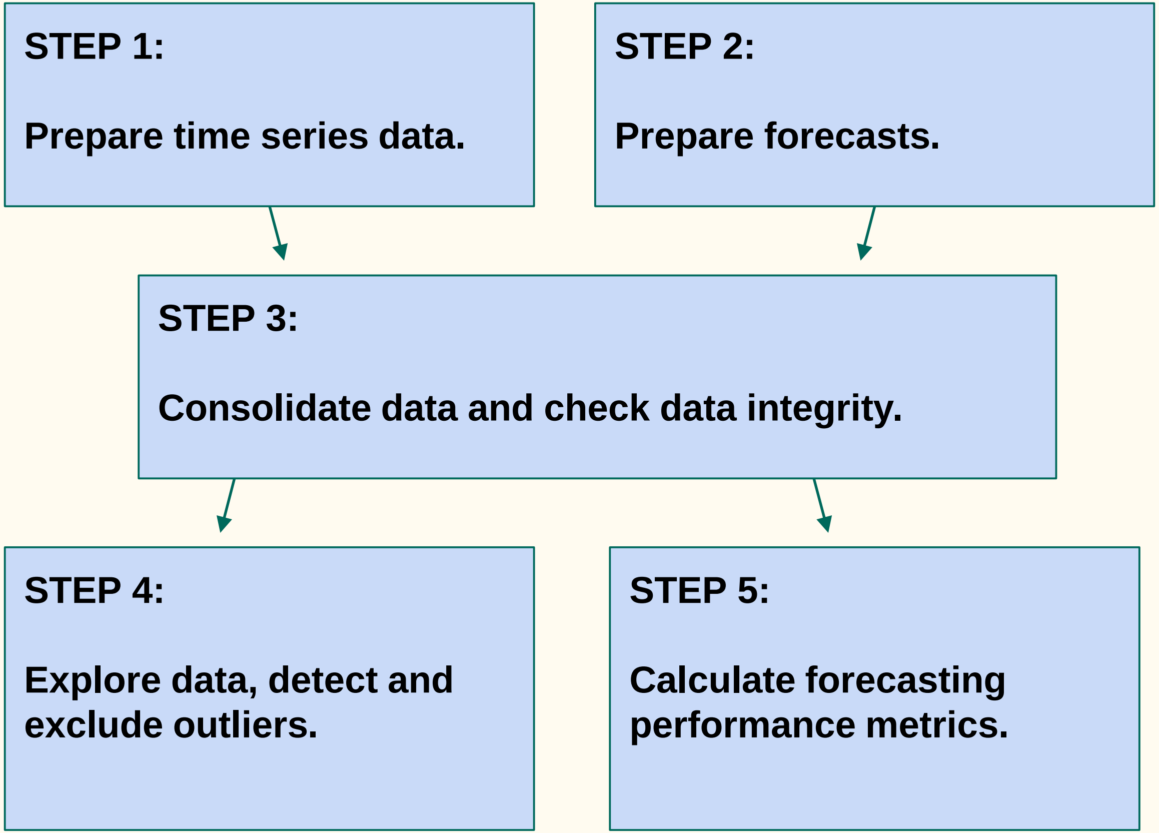
Given the above settings, we want to explore forecasts and to evaluate forecasting performance regularly.

Target audience

This presentation particularly targeted at you if you are

- a researcher wanting to conduct forecasting competitions
- a researcher wanting to compare a new forecasting methods against alternatives
- a practitioner wanting to develop software components to evaluate forecasting performance

Our approach: The general framework



STEP 1:

Prepare time series data.

STEP 2:

Prepare forecasts.

STEP 3:

Consolidate data and check data integrity.

STEP 4:

Explore data, detect and exclude outliers.

