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 <u>simple</u>, but <u>cross-platform</u>, <u>flexible</u>, and <u>sufficient</u> 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

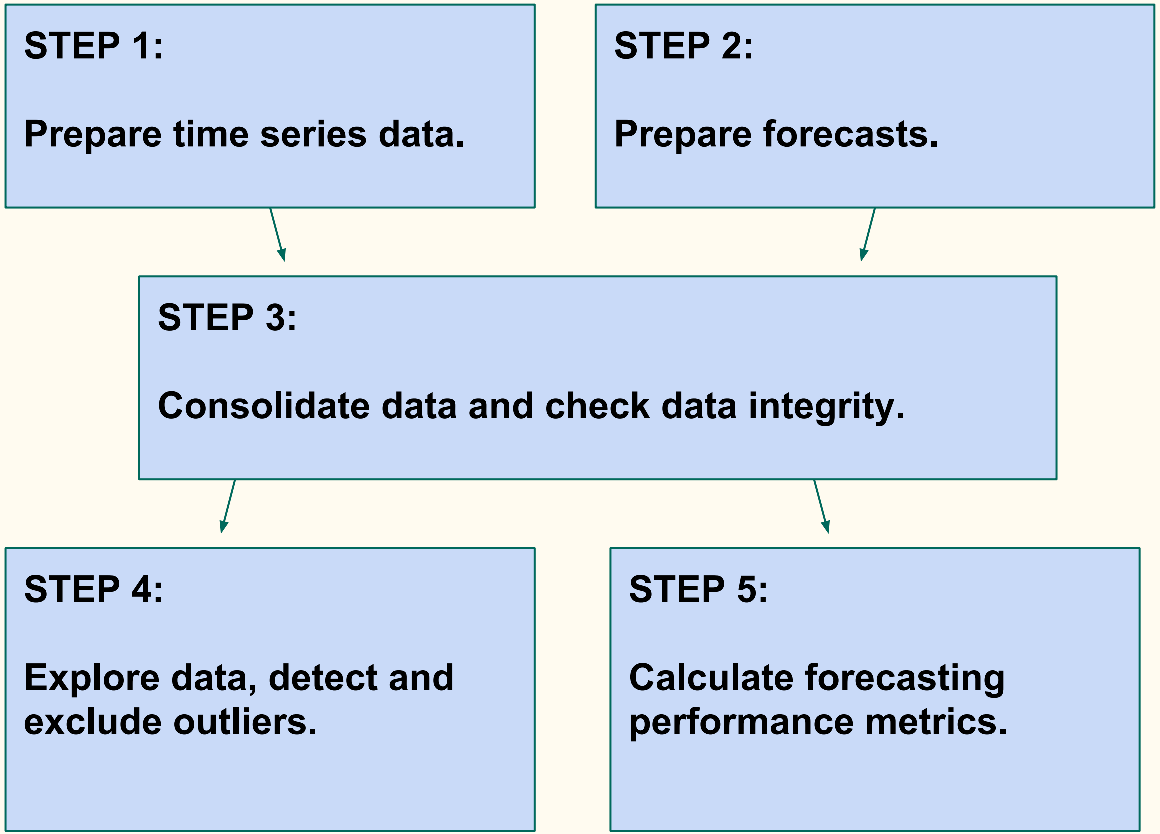
Given the above settings, we want to explore forecasts and to evaluate forecasting performance regularly.

