1. Method Description

General Information

Type of Entry (*Academic, Practitioner, Researcher, Student*)	**Practitioner**
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Country	**Greece / Germany**
Type of Affiliation (*University, Company-Organization, Individual*)	**Individual**
Affiliation	**-**

Team Members (*if applicable*):

1st Member	
First Name	-
Last Name	-
Country	-
Affiliation	-
2nd Member	
First Name	-
Last Name	-
Country	-
Affiliation	-

Information about the method utilized

Name of Method	**AGON**
Type of Method (*Statistical, Machine Learning, Combination, Other*)	**Statistical**
Short Description (up to 200 words)	The introduced method ***AGON*** *(named after the Greek word "Αγώνας", thus a competition, a fight)* is an averaging forecasting method, which combines two or three simple statistical methods. The choice of methods to be involved (and their weights) are determined by a competition between simple and easy to implement statistical methods. a. Firstly, the time serie historical data points are checked for seasonality, abnormal values, and historical data importance (to define how many historical data should we use for

	estimating forecasts). b. These methods (including: Naïve, Regression, Decomposition, Moving Average, Smoothing, and Theta methods) are compete using time serie historical data points, trying to minimize the forecasting error (MASE and sMAPE) over the post-sampling of a time serie. The best three methods are selected*[1]. c. A group of eight averaging methods (with: equal or unequal weights, two or three methods, of the same or different type) are then used, in order to detect the average method that has the least forecasting error over the post-sampling. d. As a last step, the best performing averaging method is finally used for estimating forecasts for the requested forecasting horizon, which then are combined with equal or unequal weights. *2

*[1] the selection process is clearly explained in the "Extended Description" paragraph. The code for performing model selection is included in the GitHub deliverables and it is available for usage.

*[2] more about the method can be found in the "Extended Description" section of the document.

Extended Description:

Apart from the textural description, please consider including an informative flowchart to help researchers better understand the exact steps followed for generating the forecasts. Please also try to clarify any assumptions made, the initialization and parameterization process used, etc., to facilitate reproducibility and replicability.

2. Algorithm

2.1. Naming

The introduced method ***AGON*** (named after the Greek word "***Αγώνας***", thus a competition, a fight) is an averaging forecasting method, which combines two or three simple statistical methods.

2.2. Short Description

The choice of methods to be involved (and their weights) are determined by a competition between simple and easy to implement statistical forecasting methods.

a. Firstly, the time serie historical data points are **checked for seasonality, abnormal values, and historical data importance** (to define how many historical data should we use for estimating forecasts).
b. These methods (including: Naïve, Regression, Decomposition, Moving Average, Smoothing, and Theta methods, with various parameters and initializations) are compete using time serie historical data points, trying to minimize the forecasting error (MASE and sMAPE) over the post-sampling of a time serie. The best three methods are selected. The **selection process** is clearly explained in the "Extended Description" paragraph. The code for performing model selection is included in the GitHub deliverables and it is available for usage.
c. A group of **eight averaging forecasting methods** (with: equal or unequal weights, combining two or three methods, of the same or different type) are then used, in order to detect the average method that has the least forecasting error over the post-sampling.
d. As a last step, the **best performing averaging forecasting method** is finally used for estimating forecasts for the requested forecasting horizon, which then are combined with equal or unequal weights.

More about the method can be found in the "**Extended Description**" paragraph of the document.

3. Extended Description

The scope of this document is to help the reader:

- To understand how the algorithm works, and
- To assist him on reproducing the results

For more information, please don't hesitate to contact the designer of the ***AGON*** forecasting method.

➔ **Before starting**:

- Please read **Paragraph § 7 "Simple Forecasting Methods"** which has a list of all the simple forecasting methods that we use.
- Please read **Paragraph § 8 "Averaging Forecasting Methods"** which has a list of all the average forecasting methods that we use.

Before applying a simple forecasting method, we **always** perform the following:

a. **Reduce the decimals**:
   - If a time serie average value is less than 100, we keep 2 decimals.
   - If the time serie average value is greater than or equal to 100, we keep only 1 decimal.

b. **Seasonal Indices & Deseasonalization**:
   - We use the classical decomposition method for estimating the seasonal indices and for estimating the deseasonalization time serie.
   - We perform deseasonalization only when using simple forecasting methods that they request to deseasonalize the time serie (check Paragraph § 7 for more details)

c. **Outlier detection**:
   - We check the deseasonalized time serie for outliers, by using three different methods.
   - If all three methods indicate that a historical data point is an outlier, then it is replaced by using common techniques.

Of course, after applying a simple forecasting method, we always perform the following:

d. **Seasonalization**:
   - We use the estimated seasonal indices to re-seasonalize the estimated forecasts.
   - Only when using simple forecasting methods that they request to deseasonalize the time serie (check Paragraph § 7 for more details).

In the next paragraph (§ 3.1), we will present how the introduced AGON method it works for a yearly time serie. Then, in the following paragraphs we will present how it works for quarterly (§ 3.2), monthly (§ 3.3), weekly (§ 3.4), daily (§ 3.5), and hourly (§ 3.6) data.

3.1. Yearly data: How the algorithm works

For better understanding, let's think of an example.

- We have a yearly time serie with 110 data points
- We need to forecast for 6 horizons

3.1.1. Step 1: Keep post-sampling data

We keep the **last 6 historical observations as post-sampling**, in order to evaluate our forecasts. Thus, now we have 110 - 6 = **104 historical data points** to use.

3.1.2. Step 2: Run with minimum historical data points.

We define that <u>**30 historical data points**</u> are the minimum set for starting (**5** times the requested horizon).

3.1.2.1. Step 2a: Run all Simple forecasting methods.

We use these 30 historical data points, and we estimate forecasts with all the available simple forecasting methods (Paragraph 7 has a list of all the simple forecasting methods that we use).

As a results, we have 6 forecasts for every simple forecasting method.

3.1.2.2. Step 2b: Estimate the forecasting errors for each method.

By comparing the forecasts with the post-sampling data, we can estimate the forecasting error for each method. The target is to estimate:

- The **sMAPE**,
- The **MASE**,
- The **relative sMAPE**,
- The **relative MASE**,
- And finally the **OWA error,**

for each method.

3.1.2.3. Step 2c: Rank the simple forecast methods

We rank the simple forecast method, by the OWA error.

In our example, the results could look like this:

- *Moving Average - Simple3 – Seasonal → OWA 0.756*
- *Decomposition - Multiplicative - MAD3B – Seasonal → OWA 0.782*
- *Theta 2.00 - Exponential Smoothing - Simple - A2 – Seasonal → OWA 0.811*
- *…*
- *Naive2 → OWA 1.000*
- *…*

3.1.2.4. Step 2d: Run the 8 averaging methods

We run the 8 average methods. (Paragraph 8 has the list of all averaging methods that we use).

As a results, we have 6 forecasts for every average forecasting method.

3.1.2.5. Step 2e: Estimate the forecasting errors for each averaging method.

By comparing the forecasts with the post-sampling data, we can estimate the forecasting error for each averaging method. The target is to estimate:

- The **sMAPE**,
- The **MASE**,
- The **relative sMAPE**,
- The **relative MASE**,
- And finally the **OWA error,**

for each averaging method.

3.1.2.6. Step 2f: Rank the average methods

We rank the average methods, by the OWA error.

In our example, the results could look like this:

- *Averaging - Best 2 (IDs = 601, 705) - Equal Weights → OWA 0.771*
- *Averaging - Best 2 (IDs = 401, 705) - DifCat - Equal Weights → OWA 0.792*
- *…*

3.1.3. Step 3: Run again all methods, for more historical data points.

We are now incrementally increasing the historical data points, and we repeat all steps 2a – 2f.

Thus, in our example:

- We use **60** historical data points (**10** times the horizon), and repeat steps 2a-2f.
- We use **90** historical data points (**15** times the horizon), and repeat steps 2a-2f.
- Finally, we use **104** historical data points (**max** size of the time serie, see step1), and repeat steps 2a-2f.

3.1.4. Step 4: Rank all the average methods, from all steps

We rank the average methods from all steps, by the OWA error.

As a results we have a list of ***N*** average methods sorted by OWA, where N = 8 x times repeated step2. (In our example N = 8 methods x 4 repeats = 32)

In our example, the results could look like this:

- *Averaging - Best 2 (IDs = 601, 705) - Equal Weights (Hist. Data = 60) → OWA 0.771*
- *Averaging - Best 2 (IDs = 401, 705) - DifCat - Equal Weights (Hist. Data = 30) → OWA 0.792*
- *Averaging - Best 3 (IDs = 611, 705, 201) - Estimated Weights (Hist. Data = 104) → 0.801*
- *…*

3.1.5. Step 5: Find which average method is the best

From the list that we have produced in the previous step, we select the **best averaging method**. Thus, the averaging method with the **smallest OWA**.

In case that 2 or more averaging method have exactly the same OWA, we use extra ordering criteria, which are:

- the simplest averaging method (with 2 methods to combine, with equal weights), and
- the largest set of historical data.

In our example, the best method is:

- *Averaging - Best 2 (IDs = 601, 705) - Equal Weights (Hist. Data = 60) → OWA 0.771*

✓ ***The process of selecting the best method to forecast has been completed.***

3.1.6. Step 6: Estimate final forecasts with the best average method

Since the process of selecting the best method to forecast has been completed, only the estimation of the final forecasts remains.

3.1.6.1. Step 6a: Historical data to use

In the final forecasts, we will use only the historical data (as indicated by the best averaging method), but we must add the 6 latest historical data points that we have kept as post-sampling.

In our example, and according to the best method: *Averaging - Best 2 (IDs = 601, 705) - Equal Weights (Hist. Data = 60),* we need to:

- use 60 + 6 = 66 latest historical data points.

3.1.6.2. Step 6b: Estimate final forecasts for the simple methods

We need to estimate final forecasts for each of the 2 or 3 best simple forecasting method (as indicated by the best averaging method).

In our example, and according to the best method: *Averaging - Best 2 (IDs = 601, 705) - Equal Weights (Hist. Data = 60),* we need to:

- to forecast with the first simple forecast methods with ID = 601 and
- to forecast with the second simple forecast methods with ID = 705.

3.1.6.3. Step 6c: Average the forecasts

Finally, we need to average the forecasts with equal or unequal weights (as indicated by the best averaging method).

In our example, and according to the best method: *Averaging - Best 2 (IDs = 601, 705) - Equal Weights (Hist. Data = 60)*, we need to:

- average these forecasts, by using equal weights.

✓ ***We are now ready, the final forecasts have been estimated***

3.2. Quarterly data: How the algorithm works

The algorithm has the same philosophy for handling a quarterly time serie, but some changes exist.

For better understanding, let's think again of an example.

- We have a quarterly time serie with 200 data points
- We need to forecast for 8 horizons

3.2.1. Step 1: Keep post-sampling data

We keep the **last 8 historical observations as post-sampling**, in order to evaluate our forecasts. Thus, now we have 200 - 8 = **192 historical data points** to use.

3.2.2. Step 2: Run with minimum historical data points.

We define that **<u>40 historical data points</u>** are the minimum set for starting (**5** times the requested horizon).

3.2.2.1. Step 2a: Run all Simple forecasting methods.

We use these 40 historical data points, and we estimate forecasts with all the available simple forecasting methods (Paragraph 7 has a list of all the simple forecasting methods that we use).

As a results, we have 8 forecasts for every simple forecasting method.

3.2.2.2. Extra Quarterly Step: Aggregation to Yearly

This is an extra step for the quarterly time series.
Again, we use these 40 historical data points, but now we are transforming the quarterly data to yearly. Thus, we:

➔ Estimate the quarterly seasonal indices (1 for each of the 4 periods),
➔ Deseasonalize the data,
➔ Aggregate the quarterly data to yearly, and create a new time serie with 10 yearly historical data points.

- ➔ Estimate forecasts for the new yearly time serie with all the available simple forecasting methods.
- ➔ Disaggregate the forecasts, by using the estimated quarterly seasonal indices.

As a results, we have 8 forecasts for every simple forecasting methods applied to the aggregated data.

3.2.2.3. Step 2b: Estimate the forecasting errors for each method.

By comparing the forecasts with the post-sampling data, we can estimate the forecasting error for each method. The target is to estimate:

- The **sMAPE**,
- The **MASE**,
- The **relative sMAPE**,
- The **relative MASE**,
- And finally the **OWA error,**

for each method.

3.2.2.4. Step 2c: Rank the simple forecast methods

We rank the simple forecast method, by the OWA error.
In our example, the results could look like this:

- *Moving Average - Simple3 – Seasonal (No aggregation) → OWA 0.756*
- *Decomposition - Multiplicative - MAD3B – Seasonal (With aggregation) → OWA 0.782*
- *Theta 2.00 - Exponential Smoothing - Simple - A2 – Seasonal (With aggregation) → OWA 0.811*
- *…*
- *Naive2 → OWA 1.000*
- *…*

3.2.2.5. Step 2d: Run the 8 averaging methods

We run the 8 average methods. (Paragraph 8 has the list of all averaging methods that we use).
As a results, we have 8 forecasts for every average forecasting method.