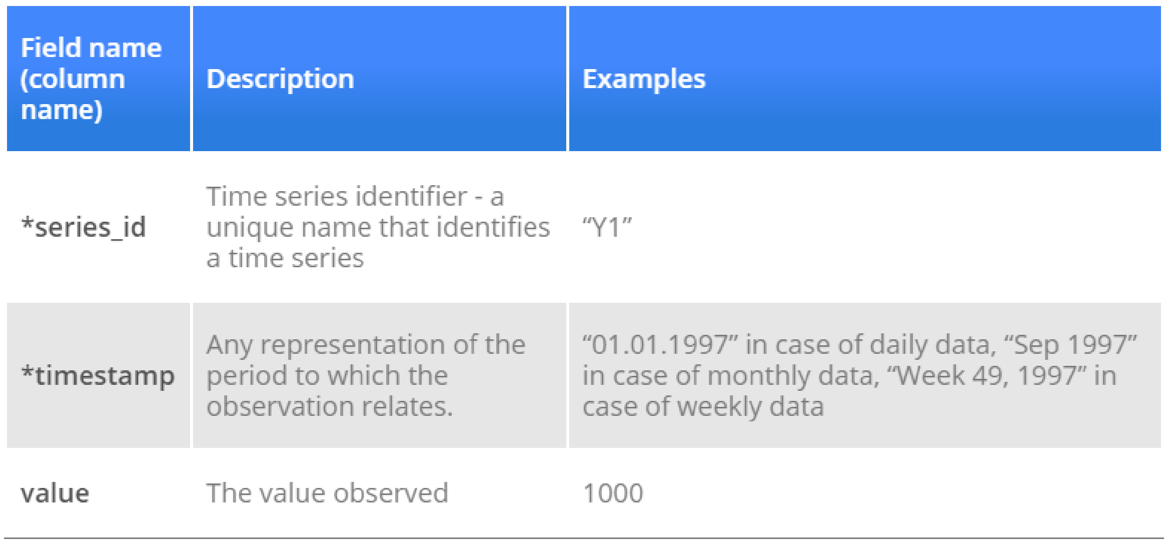
STEP 5:

Calculate forecasting performance metrics.

Step 1: Prepare time series data

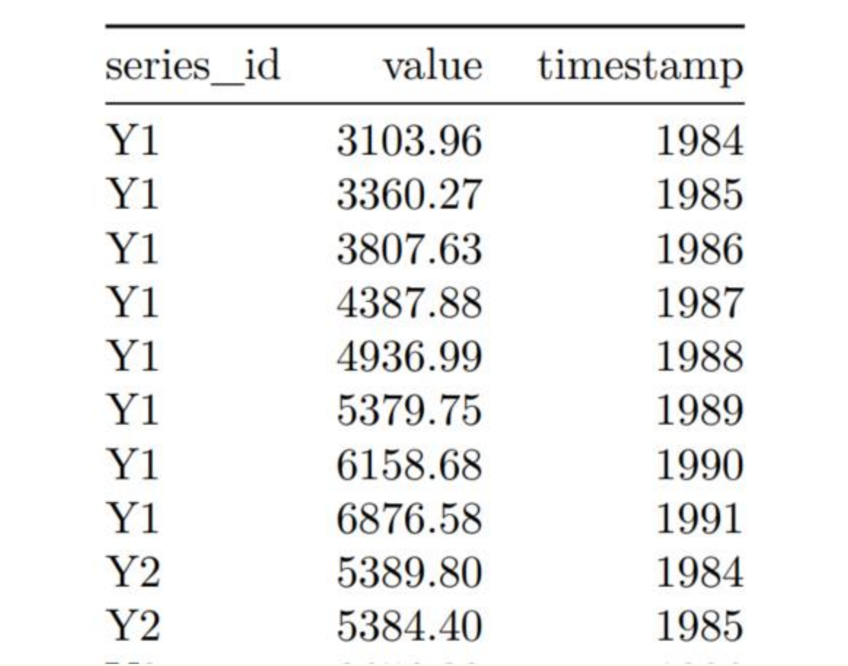
In order to store time series data, we propose the following schema:

Time Series Table Schema (**TSTS**):



Field name (column name)	Description	Examples
*series_id	Time series identifier - a unique name that identifies a time series	"Y1"
*timestamp	Any representation of the period to which the observation relates.	"01.01.1997" in case of daily data, "Sep 1997" in case of monthly data, "Week 49, 1997" in case of weekly data
value	The value observed	1000

Example:

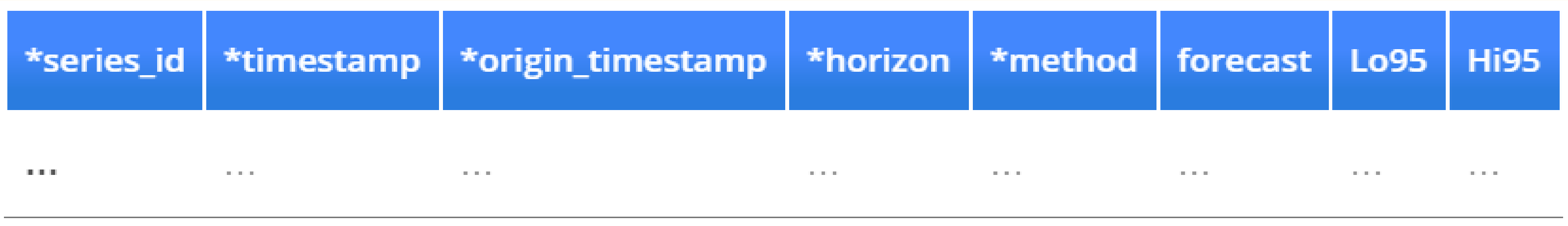


series_id	value	timestamp
Y1	3103.96	1984
Y1	3360.27	1985
Y1	3807.63	1986
Y1	4387.88	1987
Y1	4936.99	1988
Y1	5379.75	1989
Y1	6158.68	1990
Y1	6876.58	1991
Y2	5389.80	1984
Y2	5384.40	1985