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

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
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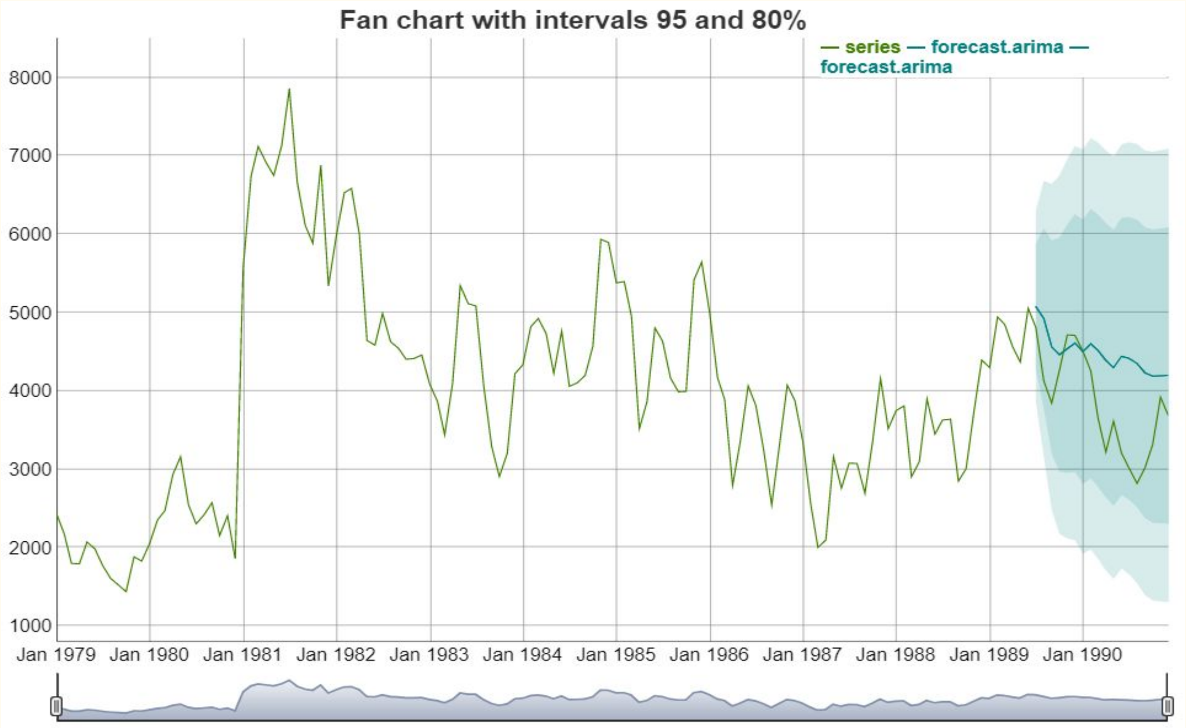
Y1	6158.68	C	1990	1988	5875.96	2	5652.879	6099.041
Y1	6876.58	C	1991	1988	6345.48	3	6122.399	6568.561
Y2	4793.20	A	1989	1988	4142.60	1	3919.519	4365.681