3.2.2.6. Step 2e: Estimate the forecasting errors for each averaging method.

By comparing the forecasts with the post-sampling data, we can estimate the forecasting error for each averaging method. The target is to estimate:

- The **sMAPE**,
- The **MASE**,
- The **relative sMAPE**,
- The **relative MASE**,
- And finally the **OWA error,**

for each averaging method.

3.2.2.7. Step 2f: Rank the average methods

We rank the average methods, by the OWA error.
In our example, the results could look like this:

- *Averaging - Best 2 (IDs = 601 with aggregation, 705 no aggregation) - Equal Weights → OWA 0.771*
- *Averaging - Best 2 (IDs = 401 no aggregation, 705 no aggregation) - DifCat - Equal Weights → OWA 0.792*
- *…*

3.2.3. Step 3: Run again all methods, for more historical data points.

We are now incrementally increasing the historical data points, and we repeat all steps 2a – 2f (including the extra step).
Thus, in our example:

- We use **80** historical data points (**10** times the horizon), and repeat steps 2a-2f.
- We use **120** historical data points (**15** times the horizon), and repeat steps 2a-2f.
- We use **160** historical data points (**20** times the horizon), and repeat steps 2a-2f.
- Finally, we use **192** historical data points (**max** size of the time serie, see step1), and repeat steps 2a-2f.

3.2.4. Step 4: Rank all the average methods, from all steps

We rank the average methods from all steps, by the OWA error.

As a results we have a list of ***N*** average methods sorted by OWA, where N = 8 x times repeated step2. (In our example N = 8 methods x 5 repeats = 40).

In our example, the results could look like this:

- *Averaging - Best 2 (IDs = 601 with aggregation, 705 no aggregation) - Equal Weights (Hist. Data = 120) → OWA 0.771*
- *Averaging - Best 2 (IDs = 401 no aggregation, 705 no aggregation) - DifCat - Equal Weights (Hist. Data = 120) → OWA 0.792*
- *Averaging - Best 3 (IDs = 611 with aggregation, 705 with aggregation, 201 no aggregation) - Estimated Weights (Hist. Data = 40) → 0.801*
- *…*

3.2.5. Step 5: Find which average method is the best

From the list that we have produced in the previous step, we select the **best averaging method**. Thus, the averaging method with the **smallest OWA**.

In case that 2 or more averaging method have exactly the same OWA, we use extra ordering criteria, which are:

- the simplest averaging method (with 2 methods to combine, with equal weights), and
- the largest set of historical data.

In our example, the best method could be something like:

- *Averaging - Best 2 (IDs = 601 with aggregation, 705 no aggregation) - Equal Weights (Hist. Data = 120) → OWA 0.771*

✓ ***The process of selecting the best method to forecast has been completed.***

3.2.6. Step 6: Estimate final forecasts with the best average method

Since the process of selecting the best method to forecast has been completed, only the estimation of the final forecasts remains.

3.2.6.1. Step 6a: Historical data to use

In the final forecasts, we will use only the historical data (as indicated by the best averaging method), but we must add the 8 latest historical data points that we have kept as post-sampling.

In our example, and according to the best method: *Averaging - Best 2 (IDs = 601 with aggregation, 705 no aggregation) - Equal Weights (Hist. Data = 120),* we need to:

- use 120 + 8 = 128 latest historical data points.

3.2.6.2. Step 6b: Estimate final forecasts for the simple methods

We need to estimate final forecasts for each of the 2 or 3 best simple forecasting method (as indicated by the best averaging method).

In our example, and according to the best method: *Averaging - Best 2 (IDs = 601 with aggregation, 705 no aggregation) - Equal Weights (Hist. Data = 120),* we need to:

- to forecast with the first simple forecast methods with ID = 601 with aggregation and
- to forecast with the second simple forecast methods with ID = 705 no aggregation.

3.2.6.3. Step 6c: Average the forecasts

Finally, we need to average the forecasts with equal or unequal weights (as indicated by the best averaging method).

In our example, and according to the best method: *Averaging - Best 2 (IDs = 601 with aggregation, 705 no aggregation) - Equal Weights (Hist. Data = 120)*, we need to:

- average these forecasts, by using equal weights.

✓ ***We are now ready, the final forecasts have been estimated***

3.3. Monthly data: How the algorithm works

The algorithm has the same philosophy for handling a monthly time serie, but some changes exist.

For better understanding, let's think again of an example.

- We have a monthly time serie with 600 data points
- We need to forecast for 18 horizons

3.3.1. Step 1: Keep post-sampling data

We keep the **last 18 historical observations as post-sampling**, in order to evaluate our forecasts. Thus, now we have 600 - 18 = **582 historical data points** to use.

3.3.2. Step 2: Run with minimum historical data points.

We define that <u>**90 historical data points**</u> are the minimum set for starting (**5** times the requested horizon).

3.3.2.1. Step 2a: Run all Simple forecasting methods.

We use these 90 historical data points, and we estimate forecasts with all the available simple forecasting methods (Paragraph 7 has a list of all the simple forecasting methods that we use).

As a results, we have 18 forecasts for every simple forecasting method.

3.3.2.2. Extra Monthly Step: Aggregation to Yearly

This is an extra step for the monthly time series.

Again, we use these 90 historical data points, but now we are transforming the monthly data to yearly. Thus, we:

➔ Estimate the monthly seasonal indices (1 for each of the 12 periods),

➔ Deseasonalize the data,

➔ Aggregate the monthly data to yearly, and create a new time serie with 7 yearly historical data points.

- → Estimate forecasts for the new yearly time serie with all the available simple forecasting methods.
- → Disaggregate the forecasts, by using the estimated monthly seasonal indices.

As a results, we have 18 forecasts for every simple forecasting methods applied to the aggregated data.

3.3.2.3. Step 2b: Estimate the forecasting errors for each method.

By comparing the forecasts with the post-sampling data, we can estimate the forecasting error for each method. The target is to estimate:

- The **sMAPE**,
- The **MASE**,
- The **relative sMAPE**,
- The **relative MASE**,
- And finally the **OWA error,**

for each method.

3.3.2.4. Step 2c: Rank the simple forecast methods

We rank the simple forecast method, by the OWA error.
In our example, the results could look like this:

- *Moving Average - Simple3 – Seasonal (No aggregation) → OWA 0.756*
- *Decomposition - Multiplicative - MAD3B – Seasonal (With aggregation) → OWA 0.782*
- *Theta 2.00 - Exponential Smoothing - Simple - A2 – Seasonal (With aggregation) → OWA 0.811*
- *…*
- *Naive2 → OWA 1.000*
- *…*

3.3.2.5. Step 2d: Run the 8 averaging methods

We run the 8 average methods. (Paragraph 8 has the list of all averaging methods that we use).
As a results, we have 18 forecasts for every average forecasting method.

3.3.2.6. Step 2e: Estimate the forecasting errors for each averaging method.

By comparing the forecasts with the post-sampling data, we can estimate the forecasting error for each averaging method. The target is to estimate:

- The **sMAPE**,
- The **MASE**,
- The **relative sMAPE**,
- The **relative MASE**,
- And finally the **OWA error,**

for each averaging method.

3.3.2.7. Step 2f: Rank the average methods

We rank the average methods, by the OWA error.
In our example, the results will look like this:

- *Averaging - Best 2 (IDs = 601 with aggregation, 705 no aggregation) - Equal Weights → OWA 0.771*
- *Averaging - Best 2 (IDs = 401 no aggregation, 705 no aggregation) - DifCat - Equal Weights → OWA 0.792*
- *…*

3.3.3. Step 3: Run again all methods, for more historical data points.

We are now incrementally increasing the historical data points, and we repeat all steps 2a – 2f (including the extra step).
Thus, in our example:

- We use **180** historical data points (**10** times the horizon), and repeat steps 2a-2f.
- We use **270** historical data points (**15** times the horizon), and repeat steps 2a-2f.
- We use **360** historical data points (**20** times the horizon), and repeat steps 2a-2f.
- We use **450** historical data points (**25** times the horizon), and repeat steps 2a-2f.
- We use **540** historical data points (**30** times the horizon), and repeat steps 2a-2f.
- Finally, we use **582** historical data points (**max** size of the time serie, see step1), and repeat steps 2a-2f.

3.3.4. Step 4: Rank all the average methods, from all steps

We rank the average methods from all steps, by the OWA error.
As a results we have a list of ***N*** average methods sorted by OWA, where N = 8 x times repeated step2. (In our example N = 8 methods x 7 repeats = 56).
In our example, the results could look like this:

- *Averaging - Best 2 (IDs = 601 with aggregation, 705 no aggregation) - Equal Weights (Hist. Data = 450) → OWA 0.771*
- *Averaging - Best 2 (IDs = 401 no aggregation, 705 no aggregation) - DifCat - Equal Weights (Hist. Data = 360) → OWA 0.792*
- *Averaging - Best 3 (IDs = 611 with aggregation, 705 with aggregation, 201 no aggregation) - Estimated Weights (Hist. Data = 90) → 0.801*
- *…*

3.3.5. Step 5: Find which average method is the best

From the list that we have produced in the previous step, we select the **best averaging method**. Thus, the averaging method with the **smallest OWA**.

In case that 2 or more averaging method have exactly the same OWA, we use extra ordering criteria, which are:

- the simplest averaging method (with 2 methods to combine, with equal weights), and
- the largest set of historical data.

In our example, the best method could be something like:

- *Averaging - Best 2 (IDs = 601 with aggregation, 705 no aggregation) - Equal Weights (Hist. Data = 450) → OWA 0.771*

✓ ***The process of selecting the best method to forecast has been completed.***

3.3.6. Step 6: Estimate final forecasts with the best average method

Since the process of selecting the best method to forecast has been completed, only the estimation of the final forecasts remains.

3.3.6.1. Step 6a: Historical data to use

In the final forecasts, we will use only the historical data (as indicated by the best averaging method), but we must add the 18 latest historical data points that we have kept as post-sampling.

In our example, and according to the best method: *Averaging - Best 2 (IDs = 601 with aggregation, 705 no aggregation) - Equal Weights (Hist. Data = 450),* we need to:

- use 450 + 8 = 458 latest historical data points.

3.3.6.2. Step 6b: Estimate final forecasts for the simple methods

We need to estimate final forecasts for each of the 2 or 3 best simple forecasting method (as indicated by the best averaging method).

In our example, and according to the best method: *Averaging - Best 2 (IDs = 601 with aggregation, 705 no aggregation) - Equal Weights (Hist. Data = 450),* we need to:

- to forecast with the first simple forecast methods with ID = 601 with aggregation and
- to forecast with the second simple forecast methods with ID = 705 no aggregation

3.3.6.3. Step 6c: Average the forecasts

Finally, we need to average the forecasts with equal or unequal weights (as indicated by the best averaging method).

In our example, and according to the best method: *Averaging - Best 2 (IDs = 601 with aggregation, 705 no aggregation) - Equal Weights (Hist. Data = 450)*, we need to:

- average these forecasts, by using equal weights.

✓ ***We are now ready, the final forecasts have been estimated***

3.4. Weekly data: How the algorithm works

The algorithm has the same philosophy for handling a weekly time serie, but some changes exist.

For better understanding, let's think again of an example.

- We have a weekly time serie with 500 data points
- We need to forecast for 13 horizons

3.4.1. Step 1: Keep post-sampling data

We keep the **last 13 historical observations as post-sampling**, in order to evaluate our forecasts. Thus, now we have 500 - 13 = **487 historical data points** to use.

3.4.2. Step 2: Run with minimum historical data points.

We define that **<u>65 historical data points</u>** are the minimum set for starting (**5** times the requested horizon).

3.4.2.1. Step 2a: Run all Simple forecasting methods.

We use these 65 historical data points, and we estimate forecasts with all the available simple forecasting methods (Paragraph 7 has a list of all the simple forecasting methods that we use).

As a results, we have 13 forecasts for every simple forecasting method.

3.4.2.2. Extra Weekly Step: Aggregation to Yearly

This is an extra step for the weekly time series.
Again, we use these 65 historical data points, but now we are transforming the weekly data to yearly. Thus, we:

➔ Estimate the weekly seasonal indices (1 for each of the 52 periods),
➔ Deseasonalize the data,
➔ Aggregate the weekly data to yearly, and create a new time serie with yearly historical data points.

- ➔ Estimate forecasts for the new yearly time serie with all the available simple forecasting methods.
- ➔ Disaggregate the forecasts, by using the estimated weekly seasonal indices.

As a results, we have 13 forecasts for every simple forecasting methods applied to the aggregated data.

Note: As it is obvious, we can't aggregate weekly data to yearly if the historical observations are too few (65 is not enough)! This extra step is used, only when the historical observations are **more than 260** (thus, enough to create a yearly time serie with 5 observations).

3.4.2.3. Step 2b: Estimate the forecasting errors for each method.

By comparing the forecasts with the post-sampling data, we can estimate the forecasting error for each method. The target is to estimate:

- The **sMAPE**,
- The **MASE**,
- The **relative sMAPE**,
- The **relative MASE**,
- And finally the **OWA error,**

for each method.