Step 2: Prepare forecasts

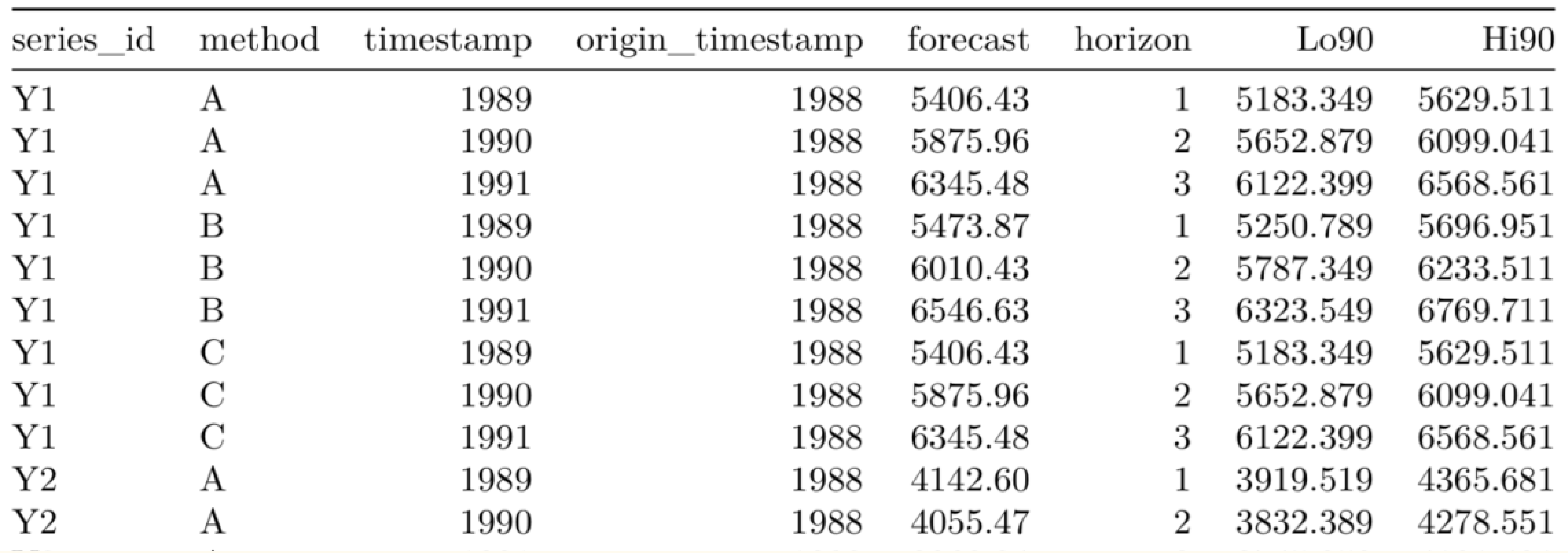
In order to store forecasts, we propose the following schema:

Forecasts Table Schema (**FTS**):



*series_id	*timestamp	*origin_timestamp	*horizon	*method	forecast	Lo95	Hi95
...	...	...	...	...	...	...	...

Example:



series_id	method	timestamp	origin_timestamp	forecast	horizon	Lo90	Hi90
Y1	A	1989	1988	5406.43	1	5183.349	5629.511
Y1	A	1990	1988	5875.96	2	5652.879	6099.041
Y1	A	1991	1988	6345.48	3	6122.399	6568.561
Y1	B	1989	1988	5473.87	1	5250.789	5696.951
Y1	B	1990	1988	6010.43	2	5787.349	6233.511
Y1	B	1991	1988	6546.63	3	6323.549	6769.711
Y1	C	1989	1988	5406.43	1	5183.349	5629.511
Y1	C	1990	1988	5875.96	2	5652.879	6099.041
Y1	C	1991	1988	6345.48	3	6122.399	6568.561
Y2	A	1989	1988	4142.60	1	3919.519	4365.681
Y2	A	1990	1988	4055.47	2	3832.389	4278.551