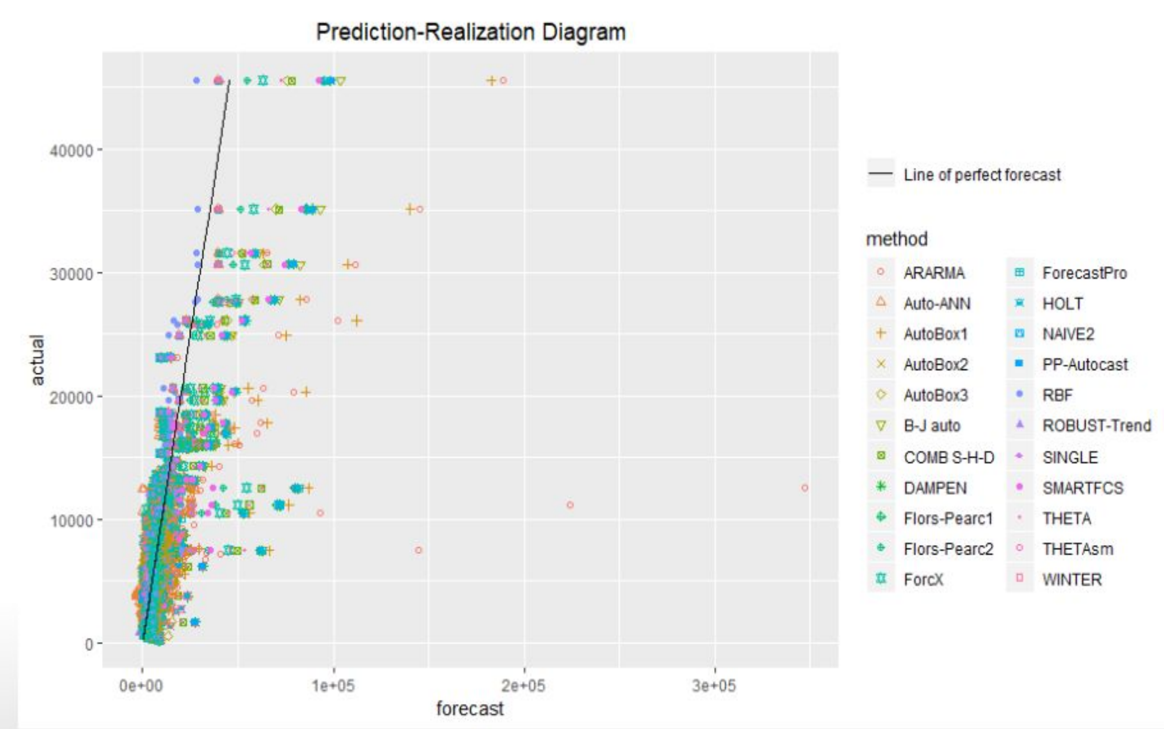
Step 4: Exploratory analysis

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



Step 4: Exploratory analysis

```
plotPRD(example1_afts)
```

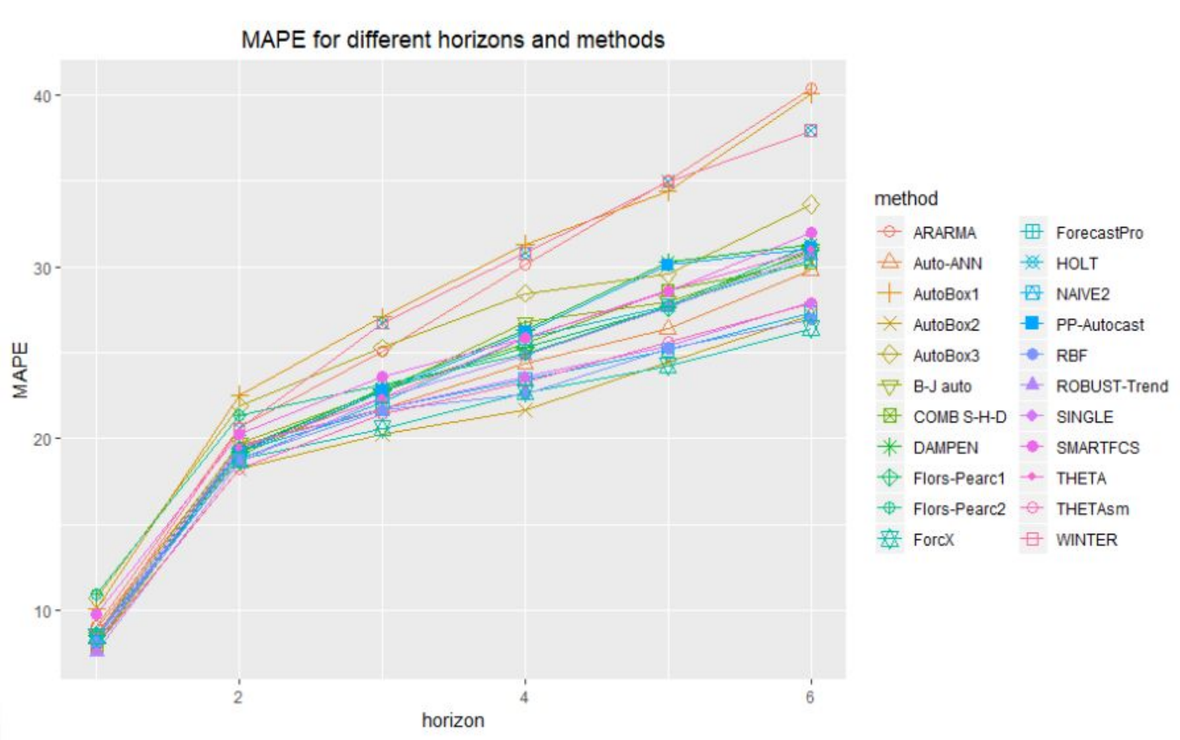


Step 5: Measuring forecasting performance

```
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

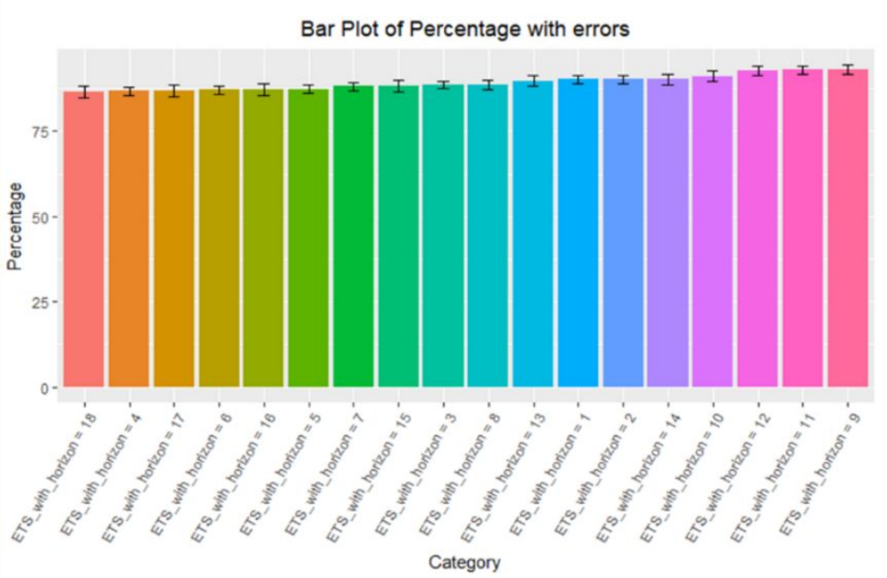
Step 5: Measuring forecasting performance



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.