3.4.2.4. Step 2c: Rank the simple forecast methods

We rank the simple forecast method, by the OWA error.

In our example, the results could look like this:

- *Moving Average - Simple3 – Seasonal (No aggregation) → OWA 0.756*
- *Decomposition - Multiplicative - MAD3B – Seasonal (With aggregation) → OWA 0.782*
- *Theta 2.00 - Exponential Smoothing - Simple - A2 – Seasonal (With aggregation) → OWA 0.811*
- *…*
- *Naive2 → OWA 1.000*
- *…*

3.4.2.5. Step 2d: Run the 8 averaging methods

We run the 8 average methods. (Paragraph 8 has the list of all averaging methods that we use).
As a results, we have 13 forecasts for every average forecasting method.

3.4.2.6. Step 2e: Estimate the forecasting errors for each averaging method.

By comparing the forecasts with the post-sampling data, we can estimate the forecasting error for each averaging method. The target is to estimate:

- The **sMAPE**,
- The **MASE**,
- The **relative sMAPE**,
- The **relative MASE**,
- And finally the **OWA error,**

for each averaging method.

3.4.2.7. Step 2f: Rank the average methods

We rank the average methods, by the OWA error.
In our example, the results will look like this:

- *Averaging - Best 2 (IDs = 601 with aggregation, 705 no aggregation) - Equal Weights → OWA 0.771*
- *Averaging - Best 2 (IDs = 401 no aggregation, 705 no aggregation) - DifCat - Equal Weights → OWA 0.792*
- *…*

3.4.3. Step 3: Run again all methods, for more historical data points.

We are now incrementally increasing the historical data points, and we repeat all steps 2a – 2f (including the extra step).
Thus, in our example:

- We use **130** historical data points (**10** times the horizon), and repeat steps 2a-2f.
- We use **195** historical data points (**15** times the horizon), and repeat steps 2a-2f.

- We use **260** historical data points (**20** times the horizon), and repeat steps 2a-2f.
- We use **325** historical data points (**25** times the horizon), and repeat steps 2a-2f.
- We use **390** historical data points (**30** times the horizon), and repeat steps 2a-2f.
- We use **455** historical data points (**35** times the horizon), and repeat steps 2a-2f.
- Finally, we use **487** historical data points (**max** size of the time serie, see step1), and repeat steps 2a-2f.

3.4.4. Step 4: Rank all the average methods, from all steps

We rank the average methods from all steps, by the OWA error.
As a results we have a list of ***N*** average methods sorted by OWA, where N = 8 x times repeated step2. (In our example N = 8 methods x 8 repeats = 64).
In our example, the results could look like this:

- *Averaging - Best 2 (IDs = 601 with aggregation, 705 no aggregation) - Equal Weights (Hist. Data = 390) → OWA 0.771*
- *Averaging - Best 2 (IDs = 401 no aggregation, 705 no aggregation) - DifCat - Equal Weights (Hist. Data = 455) → OWA 0.792*
- *Averaging - Best 3 (IDs = 611 with aggregation, 705 with aggregation, 201 no aggregation) - Estimated Weights (Hist. Data = 260) → 0.801*
- *…*

3.4.5. Step 5: Find which average method is the best

From the list that we have produced in the previous step, we select the **best averaging method**. Thus, the averaging method with the **smallest OWA**.

In case that 2 or more averaging method have exactly the same OWA, we use extra ordering criteria, which are:

- the simplest averaging method (with 2 methods to combine, with equal weights), and
- the largest set of historical data.

In our example, the best method could be something like:

- *Averaging - Best 2 (IDs = 601 with aggregation, 705 no aggregation) - Equal Weights (Hist. Data = 390) → OWA 0.771*

✓ ***The process of selecting the best method to forecast has been completed.***

3.4.6. Step 6: Estimate final forecasts with the best average method

Since the process of selecting the best method to forecast has been completed, only the estimation of the final forecasts remains.

3.4.6.1. Step 6a: Historical data to use

In the final forecasts, we will use only the historical data (as indicated by the best averaging method), but we must add the 13 latest historical data points that we have kept as post-sampling.

In our example, and according to the best method: *Averaging - Best 2 (IDs = 601 with aggregation, 705 no aggregation) - Equal Weights (Hist. Data = 390),* we need to:

- use 390 + 13 = 403 latest historical data points.

3.4.6.2. Step 6b: Estimate final forecasts for the simple methods

We need to estimate final forecasts for each of the 2 or 3 best simple forecasting method (as indicated by the best averaging method).

In our example, and according to the best method: *Averaging - Best 2 (IDs = 601 with aggregation, 705 no aggregation) - Equal Weights (Hist. Data = 390),* we need to:

- to forecast with the first simple forecast methods with ID = 601 with aggregation and
- to forecast with the second simple forecast methods with ID = 705 no aggregation

3.4.6.3. Step 6c: Average the forecasts

Finally, we need to average the forecasts with equal or unequal weights (as indicated by the best averaging method).

In our example, and according to the best method: *Averaging - Best 2 (IDs = 601 with aggregation, 705 no aggregation) - Equal Weights (Hist. Data = 390)*, we need to:

- average these forecasts, by using equal weights.

✓ ***We are now ready, the final forecasts have been estimated***

3.5. Daily data: How the algorithm works

The algorithm has the same philosophy for handling a daily time serie, but some changes exist.

For better understanding, let's think again of an example.

- We have a daily time serie with 1000 data points
- We need to forecast for 14 horizons

3.5.1. Step 1: Keep post-sampling data

We keep the **last 14 historical observations as post-sampling**, in order to evaluate our forecasts. Thus, now we have 1000 - 14 = **986 historical data points** to use.

3.5.2. Step 2: Run with minimum historical data points.

We define that **<u>70 historical data points</u>** are the minimum set for starting (**5** times the requested horizon).

3.5.2.1. Step 2a: Run all Simple forecasting methods.

We use these 70 historical data points, and we estimate forecasts with all the available simple forecasting methods (Paragraph 7 has a list of all the simple forecasting methods that we use).

As a results, we have 14 forecasts for every simple forecasting method.

3.5.2.2. Extra Daily Step: Aggregation to Weekly

This is an extra step for the daily time series.
Again, we use these 70 historical data points, but now we are transforming the daily data to weekly. Thus, we:

- ➔ Estimate the daily seasonal indices (1 for each of the 7 periods, the 7 days of a week),
- ➔ Deseasonalize the data,
- ➔ Aggregate the daily data to weekly, and create a new time serie with 10 weekly historical data points.

- ➔ Estimate forecasts for the new weekly time serie with all the available simple forecasting methods.
- ➔ Disaggregate the forecasts, by using the estimated daily seasonal indices.

As a results, we have 14 forecasts for every simple forecasting methods applied to the aggregated data.

3.5.2.3. Step 2b: Estimate the forecasting errors for each method.

By comparing the forecasts with the post-sampling data, we can estimate the forecasting error for each method. The target is to estimate:

- The **sMAPE**,
- The **MASE**,
- The **relative sMAPE**,
- The **relative MASE**,
- And finally the **OWA error,**

for each method.

3.5.2.4. Step 2c: Rank the simple forecast methods

We rank the simple forecast method, by the OWA error.
In our example, the results could look like this:

- *Moving Average - Simple3 – Seasonal (No aggregation) → OWA 0.756*
- *Decomposition - Multiplicative - MAD3B – Seasonal (With aggregation) → OWA 0.782*
- *Theta 2.00 - Exponential Smoothing - Simple - A2 – Seasonal (With aggregation) → OWA 0.811*
- *…*
- *Naive2 → OWA 1.000*
- *…*

3.5.2.5. Step 2d: Run the 8 averaging methods

We run the 8 average methods. (Paragraph 8 has the list of all averaging methods that we use).
As a results, we have 14 forecasts for every average forecasting method.

3.5.2.6. Step 2e: Estimate the forecasting errors for each averaging method.

By comparing the forecasts with the post-sampling data, we can estimate the forecasting error for each averaging method. The target is to estimate:

- The **sMAPE**,
- The **MASE**,
- The **relative sMAPE**,
- The **relative MASE**,
- And finally the **OWA error,**

for each averaging method.

3.5.2.7. Step 2f: Rank the average methods

We rank the average methods, by the OWA error.
In our example, the results will look like this:

- *Averaging - Best 2 (IDs = 601 with aggregation, 705 no aggregation) - Equal Weights → OWA 0.771*
- *Averaging - Best 2 (IDs = 401 no aggregation, 705 no aggregation) - DifCat - Equal Weights → OWA 0.792*
- *…*

3.5.3. Step 3: Run again all methods, for more historical data points.

We are now incrementally increasing the historical data points, and we repeat all steps 2a – 2f (including the extra step).
Thus, in our example:

- We use **140** historical data points (**10** times the horizon), and repeat steps 2a-2f.
- We use **210** historical data points (**15** times the horizon), and repeat steps 2a-2f.
- We use **280** historical data points (**20** times the horizon), and repeat steps 2a-2f.
- We use **350** historical data points (**25** times the horizon), and repeat steps 2a-2f.
- We use **420** historical data points (**30** times the horizon), and repeat steps 2a-2f.
- We use **490** historical data points (**35** times the horizon), and repeat steps 2a-2f.
- We use **560** historical data points (**40** times the horizon), and repeat steps 2a-2f.
- We use **630** historical data points (**45** times the horizon), and repeat steps 2a-2f.
- We use **700** historical data points (**50** times the horizon), and repeat steps 2a-2f.
- We use **770** historical data points (**55** times the horizon), and repeat steps 2a-2f.

- We use **840** historical data points (**60** times the horizon), and repeat steps 2a-2f.
- We use **910** historical data points (**65** times the horizon), and repeat steps 2a-2f.
- We use **980** historical data points (**70** times the horizon), and repeat steps 2a-2f.
- Finally, we use **986** historical data points (**max** size of the time serie, see step1), and repeat steps 2a-2f.

3.5.4. Step 4: Rank all the average methods, from all steps

We rank the average methods from all steps, by the OWA error.
As a results we have a list of ***N*** average methods sorted by OWA, where N = 8 x times repeated step2. (In our example N = 8 methods x 15 repeats = 120).
In our example, the results could look like this:

- *Averaging - Best 2 (IDs = 601 with aggregation, 705 no aggregation) - Equal Weights (Hist. Data = 630) → OWA 0.771*
- *Averaging - Best 2 (IDs = 401 no aggregation, 705 no aggregation) - DifCat - Equal Weights (Hist. Data = 910) → OWA 0.792*
- *Averaging - Best 3 (IDs = 611 with aggregation, 705 with aggregation, 201 no aggregation) - Estimated Weights (Hist. Data = 210) → 0.801*
- *…*

3.5.5. Step 5: Find which average method is the best

From the list that we have produced in the previous step, we select the **best averaging method**. Thus, the averaging method with the **smallest OWA**.

In case that 2 or more averaging method have exactly the same OWA, we use extra ordering criteria, which are:

- the simplest averaging method (with 2 methods to combine, with equal weights), and
- the largest set of historical data.

In our example, the best method could be something like:

- *Averaging - Best 2 (IDs = 601 with aggregation, 705 no aggregation) - Equal Weights (Hist. Data = 630) → OWA 0.771*

✓ ***The process of selecting the best method to forecast has been completed.***

3.5.6. Step 6: Estimate final forecasts with the best average method

Since the process of selecting the best method to forecast has been completed, only the estimation of the final forecasts remains.

3.5.6.1. Step 6a: Historical data to use

In the final forecasts, we will use only the historical data (as indicated by the best averaging method), but we must add the 14 latest historical data points that we have kept as post-sampling.

In our example, and according to the best method: *Averaging - Best 2 (IDs = 601 with aggregation, 705 no aggregation) - Equal Weights (Hist. Data = 630),* we need to:

- use 630 + 14 = 644 latest historical data points.

3.5.6.2. Step 6b: Estimate final forecasts for the simple methods

We need to estimate final forecasts for each of the 2 or 3 best simple forecasting method (as indicated by the best averaging method).

In our example, and according to the best method: *Averaging - Best 2 (IDs = 601 with aggregation, 705 no aggregation) - Equal Weights (Hist. Data = 630),* we need to:

- to forecast with the first simple forecast methods with ID = 601 with aggregation and
- to forecast with the second simple forecast methods with ID = 705 no aggregation

3.5.6.3. Step 6c: Average the forecasts

Finally, we need to average the forecasts with equal or unequal weights (as indicated by the best averaging method).

In our example, and according to the best method: *Averaging - Best 2 (IDs = 601 with aggregation, 705 no aggregation) - Equal Weights (Hist. Data = 630)*, we need to:

- average these forecasts, by using equal weights.

✓ ***We are now ready, the final forecasts have been estimated***

3.6. Hourly data: How the algorithm works

The algorithm has the same philosophy for handling an hourly time serie, but some changes exist.

For better understanding, let's think again of an example.

- We have an hourly time serie with 800 data points
- We need to forecast for 48 horizons

3.6.1. Step 1: Keep post-sampling data

We keep the **last 48 historical observations as post-sampling**, in order to evaluate our forecasts. Thus, now we have 800 - 48 = **752 historical data points** to use.