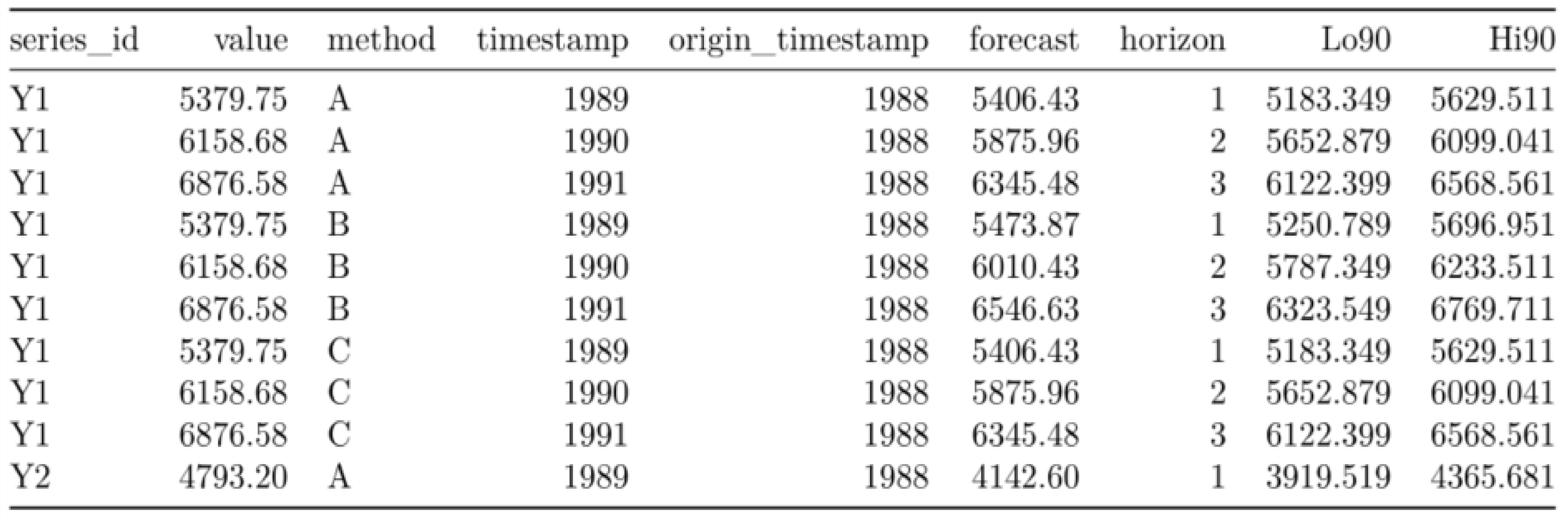
Step 3: Consolidate data

Here we need to obtain a table containing both actuals and forecasts, this will be needed to implement some elements for exploratory analysis and accuracy measurement.

In order to obtain the consolidated data set we propose to use the Actuals and Forecasts Table Schema (**AFTS**).

This schema is the same as the **FTS** schema, but additional column “value” is used to represent the actual value of time series.

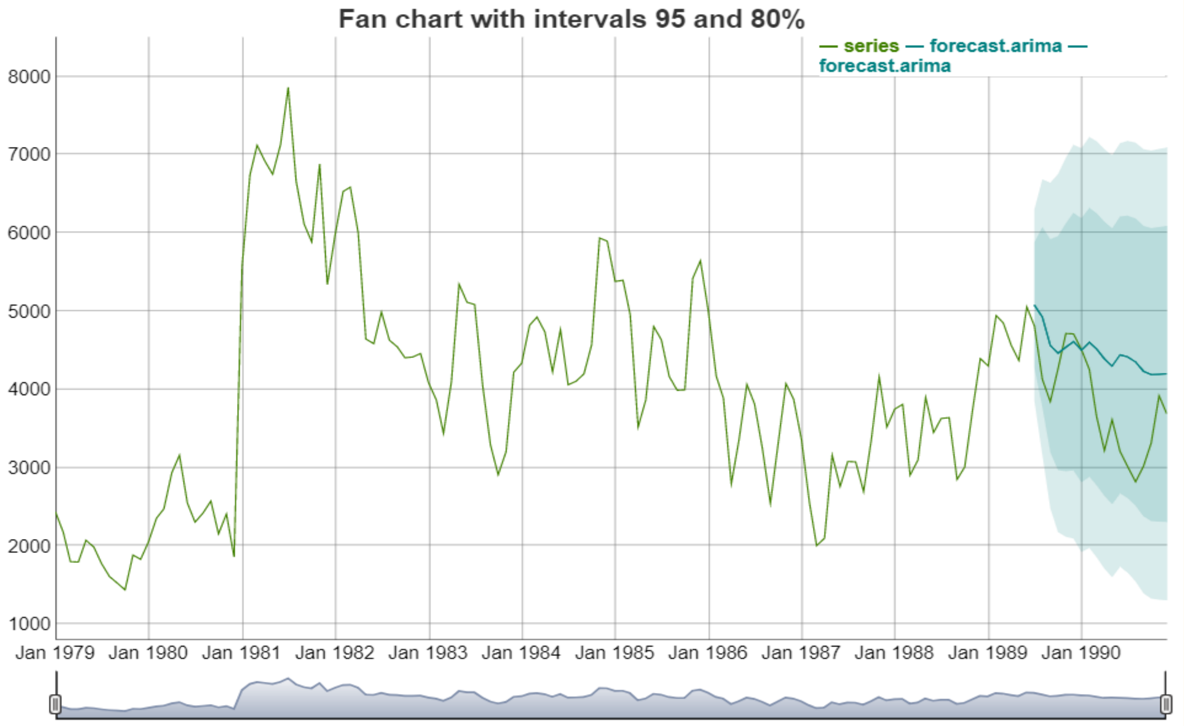
Example:



series_id	value	method	timestamp	origin_timestamp	forecast	horizon	Lo90	Hi90
Y1	5379.75	A	1989	1988	5406.43	1	5183.349	5629.511
Y1	6158.68	A	1990	1988	5875.96	2	5652.879	6099.041
Y1	6876.58	A	1991	1988	6345.48	3	6122.399	6568.561
Y1	5379.75	B	1989	1988	5473.87	1	5250.789	5696.951
Y1	6158.68	B	1990	1988	6010.43	2	5787.349	6233.511
Y1	6876.58	B	1991	1988	6546.63	3	6323.549	6769.711
Y1	5379.75	C	1989	1988	5406.43	1	5183.349	5629.511
Y1	6158.68	C	1990	1988	5875.96	2	5652.879	6099.041
Y1	6876.58	C	1991	1988	6345.48	3	6122.399	6568.561
Y2	4793.20	A	1989	1988	4142.60	1	3919.519	4365.681

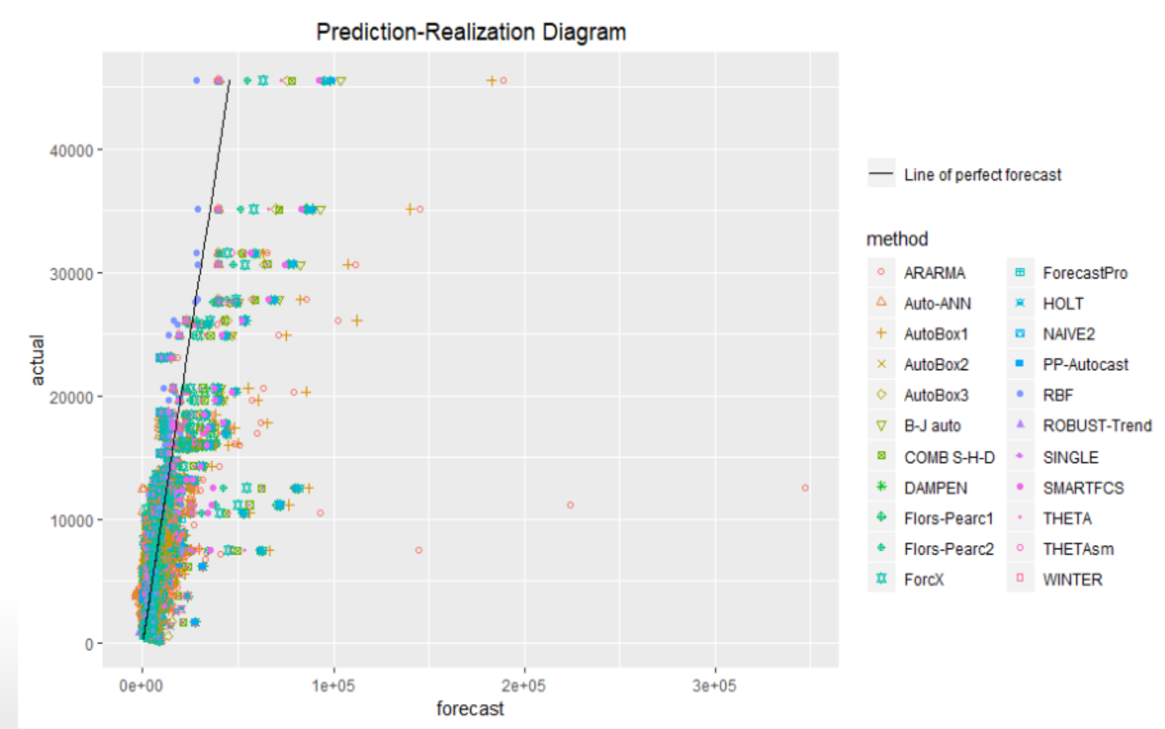
Step 4: Exploratory analysis

```
plotSeries(example1_afts, seried_id = "M1")
```