3.6.2. Step 2: Run with minimum historical data points.

We define that **240 historical data points** are the minimum set for starting (**5** times the requested horizon).

3.6.2.1. Step 2a: Run all Simple forecasting methods.

We use these 240 historical data points, and we estimate forecasts with all the available simple forecasting methods (Paragraph 7 has a list of all the simple forecasting methods that we use).

As a results, we have 48 forecasts for every simple forecasting method.

3.6.2.2. Extra Hourly Step: Aggregation to Daily

This is an extra step for the hourly time series.
Again, we use these 240 historical data points, but now we are transforming the hourly data to daily. Thus, we:

- ➔ Estimate the hourly seasonal indices (1 for each of the 24 periods, the 24 hours of a day),
- ➔ Deseasonalize the data,
- ➔ Aggregate the hourly data to daily, and create a new time serie with 10 daily historical data points.

- ➔ Estimate forecasts for the new daily time serie with all the available simple forecasting methods.
- ➔ Disaggregate the forecasts, by using the estimated hourly seasonal indices.

As a results, we have 48 forecasts for every simple forecasting methods applied to the aggregated data.

Note: As it is obvious, we can't aggregate hourly data to daily if the historical observations are too few (240 is not enough)! This extra step is used, only when the historical observations **are at least 480** (thus, enough to create a daily time serie with 20 observations).

3.6.2.3. Step 2b: Estimate the forecasting errors for each method.

By comparing the forecasts with the post-sampling data, we can estimate the forecasting error for each method. The target is to estimate:

- The **sMAPE**,
- The **MASE**,
- The **relative sMAPE**,
- The **relative MASE**,
- And finally the **OWA error,**

for each method.

3.6.2.4. Step 2c: Rank the simple forecast methods

We rank the simple forecast method, by the OWA error.
In our example, the results could look like this:

- *Moving Average - Simple3 – Seasonal (No aggregation) → OWA 0.756*
- *Decomposition - Multiplicative - MAD3B – Seasonal (With aggregation) → OWA 0.782*
- *Theta 2.00 - Exponential Smoothing - Simple - A2 – Seasonal (With aggregation) → OWA 0.811*
- *…*
- *Naive2 → OWA 1.000*
- *…*

3.6.2.5. Step 2d: Run the 8 averaging methods

We run the 8 average methods. (Paragraph 8 has the list of all averaging methods that we use).
As a results, we have 48 forecasts for every average forecasting method.

3.6.2.6. Step 2e: Estimate the forecasting errors for each averaging method.

By comparing the forecasts with the post-sampling data, we can estimate the forecasting error for each averaging method. The target is to estimate:

- The **sMAPE**,
- The **MASE**,
- The **relative sMAPE**,
- The **relative MASE**,
- And finally the **OWA error,**

for each averaging method.

3.6.2.7. Step 2f: Rank the average methods

We rank the average methods, by the OWA error.
In our example, the results will look like this:

- *Averaging - Best 2 (IDs = 601 with aggregation, 705 no aggregation) - Equal Weights → OWA 0.771*
- *Averaging - Best 2 (IDs = 401 no aggregation, 705 no aggregation) - DifCat - Equal Weights → OWA 0.792*
- *…*

3.6.3. Step 3: Run again all methods, for more historical data points.

We are now incrementally increasing the historical data points, and we repeat all steps 2a – 2f (including the extra step).
Thus, in our example:

- We use **140** historical data points (**10** times the horizon), and repeat steps 2a-2f.
- We use **210** historical data points (**15** times the horizon), and repeat steps 2a-2f.

- We use **280** historical data points (**20** times the horizon), and repeat steps 2a-2f.
- We use **350** historical data points (**25** times the horizon), and repeat steps 2a-2f.
- We use **420** historical data points (**30** times the horizon), and repeat steps 2a-2f.
- We use **490** historical data points (**35** times the horizon), and repeat steps 2a-2f.
- We use **560** historical data points (**40** times the horizon), and repeat steps 2a-2f.
- We use **630** historical data points (**45** times the horizon), and repeat steps 2a-2f.
- We use **700** historical data points (**50** times the horizon), and repeat steps 2a-2f.
- We use **770** historical data points (**55** times the horizon), and repeat steps 2a-2f.
- We use **840** historical data points (**60** times the horizon), and repeat steps 2a-2f.
- We use **910** historical data points (**65** times the horizon), and repeat steps 2a-2f.
- We use **980** historical data points (**70** times the horizon), and repeat steps 2a-2f.
- Finally, we use **986** historical data points (**max** size of the time serie, see step1), and repeat steps 2a-2f.

3.6.4. Step 4: Rank all the average methods, from all steps

We rank the average methods from all steps, by the OWA error.
As a results we have a list of ***N*** average methods sorted by OWA, where N = 8 x times repeated step2. (In our example N = 8 methods x 15 repeats = 120).
In our example, the results could look like this:

- *Averaging - Best 2 (IDs = 601 with aggregation, 705 no aggregation) - Equal Weights (Hist. Data = 840) → OWA 0.771*
- *Averaging - Best 2 (IDs = 401 no aggregation, 705 no aggregation) - DifCat - Equal Weights (Hist. Data = 700) → OWA 0.792*
- *Averaging - Best 3 (IDs = 611 with aggregation, 705 with aggregation, 201 no aggregation) - Estimated Weights (Hist. Data = 350) → 0.801*
- *…*

3.6.5. Step 5: Find which average method is the best

From the list that we have produced in the previous step, we select the **best averaging method**. Thus, the averaging method with the **smallest OWA**.

In case that 2 or more averaging method have exactly the same OWA, we use extra ordering criteria, which are:

- the simplest averaging method (with 2 methods to combine, with equal weights), and

- the largest set of historical data.

In our example, the best method could be something like:

- *Averaging - Best 2 (IDs = 601 with aggregation, 705 no aggregation) - Equal Weights (Hist. Data = 840) → OWA 0.771*

✓ ***The process of selecting the best method to forecast has been completed.***

3.6.6. Step 6: Estimate final forecasts with the best average method

Since the process of selecting the best method to forecast has been completed, only the estimation of the final forecasts remains.

3.6.6.1. Step 6a: Historical data to use

In the final forecasts, we will use only the historical data (as indicated by the best averaging method), but we must add the 48 latest historical data points that we have kept as post-sampling.

In our example, and according to the best method: *Averaging - Best 2 (IDs = 601 with aggregation, 705 no aggregation) - Equal Weights (Hist. Data = 840),* we need to:

- use 840 + 48 = 888 latest historical data points.

3.6.6.2. Step 6b: Estimate final forecasts for the simple methods

We need to estimate final forecasts for each of the 2 or 3 best simple forecasting method (as indicated by the best averaging method).

In our example, and according to the best method: *Averaging - Best 2 (IDs = 601 with aggregation, 705 no aggregation) - Equal Weights (Hist. Data = 840),* we need to:

- to forecast with the first simple forecast methods with ID = 601 with aggregation and
- to forecast with the second simple forecast methods with ID = 705 no aggregation

3.6.6.3. Step 6c: Average the forecasts

Finally, we need to average the forecasts with equal or unequal weights (as indicated by the best averaging method).

In our example, and according to the best method: *Averaging - Best 2 (IDs = 601 with aggregation, 705 no aggregation) - Equal Weights (Hist. Data = 840)*, we need to:

- average these forecasts, by using equal weights.

✓ ***We are now ready, the final forecasts have been estimated***

4. Technical Description

The scope of this document is to help the reader:

- Understand how the proposed ***AGON*** method has been developed

4.1. Software Tools and Design

The ***AGON*** method has been developed as:

- A **DLL library**, which holds all the functions and methods
- An **SQL Server Database**, which includes:
    - The time series historical data values,
    - The methodology for applying the ***AGON*** method philosophy, which is implemented by developing:
        - Tables,
        - Stored procedures, and
        - Functions.
    - The forecasts submitted to the M4 competition.

The following tools have been used:

- Microsoft Visual Studio 2017, and
- Microsoft SQL Server Management Studio 2014 with an SQL Server 2014 Express Instance.

4.2. The DLL Library

4.2.1. Description

The “Microsoft Visual Studio 2017” has been used for developing a .NET library.
This library, named ***MathNLIBSQL***, has been created from scratch using **VB.net code**.

4.2.2. Explaining the DLL

<u>Methods</u>

It includes all methods and functions needed for supporting the ***AGON*** averaging forecasting method, thus:

- Common mathematical functions, such as mean, median, max, min, variance, seasonality checks, etc.
- Detecting and removing outliers functions.
- Seasonalization and deseasonalization functions.
- The main function Forecast (which triggers all the forecasting methods)
- The simple forecasting methods, including: Naïve, Regression, Decomposition, Moving Average, Smoothing, and Theta methods.
- The Averaging forecasting functions.
- The Level-up forecasting functions (which are used in specific types of time series).
- Specific functions that can be called from an SQL server database.

The DLL has been compiled and build (under the name **MathNLIBSQL.dll**), and then added to the SQL Server database as an assembly.

<u>Source Code</u>

Both the VB.net source code of the DLL library, as well as the DLL binary file, are included in the GitHub.
However, the code and the binary file are not needed for reproducing the results of the M4 competition. The source code has already been compiled, a DLL file has been build, and the DLL file has been added to the SQL server database as an assembly.

4.3. The SQL Server Database

4.3.1. Description

The "Microsoft SQL Server Management Studio 2014" has been used for creating an SQL database. This database, named "***PatelisM4***" has been created from scratch using the management studio and sql code for programming stored procedures and functions.
It includes everything that needed to support the ***AGON*** averaging forecasting method, thus:

- The time series historical data values,
- The methodology for applying the AGON method philosophy, which is implemented by developing:
    - Tables,
    - Stored procedures, and
    - Functions.
- The forecasts submitted to the M4 competition.

4.3.2. Explaining the database

Database Tables

The database includes 25 tables. The most important tables will be described in this paragraph:

- **SF_Timeseries**: Stores the information (code, name, type, horizon, frequency, etc.) of the 100.000 time series of the M4 competition.
- **SF_Data**: Stores all the historical data points (24,002,047 data points) for all time series (100,000) of the M4 competition.
- **SF_ForecastingMethods:** Stores all simple statistical methods that are being used within the **AGON** averaging forecasting method.
- **SF_TimeseriesTypes:** Stores all information about the time series types.
- **M4_BestMethods:** Stores all information about the best method for all M4 time series. Information includes (for each time serie):
  - Time serie Code
  - Best Averaging method
  - Size of the historical data points to be used
  - Three Best performing simple statistical methods
  - Estimated weights for the three Best performing simple statistical methods
  - Error indexes over the post-sample of the time serie.
- **M4_Forecasts:** Stores all forecasts for the requested forecasting horizon for all M4 time series. Information includes (for each time serie):
  - Time serie Code
  - Forecast horizon
  - Forecast value
- **M4_BestMethods_ReEstimated:** If the user wants to re-estimate the best averaging method for a time serie, this table will be used for storing the results.
- **M4_Forecasts_ReEstimated:** If the user wants to re-estimate the forecasts for a time serie, this table will be used for storing the results.
- All other tables, are internally used from the **AGON** averaging forecasting method.

Database Stored Procedures

The database includes 35 stored procedures. The most important will be described in this paragraph:

- **M4_ReEstimateBestMethod**: This stored procedure can be used for re-estimating the best method for a time serie. Arguments:

    - Time serie Code (example 'Y1')
    - A bit value (1 or 0), for using a pre-defined length of historical data, or search again for the best historical data length to use.

  More information can be found on the "How to reproduce the results" paragraph.

- **M4_ReEstimateForecasts**: This stored procedure can be used for re-estimating the forecasts for a time serie. Arguments:
    - Time serie Code (example 'Y1')

  More information can be found on the "How to reproduce the results" paragraph.
- **M4_ReEstimateBestMethods_Compare**: A stored procedure for automatically compare the M4 results with the re-estimated results. More information can be found on the "How to reproduce the results" paragraph.
- **M4_ReEstimateForecasts_Compare**: A stored procedure for automatically compare the **submitted** M4 forecasts with the **re-estimated** forecasts. More information can be found on the "How to reproduce the results" paragraph.
- **M4_ExtractForecasts_To_CSV**: A stored procedure for automatically export all M4 submitted forecasts into a csv file format. More information can be found on the "How to reproduce the results" paragraph.
- **M4_Extract_ReEstimatedForecasts_To_CSV**: A stored procedure for automatically export all M4 re-estimated forecasts into a csv file format. More information can be found on the "How to reproduce the results" paragraph.
- **M4_Run_01_Yearly**: Initiates the forecast for an M4 yearly time serie. Arguments:
    - Time serie Code (example 'Y1')
    - A bit value (1 or 0), for using a pre-defined length of historical data, or search again for the best historical data length to use.
- **M4_Run_04_Quarterly**: Initiates the forecast for an M4 quarterly time serie. Arguments:
    - Time serie Code (example 'Q1')
    - A bit value (1 or 0), for using a pre-defined length of historical data, or search again for the best historical data length to use.
- **M4_Run_06_Monthly**: Initiates the forecast for an M4 monthly time serie. Arguments:
    - Time serie Code (example 'M1')
    - A bit value (1 or 0), for using a pre-defined length of historical data, or search again for the best historical data length to use.
- **M4_Run_08_Weekly**: Initiates the forecast for an M4 weekly time serie. Arguments:
    - Time serie Code (example 'W1')
    - A bit value (1 or 0), for using a pre-defined length of historical data, or search again for the best historical data length to use.