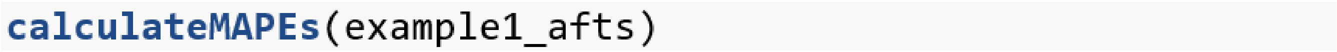


Step 4: Exploratory analysis

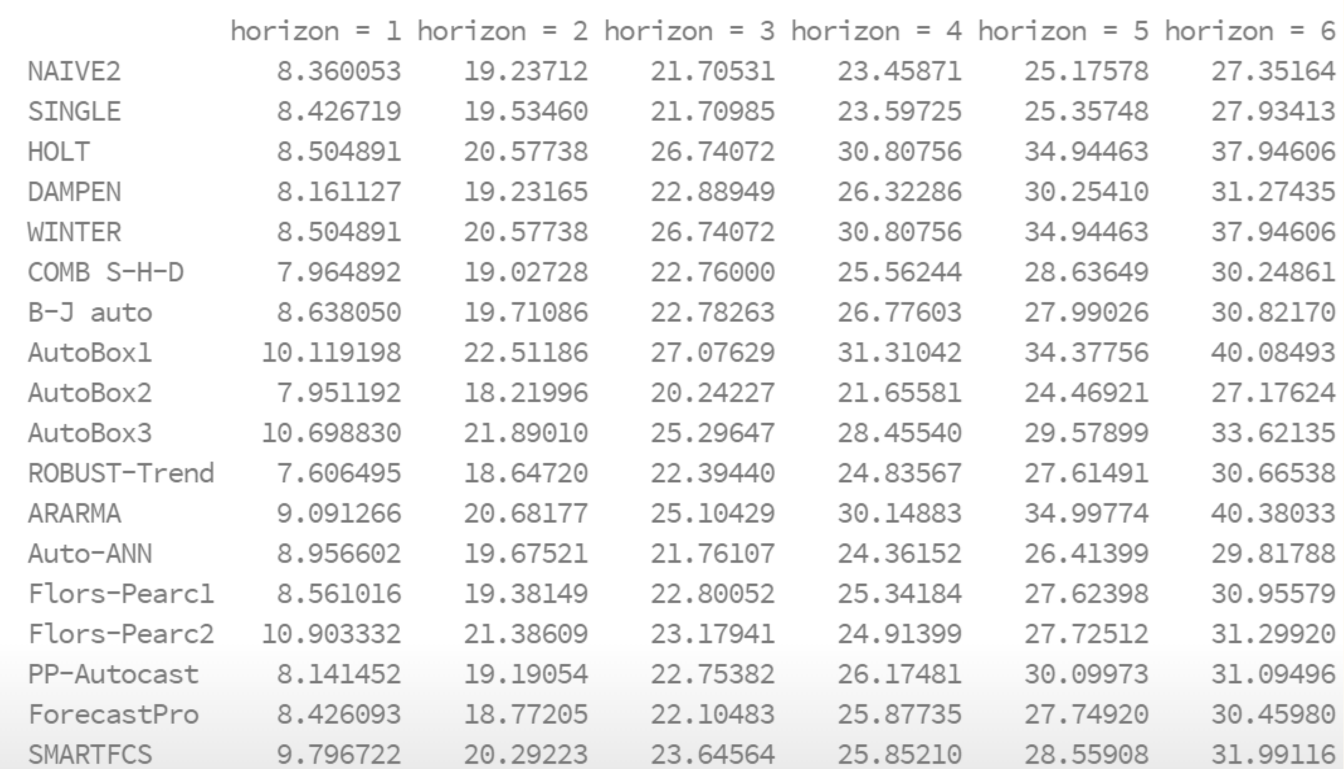
```
plotPRD(example1_afts)
```



Step 5: Measuring forecasting performance

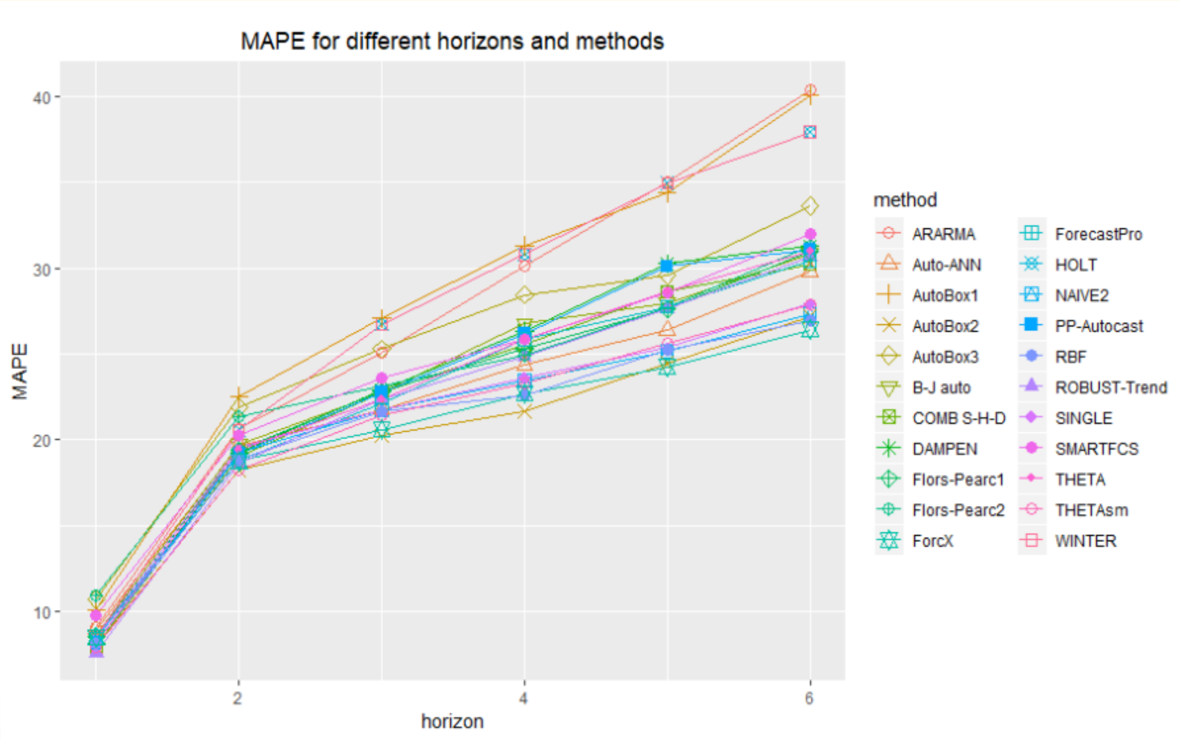


```
calculateMAPEs(example1_afts)
```

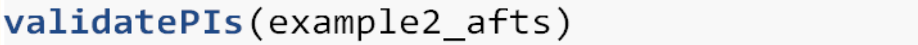


```
             horizon = 1 horizon = 2 horizon = 3 horizon = 4 horizon = 5 horizon = 6
NAIVE2          8.360053    19.23712    21.70531    23.45871    25.17578    27.35164
SINGLE          8.426719    19.53460    21.70985    23.59725    25.35748    27.93413
HOLT            8.504891    20.57738    26.74072    30.80756    34.94463    37.94606
DAMPEN          8.161127    19.23165    22.88949    26.32286    30.25410    31.27435
WINTER          8.504891    20.57738    26.74072    30.80756    34.94463    37.94606
COMB S-H-D      7.964892    19.02728    22.76000    25.56244    28.63649    30.24861
B-J auto        8.638050    19.71086    22.78263    26.77603    27.99026    30.82170
AutoBox1       10.119198    22.51186    27.07629    31.31042    34.37756    40.08493
AutoBox2        7.951192    18.21996    20.24227    21.65581    24.46921    27.17624
AutoBox3       10.698830    21.89010    25.29647    28.45540    29.57899    33.62135
ROBUST-Trend    7.606495    18.64720    22.39440    24.83567    27.61491    30.66538
ARARMA          9.091266    20.68177    25.10429    30.14883    34.99774    40.38033
Auto-ANN        8.956602    19.67521    21.76107    24.36152    26.41399    29.81788
Flors-Pearc1    8.561016    19.38149    22.80052    25.34184    27.62398    30.95579
Flors-Pearc2   10.903332    21.38609    23.17941    24.91399    27.72512    31.29920
PP-Autocast     8.141452    19.19054    22.75382    26.17481    30.09973    31.09496
ForecastPro     8.426093    18.77205    22.10483    25.87735    27.74920    30.45980
SMARTFCS        9.796722    20.29223    23.64564    25.85210    28.55908    31.99116
```