- **M4_Run_09_Daily**: Initiates the forecast for an M4 daily time serie. Arguments:
    - Time serie Code (example ‘D1’)
    - A bit value (1 or 0), for using a pre-defined length of historical data, or search again for the best historical data length to use.
- **M4_Run_10_Hourly**: Initiates the forecast for an M4 hourly time serie. Arguments:
    - Time serie Code (example ‘H1’)
    - A bit value (1 or 0), for using a pre-defined length of historical data, or search again for the best historical data length to use.
- **Competition_Run**: This stored procedure is called internally, for executing all forecasting methods for a time serie.
- **Forecast_Run**: This stored procedure is called internally, for executing a specific simple forecasting method for a time serie.
- **Forecast_Run_Average**: This stored procedure is called internally, for executing an averaging forecasting method for a time serie.
- **Forecast_Run_SQ_LevelUp**: This stored procedure is called internally, for executing a simple forecasting method for a time serie, over the aggregated data.
- All other stored procedures, are internally used from the **AGON** averaging forecasting method.

<u>Database Functions</u>

The database includes 70 scalar-valued functions. The most important will be described in this paragraph:

- **fn_SQL_Forecast**: a function for calling the Forecast function from the MathNLIBSQL.dll, and receiving back the results.
- **fn_SQL_Forecast_SQ_LevelUp**: a function for calling the Forecast Level Up function from the MathNLIBSQL.dll, and receiving back the results.
- **fn_SQL_ForecastAverageTwo**: a function for calling the averaging forecast function (averaging with 2 forecasting methods) from the MathNLIBSQL.dll, and receiving back the results.
- **fn_SQL_ForecastAverageThree**: a function for calling the averaging forecast function (averaging with 3 forecasting methods) from the MathNLIBSQL.dll, and receiving back the results.
- All other functions are internally used from the ***AGON*** averaging forecasting method.

<u>Database Assemblies</u>

The database includes 2 assemblies:

- The **MathNLIBSQL.dll**, which is important for calling the functions included in the DLL library.
- The **Microsoft.SQLServer.Types**, which is needed for setting parameters for calling the functions from the DLL library.

5. GitHub content

5.1. Contents description

All available files (database, dll code, documentation) have been uploaded in the GitHub.

5.2. Database file

The file **“PatelisM4.bak”** is an SQL server database backup file, which can be used for restoring the **PatelisM4** database.
Since the size of the file is about 2.4 GB, it is too big to be uploaded in GitHub (max 25MB per file). That’s why we have **<u>zipped the file, and splitted into 19 files</u>**.
By using the “**PatelisM4.zip.001**” file, the “**PatelisM4.bak**” file can be recreated.

5.3. Dll code

The file “**MathNLIBSQL.zip**” is a zip file containing the VB.net code of the MathNLIBSQL DLL library.

5.4. Method Description file

The file “**Patelis_M4-Method-Description.pdf**” (thus this file) is a pdf file which describes the ***AGON*** method.

6. How to reproduce the results

This paragraph provides the necessary guidance for using the GitHub content in order to reproduce both:

- **The ReEstimation of BestMethod**: Thus, the selection process of the forecasting method for each M4 time serie.
- **The ReEstimation of Forecasts**: Thus, the process for estimating the forecasts for the requested forecasting horizon of a time serie.

Note: This paragraph explains **ONLY** the above, thus how to reproduce all results. If you want to find out how the methods works, please read the **"Extended Description"** paragraph.

6.1. Software Installation

You must firstly **download** all content from the GitHub.

6.1.1. Mandatory Software

You should setup the following software in your computer (they are mandatory for working with the ***AGON*** method and reproduce a) the method selection process and b) the forecasts):

- Microsoft SQL Server Management Studio 2014 (or newer),
- SQL Server 2014 Express Instance (or newer "Express" version, or a "Developer" version, both are free to use),

6.1.2. Optional Software

You may also install the following visual studio, although it is not mandatory for reproduce the results (you will need it only for viewing the DLL code):

- Microsoft Visual Studio 2017

6.2. Restore the Database

Step 1: Use the zip files of the database to unzip the file **"PatelisM4.bak"**. This file is the backup file of the database. It must be used for restoring the database.

Step2: Use the Microsoft SQL Server Management Studio to restore the database (On the Object explorer of Management studio, right click “Databases” and select “Restore”. Continue by restoring the database from device, thus from the file.

When the restore process is completed, the database “**PatelisM4**” is ready to be used.

6.3. How to re-estimate the Best Method

As we have already describe in the “Extended Description” paragraph, the ***AGON*** method follows a specific process for selecting the best method for forecasting an M4 time serie.

So, let’s assume that we want to run this selection process again for a time serie. These are the steps we need to follow:

6.3.1. Step 1: Select an M4 time serie

As an example, let’s select the time serie “**M10062**”, a monthly time serie.

6.3.2. Step 2: Run the BestMethod Selection Process

In the SQL Server Management studio, open a “**New Query**” and type:

```
exec dbo.M4_ReEstimateBestMethods 'M10062', 0
```

Then press “**Execute**” from the Query menu, and wait until query completes the execution. The **results** will be like this:

```
Started Timeserie: 57062
Completed with TrainingData: 90
Completed with TrainingData: 180
Completed with TrainingData: 270
Completed with TrainingData: 310
Completed Timeserie: 57062
************************************************************************************************************************************
Results for Time serie --> M10062
************************************************************************************************************************************
Best Averaging Method --> Averaging - Best 3 - DifCat- Estimated Weights
Historical Data-points to use --> 180
1st Method to combine --> Exponential Smoothing - Holt - A2 - Seasonal (Code: 602), Aggregate: No, Weight = 71
2nd Method to combine --> Theta 0.50 - Exponential Smoothing - Simple - F6 - NonSeasonal (Code: 977), Aggregate: Yes, Weight = 67
3rd Method to combine --> Exponential Smoothing - Damped - A2 - NonSeasonal (Code: 651), Aggregate: No, Weight = 62
************************************************************************************************************************************
************************************************************************************************************************************
Re-Estimate of Best Methods Completed!
You can compare the M4-BestMethods with the Re-Estimated BestMethods, by using the procedure --> M4_ReEstimateBestMethods_Compare
************************************************************************************************************************************
```

Let’s explain the results:

- **“Started Timeserie…”**
    - A message indicating that the process has started. The number, in our example: 57062, is only an internal ID that the database is using.

- "**Completed with TrainingData...**"
  - Messages indicating that the process is trying to estimate how many historical data points should use. In our example: Firstly tries with 90 historical data points, then with 180, then 270, etc.….
- "**Completed Timeserie…**"
  - A message indicating that the process has completed.
- "**Results for time serie -->…**"
  - Just a header, for printing the results. The time serie code is also printed here.
- "**Best Averaging Method -->**"
  - A message indicating the best averaging method to use for this time serie. In our example: An averaging method of 3 simple methods, from different categories and with estimated (not equal) weights.
- "**Historical Data-points to use -->**"
  - A message indicating the size of the historical data points to use. In our example the 180 last historical data points will be used for forecasting.
- "**1st Method to combine -->**"
  - The 1^{st} method to combine in the average. In our example:
    - Exponential Smoothing – Holt – A2 – Seasonal (see "Extended description for more information about this method).
    - Internal ID of the method: 602
    - With aggregation: NO
    - Weight of this method = 71
- "**2nd Method to combine -->**"
  - The 2^{nd} method to combine in the average. In our example:
    - Theta 0.50 - Exponential Smoothing - Simple - F6 - NonSeasonal (see "Extended description for more information about this method).
    - Internal ID of the method: 977
    - With aggregation: YES
    - Weight of this method = 67
- "**3rd Method to combine -->**"
  - The 3rd method to combine in the average. In our example:
    - Exponential Smoothing – Damped – A2 – NonSeasonal (see "Extended description for more information about this method).
    - Internal ID of the method: 651
    - With aggregation: NO
    - Weight of this method = 62

- o <u>Note:</u> If the best averaging method selected needs to combine only 2 methods, then this message will be empty.

6.3.3. Step 3: Validate BestMethod Selection Process

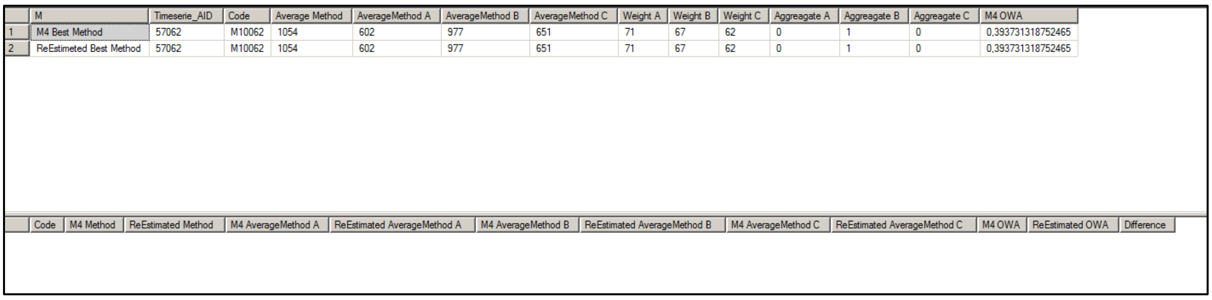
The database includes a tool for validating the best methods selection process.
The user can compare:

- The best method used in the M4 competition, with
- The best method selected in the previous step (re-estimate of Best method).

So, the user can open a Query window, and type:

```
exec dbo.M4_ReEstimateBestMethods_Compare 'M10062'
```

The results are the shown in the following image:



	M	Timeserie_AID	Code	Average Method	AverageMethod A	AverageMethod B	AverageMethod C	Weight A	Weight B	Weight C	Aggreagate A	Aggreagate B	Aggreagate C	M4 OWA
1	M4 Best Method	57062	M10062	1054	602	977	651	71	67	62	0	1	0	0,393731318752465
2	ReEstimeted Best Method	57062	M10062	1054	602	977	651	71	67	62	0	1	0	0,393731318752465

	Code	M4 Method	ReEstimated Method	M4 AverageMethod A	ReEstimated AverageMethod A	M4 AverageMethod B	ReEstimated AverageMethod B	M4 AverageMethod C	ReEstimated AverageMethod C	M4 OWA	ReEstimated OWA	Difference

The first table (dataset) shows the results of both the M4 and the re-estimation. Thus, it is easy for the user to observe that the results are identical
The second table (dataset) is empty, which means that the 2 results are identical.

6.4. How to re-estimate the forecasts

If the user wants to estimate the forecasts of an M4 time serie, the following steps must be followed:

6.4.1. Step 1: Select an M4 time serie

As an example, let's select the time serie "**M10062**", a monthly time serie.

6.4.2. Step 2: Run the Forecasts

In the SQL Server Management studio, open a "**New Query**" and type:

```
exec dbo.M4_ReEstimateBestMethods 'M10062', 0
```

Then press "**Execute**" from the Query menu, and wait until query completes the execution.

The **results** will be like this:

```
Completed Timeserie: M10062
****************************************************************************************************************************
Forecasts for Time serie --> M10062
****************************************************************************************************************************
Horizon: 1, Value: 998.05
Horizon: 2, Value: 1011.14
Horizon: 3, Value: 1021.9
Horizon: 4, Value: 1034.53
Horizon: 5, Value: 1046.85
Horizon: 6, Value: 1058.75
Horizon: 7, Value: 1070.66
Horizon: 8, Value: 1082.52
Horizon: 9, Value: 1094.67
Horizon: 10, Value: 1107.79
Horizon: 11, Value: 1120.87
Horizon: 12, Value: 1132.86
Horizon: 13, Value: 1154.12
Horizon: 14, Value: 1167.4
Horizon: 15, Value: 1177.89
Horizon: 16, Value: 1190.5
Horizon: 17, Value: 1202.96
Horizon: 18, Value: 1214.79
****************************************************************************************************************************
Re-Estimate of Forecasts Completed!
You can compare the M4-Forecasts with the Re-Estimated Forecasts, by using the procedure --> M4_ReEstimateForecasts_Compare
****************************************************************************************************************************
```

Let's explain the results:

- **"Completed Timeserie…"**
  - A message indicating that the process has completed.
- "**Forecasts for time serie -->…**"
  - Just a header, for printing the results. The time serie code is also printed here.
- "**Horizon: X, Value: V**"
  - The forecasts for each horizon are printed. In our example, the forecasts for 18 horizons (1 to 18) are printed, since the time serie was monthly and the requested horizon was 18.

6.4.3. Step 3: Validate the forecasts

The database includes a tool for validating the forecasts selection process.

The user can compare:

- The forecasts submitted in the M4 competition, with
- The forecasts estimated in the previous step (re-estimate of forecasts).

So, the user can open a Query window, and type:

```
exec dbo.M4_ReEstimateForecasts_Compare 'M10062'
```

The results are the shown in the following image:

	Code	Horizon	M4 Forecast	Re-estimated Forecast	Difference
1	M10062	1	998,0504	998,0504	0
2	M10062	2	1011,137	1011,137	0
3	M10062	3	1021,897	1021,897	0
4	M10062	4	1034,527	1034,527	0
5	M10062	5	1046,85	1046,85	0
6	M10062	6	1058,751	1058,751	0
7	M10062	7	1070,662	1070,662	0
8	M10062	8	1082,524	1082,524	0
9	M10062	9	1094,665	1094,665	0
10	M10062	10	1107,785	1107,785	0
11	M10062	11	1120,874	1120,874	0
12	M10062	12	1132,862	1132,862	0
13	M10062	13	1154,116	1154,116	0
14	M10062	14	1167,396	1167,396	0
15	M10062	15	1177,885	1177,885	0
16	M10062	16	1190,497	1190,497	0
17	M10062	17	1202,963	1202,963	0
18	M10062	18	1214,788	1214,788	0

	Code	Horizon	M4 Forecast	Re-estimated Forecast	Difference

The first table (dataset) shows the forecasts of both the M4 and the re-estimation. Thus, it is easy for the user to observe that the forecasts are identical

The second table (dataset) is empty, which means that all forecasts are identical.

6.5. How to export forecasts into csv file

The database includes a tool for exporting the M4 submitted forecasts into a csv file.

So, the user can open a Query window, and type:

```
exec dbo.M4_ExtractForecasts_To_CSV
```

Note: If the user wants to export the re-estimated forecasts, he/she must type:

```
exec dbo.M4_Extract_ReEstimatedForecasts_To_CSV
```

The results are the shown in the following image:

```
id,F1,F2,F3,F4,F5,F6,F7,F8,F9,F10,F11,F12,F13,F14,F15,F16,F17,F18,F19,F20,F21,F22,F23,F24,F25,F26,F27,F28,F29,F30,F31,F32,F33,F34,F35,F36,F37,F38,F39,F40,F41,F42,F43,F44,F45,F46,F47,F48
Y1,7546.71,7536.44,7526.17,7515.9,7505.63,7495.37,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA
Y2,1302.29,1302.29,1302.29,1302.29,1302.29,1302.29,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA
Y3,8507.54,8689.58,8871.61,9053.64,9235.67,9417.71,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA
Y4,9739.51,9935.93,10132.4,10328.8,10525.2,10721.6,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA
Y5,6745.55,7018.7,7291.86,7565.02,7838.18,8111.34,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA
Y6,3669.75,3852.93,4036.11,4219.29,4402.47,4585.65,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA
Y7,3476.1,3680.6,3885.1,4089.61,4294.11,4498.61,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA
Y8,2386.52,2383.54,2380.57,2377.59,2374.61,2371.64,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA
Y9,2216.86,2240.25,2263.64,2287.03,2310.42,2333.81,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA
Y10,2166.04,2169.63,2173.22,2176.81,2180.4,2183.99,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA
Y11,1470.38,1491.43,1512.48,1533.52,1554.57,1575.62,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA
Y12,1960.24,2002.02,2043.81,2085.59,2127.38,2169.17,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA
Y13,5012.61,5139.69,5266.77,5393.85,5520.93,5648.01,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA
Y14,5127.04,5189.24,5251.44,5313.63,5375.83,5438.02,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA
Y15,5324.04,5447.56,5571.09,5694.62,5818.15,5941.67,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA
Y16,2853.53,2888.15,2922.77,2957.4,2992.02,3026.64,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA
Y17,3898.21,3937,3975.8,4014.59,4053.39,4092.18,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA
Y18,3386.99,3421.72,3456.46,3491.19,3525.93,3560.66,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA
Y19,2818.21,3096.71,3375.21,3653.71,3932.21,4210.7,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA
Y20,6224.58,6319.91,6415.24,6510.57,6605.9,6701.23,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA
Y21,8224.99,8418.35,8611.7,8805.06,8998.41,9191.76,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA
Y22,3548.66,3634.06,3719.45,3804.85,3890.24,3975.64,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA
Y23,9083.08,9099.75,9116.42,9133.09,9149.75,9166.42,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA
Y24,6869.28,6830.59,6791.89,6753.19,6714.5,6675.8,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA
Y25,2026.79,2060.82,2094.86,2128.9,2162.93,2196.97,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA
Y26,5790.29,5896.14,6001.99,6107.84,6213.69,6319.54,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA
Y27,1428.39,1449.84,1471.28,1492.73,1514.18,1535.63,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA
Y28,1411.65,1431.56,1451.47,1471.38,1491.29,1511.2,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA
Y29,3844.55,3908.36,3972.16,4035.97,4099.77,4163.58,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA
Y30,4256.39,4336.12,4415.86,4495.6,4575.33,4655.07,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA
Y31,3692.13,3682.98,3673.83,3664.68,3655.52,3646.37,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA,NA
```

7. Simple Forecasting Methods

The following table contains the Simple Forecasting Methods that ***AGON*** is using for selecting the best performing methods to be included in the averaging:

- ✓ **ID**: An internal ID of the method, used internally from the ***AGON*** method.
- ✓ **Forecasting Method**: The name of the simple forecasting method
- ✓ **Category**: The category of the method. We have the following categories:
    - **N**: naïve
    - **LR**: Linear Regression
    - **DA**: Decomposition Additive
    - **DM**: Decomposition Multiplicative
    - **MA**: Moving Average
    - **ESS**: Exponential Smoothing simple
    - **EST**: Exponential Smoothing Trend
    - **ESH**: Exponential Smoothing Holt
    - **ESD**: Exponential Smoothing Damped
    - **TH**: Theta
- ✓ **Apply Seasonality**: A Boolean field:
    - If **No**, then the method will be applied on the actual values of the time serie (without deseasonalization).
    - If **Yes**, then the method will be applied on the deseasonalized values of the time serie.
- ✓ **Comments**: A text field which includes information about the method, such as:
    - Characteristics of the method
    - Initial values
    - Parameters

ID	Forecasting Method	Category	Apply Seasonality	Comments
101	Naive - NonSeasonal	N	no	Naive 1
102	Naive - Seasonal	N	yes	Naive 2
103	Naive - Trend - NonSeasonal	N	no	
104	Naive - Trend - Seasonal	N	yes	
105	Mean - NonSeasonal	N	no	
106	Mean - Seasonal	N	yes	
107	Median - NonSeasonal	N	no	
108	Median - Seasonal	N	yes	
109	NaiveRep - NonSeasonal	N	no	Seasonal Naive
110	NaiveRep - Seasonal	N	yes	
201	Linear Regression - Simple - NonSeasonal	LR	no	

ID	Forecasting Method	Category	Apply Seasonality	Comments
202	Linear Regression - Simple - Seasonal	LR	yes	
301	Decomposition Additive - Classical - NonSeasonal	DA	no	
302	Decomposition Additive - Classical - Seasonal	DA	yes	
303	Decomposition - Additive - MAS3B - NonSeasonal	DA	no	Simple Moving Average, With Backstaging, Order = 3
304	Decomposition - Additive - MAS3B - Seasonal	DA	yes	Simple Moving Average, With Backstaging, Order = 3
305	Decomposition - Additive - MAS5B - NonSeasonal	DA	no	Simple Moving Average, With Backstaging, Order = 5
306	Decomposition - Additive - MAS5B - Seasonal	DA	yes	Simple Moving Average, With Backstaging, Order = 5
307	Decomposition - Additive - MASNB - NonSeasonal	DA	no	Simple Moving Average, With Backstaging, Order = seasonality
308	Decomposition - Additive - MASNB - Seasonal	DA	yes	Simple Moving Average, With Backstaging, Order = seasonality
309	Decomposition - Additive - MAW3B - NonSeasonal	DA	no	Weighted Moving Average, With Backstaging, Order = 3
310	Decomposition - Additive - MAW3B - Seasonal	DA	yes	Weighted Moving Average, With Backstaging, Order = 3
311	Decomposition - Additive - MAW5B - NonSeasonal	DA	no	Weighted Moving Average, With Backstaging, Order = 5
312	Decomposition - Additive - MAW5B - Seasonal	DA	yes	Weighted Moving Average, With Backstaging, Order = 5
313	Decomposition - Additive - MAWNB - NonSeasonal	DA	no	Weighted Moving Average, With Backstaging, Order = seasonality
314	Decomposition - Additive - MAWNB - Seasonal	DA	yes	Weighted Moving Average, With Backstaging, Order = seasonality
315	Decomposition - Additive - MAD3B - NonSeasonal	DA	no	Double Moving Average, With Backstaging, Order = 3
316	Decomposition - Additive - MAD3B - Seasonal	DA	yes	Double Moving Average, With Backstaging, Order = 3
317	Decomposition - Additive - MAD5B - NonSeasonal	DA	no	Double Moving Average, With Backstaging, Order = 5
318	Decomposition - Additive - MAD5B - Seasonal	DA	yes	Double Moving Average, With Backstaging, Order = 5
319	Decomposition - Additive - MADNB - NonSeasonal	DA	no	Double Moving Average, With Backstaging, Order = seasonality
320	Decomposition - Additive - MADNB - Seasonal	DA	yes	Double Moving Average, With Backstaging, Order = seasonality
351	Decomposition Multiplicative - Classical - NonSeasonal	DM	no	
352	Decomposition Multiplicative - Classical - Seasonal	DM	yes	
353	Decomposition - Multiplicative - MAS3B - NonSeasonal	DM	no	Simple Moving Average, With Backstaging, Order = 3
354	Decomposition - Multiplicative - MAS3B - Seasonal	DM	yes	Simple Moving Average, With Backstaging, Order = 3
355	Decomposition - Multiplicative - MAS5B - NonSeasonal	DM	no	Simple Moving Average, With Backstaging, Order = 5
356	Decomposition - Multiplicative - MAS5B - Seasonal	DM	yes	Simple Moving Average, With Backstaging, Order = 5
357	Decomposition - Multiplicative - MASNB - NonSeasonal	DM	no	Simple Moving Average, With Backstaging, Order = seasonality

ID	Forecasting Method	Category	Apply Seasonality	Comments
358	Decomposition - Multiplicative - MASNB - Seasonal	DM	yes	Simple Moving Average, With Backstaging, Order = seasonality
359	Decomposition - Multiplicative - MAW3B - NonSeasonal	DM	no	Weighted Moving Average, With Backstaging, Order = 3
360	Decomposition - Multiplicative - MAW3B - Seasonal	DM	yes	Weighted Moving Average, With Backstaging, Order = 3
361	Decomposition - Multiplicative - MAW5B - NonSeasonal	DM	no	Weighted Moving Average, With Backstaging, Order = 5
362	Decomposition - Multiplicative - MAW5B - Seasonal	DM	yes	Weighted Moving Average, With Backstaging, Order = 5
363	Decomposition - Multiplicative - MAWNB - NonSeasonal	DM	no	Weighted Moving Average, With Backstaging, Order = seasonality
364	Decomposition - Multiplicative - MAWNB - Seasonal	DM	yes	Weighted Moving Average, With Backstaging, Order = seasonality
365	Decomposition - Multiplicative - MAD3B - NonSeasonal	DM	no	Double Moving Average, With Backstaging, Order = 3
366	Decomposition - Multiplicative - MAD3B - Seasonal	DM	yes	Double Moving Average, With Backstaging, Order = 3
367	Decomposition - Multiplicative - MAD5B - NonSeasonal	DM	no	Double Moving Average, With Backstaging, Order = 5
368	Decomposition - Multiplicative - MAD5B - Seasonal	DM	yes	Double Moving Average, With Backstaging, Order = 5
369	Decomposition - Multiplicative - MADNB - NonSeasonal	DM	no	Double Moving Average, With Backstaging, Order = seasonality
370	Decomposition - Multiplicative - MADNB - Seasonal	DM	yes	Double Moving Average, With Backstaging, Order = seasonality
401	Moving Average - Simple3 - NonSeasonal	MA	no	Order = 3
402	Moving Average - Simple3 - Seasonal	MA	yes	Order = 3
403	Moving Average - Simple5 - NonSeasonal	MA	no	Order = 5
404	Moving Average - Simple5 - Seasonal	MA	yes	Order = 5
405	Moving Average - SimpleN - NonSeasonal	MA	no	Order = seasonality
406	Moving Average - SimpleN - Seasonal	MA	yes	Order = seasonality
407	Moving Average - Simple3 Backstaging - NonSeasonal	MA	no	With Backstaging, Order = 3
408	Moving Average - Simple3 Backstaging - Seasonal	MA	yes	With Backstaging, Order = 3
409	Moving Average - Simple5 Backstaging - NonSeasonal	MA	no	With Backstaging, Order = 5
410	Moving Average - Simple5 Backstaging - Seasonal	MA	yes	With Backstaging, Order = 5
411	Moving Average - SimpleN Backstaging - NonSeasonal	MA	no	With Backstaging, Order = seasonality
412	Moving Average - SimpleN Backstaging - Seasonal	MA	yes	With Backstaging, Order = seasonality
413	Moving Average - Weighted3 - NonSeasonal	MA	no	Order = 3
414	Moving Average - Weighted3 - Seasonal	MA	yes	Order = 3
415	Moving Average - Weighted5 - NonSeasonal	MA	no	Order = 5