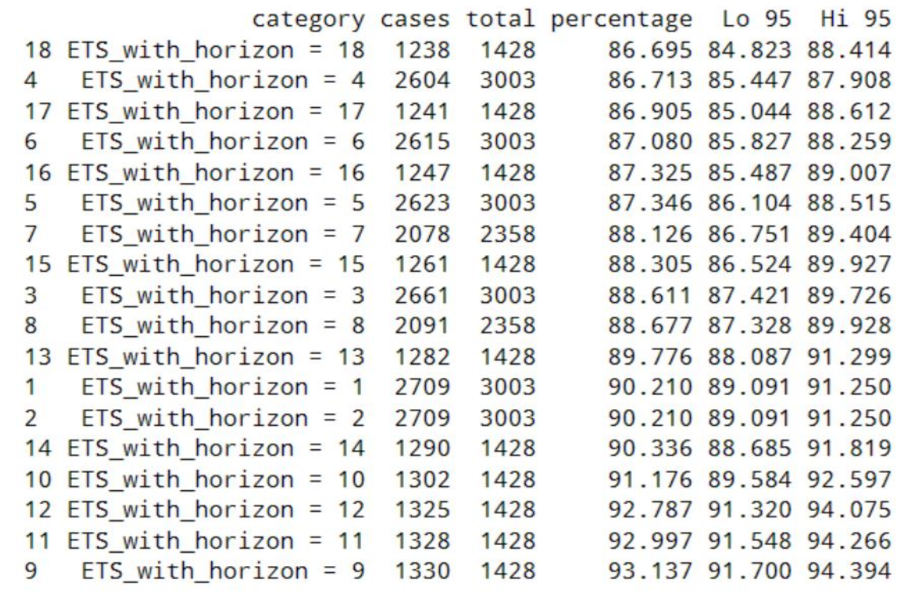
Step 5: Measuring forecasting performance



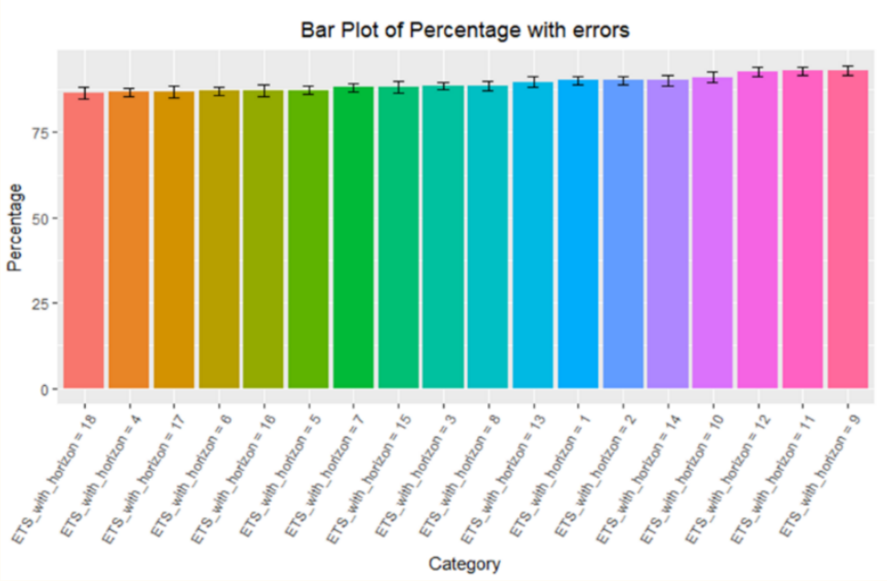
Step 5: Measuring forecasting performance



```
validatePIs(example2_afts)
```



```
                 category cases total percentage  Lo 95  Hi 95
18 ETS_with_horizon = 18  1238  1428     86.695 84.823 88.414
4   ETS_with_horizon = 4  2604  3003     86.713 85.447 87.908
17 ETS_with_horizon = 17  1241  1428     86.905 85.044 88.612
6   ETS_with_horizon = 6  2615  3003     87.080 85.827 88.259
16 ETS_with_horizon = 16  1247  1428     87.325 85.487 89.007
5   ETS_with_horizon = 5  2623  3003     87.346 86.104 88.515
7   ETS_with_horizon = 7  2078  2358     88.126 86.751 89.404
15 ETS_with_horizon = 15  1261  1428     88.305 86.524 89.927
3   ETS_with_horizon = 3  2661  3003     88.611 87.421 89.726
8   ETS_with_horizon = 8  2091  2358     88.677 87.328 89.928
13 ETS_with_horizon = 13  1282  1428     89.776 88.087 91.299
1   ETS_with_horizon = 1  2709  3003     90.210 89.091 91.250
2   ETS_with_horizon = 2  2709  3003     90.210 89.091 91.250
14 ETS_with_horizon = 14  1290  1428     90.336 88.685 91.819
10 ETS_with_horizon = 10  1302  1428     91.176 89.584 92.597
12 ETS_with_horizon = 12  1325  1428     92.787 91.320 94.075
11 ETS_with_horizon = 11  1328  1428     92.997 91.548 94.266
9   ETS_with_horizon = 9  1330  1428     93.137 91.700 94.394
```



Conclusions

The approach proposed allows:

- to represent your forecast data in the form suitable for further analysis of forecasting performance and for the exchange with other researchers

- to explore forecasts in order to make sure that your data is correct and ready for accuracy evaluation

- to evaluate forecasting performance based on the data formats defined

Our approach does not depend on any platform or programming language, it just defines the general methodology for handling forecast data.

For more info on this project, please visit

forvis.github.io