ID	Forecasting Method	Category	Apply Seasonality	Comments
416	Moving Average - Weighted5 - Seasonal	MA	yes	Order = 5
417	Moving Average - WeightedN - NonSeasonal	MA	no	Order = seasonality
418	Moving Average - WeightedN - Seasonal	MA	yes	Order = seasonality
419	Moving Average - Weighted3 Backstaging - NonSeasonal	MA	no	With Backstaging, Order = 3
420	Moving Average - Weighted3 Backstaging - Seasonal	MA	yes	With Backstaging, Order = 3
421	Moving Average - Weighted5 Backstaging - NonSeasonal	MA	no	With Backstaging, Order = 5
422	Moving Average - Weighted5 Backstaging - Seasonal	MA	yes	With Backstaging, Order = 5
423	Moving Average - WeightedN Backstaging - NonSeasonal	MA	no	With Backstaging, Order = seasonality
424	Moving Average - WeightedN Backstaging - Seasonal	MA	yes	With Backstaging, Order = seasonality
425	Moving Average - Double3 - NonSeasonal	MA	no	Order = 3
426	Moving Average - Double3 - Seasonal	MA	yes	Order = 3
427	Moving Average - Double5 - NonSeasonal	MA	no	Order = 5
428	Moving Average - Double5 - Seasonal	MA	yes	Order = 5
429	Moving Average - DoubleN - NonSeasonal	MA	no	Order = seasonality
430	Moving Average - DoubleN - Seasonal	MA	yes	Order = seasonality
431	Moving Average - Double3 Backstaging - NonSeasonal	MA	no	With Backstaging, Order = 3
432	Moving Average - Double3 Backstaging - Seasonal	MA	yes	With Backstaging, Order = 3
433	Moving Average - Double5 Backstaging - NonSeasonal	MA	no	With Backstaging, Order = 5
434	Moving Average - Double5 Backstaging - Seasonal	MA	yes	With Backstaging, Order = 5
435	Moving Average - DoubleN Backstaging - NonSeasonal	MA	no	With Backstaging, Order = seasonality
436	Moving Average - DoubleN Backstaging - Seasonal	MA	yes	With Backstaging, Order = seasonality
501	Exponential Smoothing - Simple - A2 - NonSeasonal	ESS	no	Smoothing parameter = 0.2, S(0) = average of all historical data
502	Exponential Smoothing - Simple - A2 - Seasonal	ESS	yes	Smoothing parameter = 0.2, S(0) = average of all historical data
503	Exponential Smoothing - Simple - A4 - NonSeasonal	ESS	no	Smoothing parameter = 0.4, S(0) = average of all historical data
504	Exponential Smoothing - Simple - A4 - Seasonal	ESS	yes	Smoothing parameter = 0.4, S(0) = average of all historical data
505	Exponential Smoothing - Simple - A5 - NonSeasonal	ESS	no	Smoothing parameter = 0.5, S(0) = average of all historical data
506	Exponential Smoothing - Simple - A5 - Seasonal	ESS	yes	Smoothing parameter = 0.5, S(0) = average of all historical data
507	Exponential Smoothing - Simple - A6 - NonSeasonal	ESS	no	Smoothing parameter = 0.6, S(0) = average of all historical data

ID	Forecasting Method	Category	Apply Seasonality	Comments
508	Exponential Smoothing - Simple - A6 - Seasonal	ESS	yes	Smoothing parameter = 0.6, S(0) = average of all historical data
509	Exponential Smoothing - Simple - A8 - NonSeasonal	ESS	no	Smoothing parameter = 0.8, S(0) = average of all historical data
510	Exponential Smoothing - Simple - A8 - Seasonal	ESS	yes	Smoothing parameter = 0.8, S(0) = average of all historical data
511	Exponential Smoothing - Simple - M2 - NonSeasonal	ESS	no	Smoothing parameter = 0.2, S(0) = mean of first 4 historical data
512	Exponential Smoothing - Simple - M2 - Seasonal	ESS	yes	Smoothing parameter = 0.2, S(0) = mean of first 4 historical data
513	Exponential Smoothing - Simple - M4 - NonSeasonal	ESS	no	Smoothing parameter = 0.4, S(0) = mean of first 4 historical data
514	Exponential Smoothing - Simple - M4 - Seasonal	ESS	yes	Smoothing parameter = 0.4, S(0) = mean of first 4 historical data
515	Exponential Smoothing - Simple - M5 - NonSeasonal	ESS	no	Smoothing parameter = 0.5, S(0) = mean of first 4 historical data
516	Exponential Smoothing - Simple - M5 - Seasonal	ESS	yes	Smoothing parameter = 0.5, S(0) = mean of first 4 historical data
517	Exponential Smoothing - Simple - M6 - NonSeasonal	ESS	no	Smoothing parameter = 0.6, S(0) = mean of first 4 historical data
518	Exponential Smoothing - Simple - M6 - Seasonal	ESS	yes	Smoothing parameter = 0.6, S(0) = mean of first 4 historical data
519	Exponential Smoothing - Simple - M8 - NonSeasonal	ESS	no	Smoothing parameter = 0.8, S(0) = mean of first 4 historical data
520	Exponential Smoothing - Simple - M8 - Seasonal	ESS	yes	Smoothing parameter = 0.8, S(0) = mean of first 4 historical data
521	Exponential Smoothing - Simple - F2 - NonSeasonal	ESS	no	Smoothing parameter = 0.2, S(0) = first historical data point
522	Exponential Smoothing - Simple - F2 - Seasonal	ESS	yes	Smoothing parameter = 0.2, S(0) = first historical data point
523	Exponential Smoothing - Simple - F4 - NonSeasonal	ESS	no	Smoothing parameter = 0.4, S(0) = first historical data point
524	Exponential Smoothing - Simple - F4 - Seasonal	ESS	yes	Smoothing parameter = 0.4, S(0) = first historical data point
525	Exponential Smoothing - Simple - F5 - NonSeasonal	ESS	no	Smoothing parameter = 0.5, S(0) = first historical data point
526	Exponential Smoothing - Simple - F5 - Seasonal	ESS	yes	Smoothing parameter = 0.5, S(0) = first historical data point
527	Exponential Smoothing - Simple - F6 - NonSeasonal	ESS	no	Smoothing parameter = 0.6, S(0) = first historical data point
528	Exponential Smoothing - Simple - F6 - Seasonal	ESS	yes	Smoothing parameter = 0.6, S(0) = first historical data point
529	Exponential Smoothing - Simple - F8 - NonSeasonal	ESS	no	Smoothing parameter = 0.8, S(0) = first historical data point
530	Exponential Smoothing - Simple - F8 - Seasonal	ESS	yes	Smoothing parameter = 0.8, S(0) = first historical data point
531	Exponential Smoothing - Simple - L2 - NonSeasonal	ESS	no	Smoothing parameter = 0.2, S(0) = the level for the model of the linear regression
532	Exponential Smoothing - Simple - L2 - Seasonal	ESS	yes	Smoothing parameter = 0.2, S(0) = the level for the model of the linear regression
533	Exponential Smoothing - Simple - L4 - NonSeasonal	ESS	no	Smoothing parameter = 0.4, S(0) = the level for the model of the linear regression

ID	Forecasting Method	Category	Apply Seasonality	Comments
534	Exponential Smoothing - Simple - L4 - Seasonal	ESS	yes	Smoothing parameter = 0.4, S(0) = the level for the model of the linear regression
535	Exponential Smoothing - Simple - L5 - NonSeasonal	ESS	no	Smoothing parameter = 0.5, S(0) = the level for the model of the linear regression
536	Exponential Smoothing - Simple - L5 - Seasonal	ESS	yes	Smoothing parameter = 0.5, S(0) = the level for the model of the linear regression
537	Exponential Smoothing - Simple - L6 - NonSeasonal	ESS	no	Smoothing parameter = 0.6, S(0) = the level for the model of the linear regression
538	Exponential Smoothing - Simple - L6 - Seasonal	ESS	yes	Smoothing parameter = 0.6, S(0) = the level for the model of the linear regression
539	Exponential Smoothing - Simple - L8 - NonSeasonal	ESS	no	Smoothing parameter = 0.8, S(0) = the level for the model of the linear regression
540	Exponential Smoothing - Simple - L8 - Seasonal	ESS	yes	Smoothing parameter = 0.8, S(0) = the level for the model of the linear regression
551	Exponential Smoothing - Simple Trend - A2 - NonSeasonal	EST	no	Smoothing parameter = 0.2, S(0) = average of all historical data
552	Exponential Smoothing - Simple Trend - A2 - Seasonal	EST	yes	Smoothing parameter = 0.2, S(0) = average of all historical data
553	Exponential Smoothing - Simple Trend - A4 - NonSeasonal	EST	no	Smoothing parameter = 0.4, S(0) = average of all historical data
554	Exponential Smoothing - Simple Trend - A4 - Seasonal	EST	yes	Smoothing parameter = 0.4, S(0) = average of all historical data
555	Exponential Smoothing - Simple Trend - A5 - NonSeasonal	EST	no	Smoothing parameter = 0.5, S(0) = average of all historical data
556	Exponential Smoothing - Simple Trend - A5 - Seasonal	EST	yes	Smoothing parameter = 0.5, S(0) = average of all historical data
557	Exponential Smoothing - Simple Trend - A6 - NonSeasonal	EST	no	Smoothing parameter = 0.6, S(0) = average of all historical data
558	Exponential Smoothing - Simple Trend - A6 - Seasonal	EST	yes	Smoothing parameter = 0.6, S(0) = average of all historical data
559	Exponential Smoothing - Simple Trend - A8 - NonSeasonal	EST	no	Smoothing parameter = 0.8, S(0) = average of all historical data
560	Exponential Smoothing - Simple Trend - A8 - Seasonal	EST	yes	Smoothing parameter = 0.8, S(0) = average of all historical data
561	Exponential Smoothing - Simple Trend - M2 - NonSeasonal	EST	no	Smoothing parameter = 0.2, S(0) = mean of first 4 historical data
562	Exponential Smoothing - Simple Trend - M2 - Seasonal	EST	yes	Smoothing parameter = 0.2, S(0) = mean of first 4 historical data
563	Exponential Smoothing - Simple Trend - M4 - NonSeasonal	EST	no	Smoothing parameter = 0.4, S(0) = mean of first 4 historical data
564	Exponential Smoothing - Simple Trend - M4 - Seasonal	EST	yes	Smoothing parameter = 0.4, S(0) = mean of first 4 historical data
565	Exponential Smoothing - Simple Trend - M5 - NonSeasonal	EST	no	Smoothing parameter = 0.5, S(0) = mean of first 4 historical data
566	Exponential Smoothing - Simple Trend - M5 - Seasonal	EST	yes	Smoothing parameter = 0.5, S(0) = mean of first 4 historical data
567	Exponential Smoothing - Simple Trend - M6 - NonSeasonal	EST	no	Smoothing parameter = 0.6, S(0) = mean of first 4 historical data
568	Exponential Smoothing - Simple Trend - M6 - Seasonal	EST	yes	Smoothing parameter = 0.6, S(0) = mean of first 4 historical data

ID	Forecasting Method	Category	Apply Seasonality	Comments
569	Exponential Smoothing - Simple Trend - M8 - NonSeasonal	EST	no	Smoothing parameter = 0.8, S(0) = mean of first 4 historical data
570	Exponential Smoothing - Simple Trend - M8 - Seasonal	EST	yes	Smoothing parameter = 0.8, S(0) = mean of first 4 historical data
571	Exponential Smoothing - Simple Trend - F2 - NonSeasonal	EST	no	Smoothing parameter = 0.2, S(0) = first historical data point
572	Exponential Smoothing - Simple Trend - F2 - Seasonal	EST	yes	Smoothing parameter = 0.2, S(0) = first historical data point
573	Exponential Smoothing - Simple Trend - F4 - NonSeasonal	EST	no	Smoothing parameter = 0.4, S(0) = first historical data point
574	Exponential Smoothing - Simple Trend - F4 - Seasonal	EST	yes	Smoothing parameter = 0.4, S(0) = first historical data point
575	Exponential Smoothing - Simple Trend - F5 - NonSeasonal	EST	no	Smoothing parameter = 0.5, S(0) = first historical data point
576	Exponential Smoothing - Simple Trend - F5 - Seasonal	EST	yes	Smoothing parameter = 0.5, S(0) = first historical data point
577	Exponential Smoothing - Simple Trend - F6 - NonSeasonal	EST	no	Smoothing parameter = 0.6, S(0) = first historical data point
578	Exponential Smoothing - Simple Trend - F6 - Seasonal	EST	yes	Smoothing parameter = 0.6, S(0) = first historical data point
579	Exponential Smoothing - Simple Trend - F8 - NonSeasonal	EST	no	Smoothing parameter = 0.8, S(0) = first historical data point
580	Exponential Smoothing - Simple Trend - F8 - Seasonal	EST	yes	Smoothing parameter = 0.8, S(0) = first historical data point
581	Exponential Smoothing - Simple Trend - L2 - NonSeasonal	EST	no	Smoothing parameter = 0.2, S(0) = the level for the model of the linear regression
582	Exponential Smoothing - Simple Trend - L2 - Seasonal	EST	yes	Smoothing parameter = 0.2, S(0) = the level for the model of the linear regression
583	Exponential Smoothing - Simple Trend - L4 - NonSeasonal	EST	no	Smoothing parameter = 0.4, S(0) = the level for the model of the linear regression
584	Exponential Smoothing - Simple Trend - L4 - Seasonal	EST	yes	Smoothing parameter = 0.4, S(0) = the level for the model of the linear regression
585	Exponential Smoothing - Simple Trend - L5 - NonSeasonal	EST	no	Smoothing parameter = 0.5, S(0) = the level for the model of the linear regression
586	Exponential Smoothing - Simple Trend - L5 - Seasonal	EST	yes	Smoothing parameter = 0.5, S(0) = the level for the model of the linear regression
587	Exponential Smoothing - Simple Trend - L6 - NonSeasonal	EST	no	Smoothing parameter = 0.6, S(0) = the level for the model of the linear regression
588	Exponential Smoothing - Simple Trend - L6 - Seasonal	EST	yes	Smoothing parameter = 0.6, S(0) = the level for the model of the linear regression
589	Exponential Smoothing - Simple Trend - L8 - NonSeasonal	EST	no	Smoothing parameter = 0.8, S(0) = the level for the model of the linear regression
590	Exponential Smoothing - Simple Trend - L8 - Seasonal	EST	yes	Smoothing parameter = 0.8, S(0) = the level for the model of the linear regression
601	Exponential Smoothing - Holt - A2 - NonSeasonal	ESH	no	Smoothing parameter = 0.2, 0.1, S(0) = average of all historical data

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602	Exponential Smoothing - Holt - A2 - Seasonal	ESH	yes	Smoothing parameter = 0.2, 0.1, S(0) = average of all historical data
603	Exponential Smoothing - Holt - A4 - NonSeasonal	ESH	no	Smoothing parameter = 0.4, 0.13, S(0) = average of all historical data
604	Exponential Smoothing - Holt - A4 - Seasonal	ESH	yes	Smoothing parameter = 0.4, 0.13, S(0) = average of all historical data
605	Exponential Smoothing - Holt - A5 - NonSeasonal	ESH	no	Smoothing parameter = 0.5, 0.15, S(0) = average of all historical data
606	Exponential Smoothing - Holt - A5 - Seasonal	ESH	yes	Smoothing parameter = 0.5, 0.15, S(0) = average of all historical data
607	Exponential Smoothing - Holt - A6 - NonSeasonal	ESH	no	Smoothing parameter = 0.6, 0.17, S(0) = average of all historical data
608	Exponential Smoothing - Holt - A6 - Seasonal	ESH	yes	Smoothing parameter = 0.6, 0.17, S(0) = average of all historical data
609	Exponential Smoothing - Holt - A8 - NonSeasonal	ESH	no	Smoothing parameter = 0.8, 0.2, S(0) = average of all historical data
610	Exponential Smoothing - Holt - A8 - Seasonal	ESH	yes	Smoothing parameter = 0.8, 0.2, S(0) = average of all historical data
611	Exponential Smoothing - Holt - M2 - NonSeasonal	ESH	no	Smoothing parameter = 0.2, 0.1, S(0) = mean of first 4 historical data
612	Exponential Smoothing - Holt - M2 - Seasonal	ESH	yes	Smoothing parameter = 0.2, 0.1, S(0) = mean of first 4 historical data
613	Exponential Smoothing - Holt - M4 - NonSeasonal	ESH	no	Smoothing parameter = 0.4, 0.13, S(0) = mean of first 4 historical data
614	Exponential Smoothing - Holt - M4 - Seasonal	ESH	yes	Smoothing parameter = 0.4, 0.13, S(0) = mean of first 4 historical data
615	Exponential Smoothing - Holt - M5 - NonSeasonal	ESH	no	Smoothing parameter = 0.5, 0.15, S(0) = mean of first 4 historical data
616	Exponential Smoothing - Holt - M5 - Seasonal	ESH	yes	Smoothing parameter = 0.5, 0.15, S(0) = mean of first 4 historical data
617	Exponential Smoothing - Holt - M6 - NonSeasonal	ESH	no	Smoothing parameter = 0.6, 0.17, S(0) = mean of first 4 historical data
618	Exponential Smoothing - Holt - M6 - Seasonal	ESH	yes	Smoothing parameter = 0.6, 0.17, S(0) = mean of first 4 historical data
619	Exponential Smoothing - Holt - M8 - NonSeasonal	ESH	no	Smoothing parameter = 0.8, 0.2, S(0) = mean of first 4 historical data
620	Exponential Smoothing - Holt - M8 - Seasonal	ESH	yes	Smoothing parameter = 0.8, 0.2, S(0) = mean of first 4 historical data
621	Exponential Smoothing - Holt - F2 - NonSeasonal	ESH	no	Smoothing parameter = 0.2, 0.1, S(0) = first historical data point
622	Exponential Smoothing - Holt - F2 - Seasonal	ESH	yes	Smoothing parameter = 0.2, 0.1, S(0) = first historical data point
623	Exponential Smoothing - Holt - F4 - NonSeasonal	ESH	no	Smoothing parameter = 0.4, 0.13, S(0) = first historical data point
624	Exponential Smoothing - Holt - F4 - Seasonal	ESH	yes	Smoothing parameter = 0.4, 0.13, S(0) = first historical data point
625	Exponential Smoothing - Holt - F5 - NonSeasonal	ESH	no	Smoothing parameter = 0.5, 0.15, S(0) = first historical data point
626	Exponential Smoothing - Holt - F5 - Seasonal	ESH	yes	Smoothing parameter = 0.5, 0.15, S(0) = first historical data point
627	Exponential Smoothing - Holt - F6 - NonSeasonal	ESH	no	Smoothing parameter = 0.6, 0.17, S(0) = first historical data point
628	Exponential Smoothing - Holt - F6 - Seasonal	ESH	yes	Smoothing parameter = 0.6, 0.17, S(0) = first historical data point
629	Exponential Smoothing - Holt - F8 - NonSeasonal	ESH	no	Smoothing parameter = 0.8, 0.2, S(0) = first historical data point

ID	Forecasting Method	Category	Apply Seasonality	Comments
630	Exponential Smoothing - Holt - F8 - Seasonal	ESH	yes	Smoothing parameter = 0.8, 0.2, S(0) = first historical data point
631	Exponential Smoothing - Holt - L2 - NonSeasonal	ESH	no	Smoothing parameter = 0.2, 0.1, S(0) = the level for the model of the linear regression
632	Exponential Smoothing - Holt - L2 - Seasonal	ESH	yes	Smoothing parameter = 0.2, 0.1, S(0) = the level for the model of the linear regression
633	Exponential Smoothing - Holt - L4 - NonSeasonal	ESH	no	Smoothing parameter = 0.4, 0.13, S(0) = the level for the model of the linear regression
634	Exponential Smoothing - Holt - L4 - Seasonal	ESH	yes	Smoothing parameter = 0.4, 0.13, S(0) = the level for the model of the linear regression
635	Exponential Smoothing - Holt - L5 - NonSeasonal	ESH	no	Smoothing parameter = 0.5, 0.15, S(0) = the level for the model of the linear regression
636	Exponential Smoothing - Holt - L5 - Seasonal	ESH	yes	Smoothing parameter = 0.5, 0.15, S(0) = the level for the model of the linear regression
637	Exponential Smoothing - Holt - L6 - NonSeasonal	ESH	no	Smoothing parameter = 0.6, 0.17, S(0) = the level for the model of the linear regression
638	Exponential Smoothing - Holt - L6 - Seasonal	ESH	yes	Smoothing parameter = 0.6, 0.17, S(0) = the level for the model of the linear regression
639	Exponential Smoothing - Holt - L8 - NonSeasonal	ESH	no	Smoothing parameter = 0.8, 0.2, S(0) = the level for the model of the linear regression
640	Exponential Smoothing - Holt - L8 - Seasonal	ESH	yes	Smoothing parameter = 0.8, 0.2, S(0) = the level for the model of the linear regression
651	Exponential Smoothing - Damped - A2 - NonSeasonal	ESD	no	Smoothing parameter = 0.2, 0.1, 0.8, S(0) = average of all historical data
652	Exponential Smoothing - Damped - A2 - Seasonal	ESD	yes	Smoothing parameter = 0.2, 0.1, 0.8, S(0) = average of all historical data
653	Exponential Smoothing - Damped - A4 - NonSeasonal	ESD	no	Smoothing parameter = 0.4, 0.13, 0.8, S(0) = average of all historical data
654	Exponential Smoothing - Damped - A4 - Seasonal	ESD	yes	Smoothing parameter = 0.4, 0.13, 0.8, S(0) = average of all historical data
655	Exponential Smoothing - Damped - A5 - NonSeasonal	ESD	no	Smoothing parameter = 0.5, 0.15, 0.8, S(0) = average of all historical data
656	Exponential Smoothing - Damped - A5 - Seasonal	ESD	yes	Smoothing parameter = 0.5, 0.15, 0.8, S(0) = average of all historical data
657	Exponential Smoothing - Damped - A6 - NonSeasonal	ESD	no	Smoothing parameter = 0.6, 0.17, 0.8, S(0) = average of all historical data
658	Exponential Smoothing - Damped - A6 - Seasonal	ESD	yes	Smoothing parameter = 0.6, 0.17, 0.8, S(0) = average of all historical data
659	Exponential Smoothing - Damped - A8 - NonSeasonal	ESD	no	Smoothing parameter = 0.8, 0.2, 0.8, S(0) = average of all historical data
660	Exponential Smoothing - Damped - A8 - Seasonal	ESD	yes	Smoothing parameter = 0.8, 0.2, 0.8, S(0) = average of all historical data
661	Exponential Smoothing - Damped - M2 - NonSeasonal	ESD	no	Smoothing parameter = 0.2, 0.1, 0.8, S(0) = mean of first 4 historical data
662	Exponential Smoothing - Damped - M2 - Seasonal	ESD	yes	Smoothing parameter = 0.2, 0.1, 0.8, S(0) = mean of first 4 historical data

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663	Exponential Smoothing - Damped - M4 - NonSeasonal	ESD	no	Smoothing parameter = 0.4, 0.13, 0.8, S(0) = mean of first 4 historical data
664	Exponential Smoothing - Damped - M4 - Seasonal	ESD	yes	Smoothing parameter = 0.4, 0.13, 0.8, S(0) = mean of first 4 historical data
665	Exponential Smoothing - Damped - M5 - NonSeasonal	ESD	no	Smoothing parameter = 0.5, 0.15, 0.8, S(0) = mean of first 4 historical data
666	Exponential Smoothing - Damped - M5 - Seasonal	ESD	yes	Smoothing parameter = 0.5, 0.15, 0.8, S(0) = mean of first 4 historical data
667	Exponential Smoothing - Damped - M6 - NonSeasonal	ESD	no	Smoothing parameter = 0.6, 0.17, 0.8, S(0) = mean of first 4 historical data
668	Exponential Smoothing - Damped - M6 - Seasonal	ESD	yes	Smoothing parameter = 0.6, 0.17, 0.8, S(0) = mean of first 4 historical data
669	Exponential Smoothing - Damped - M8 - NonSeasonal	ESD	no	Smoothing parameter = 0.8, 0.2, 0.8, S(0) = mean of first 4 historical data
670	Exponential Smoothing - Damped - M8 - Seasonal	ESD	yes	Smoothing parameter = 0.8, 0.2, 0.8, S(0) = mean of first 4 historical data
671	Exponential Smoothing - Damped - F2 - NonSeasonal	ESD	no	Smoothing parameter = 0.2, 0.1, 0.8, S(0) = first historical data point
672	Exponential Smoothing - Damped - F2 - Seasonal	ESD	yes	Smoothing parameter = 0.2, 0.1, 0.8, S(0) = first historical data point
673	Exponential Smoothing - Damped - F4 - NonSeasonal	ESD	no	Smoothing parameter = 0.4, 0.13, 0.8, S(0) = first historical data point
674	Exponential Smoothing - Damped - F4 - Seasonal	ESD	yes	Smoothing parameter = 0.4, 0.13, 0.8, S(0) = first historical data point
675	Exponential Smoothing - Damped - F5 - NonSeasonal	ESD	no	Smoothing parameter = 0.5, 0.15, 0.8, S(0) = first historical data point
676	Exponential Smoothing - Damped - F5 - Seasonal	ESD	yes	Smoothing parameter = 0.5, 0.15, 0.8, S(0) = first historical data point
677	Exponential Smoothing - Damped - F6 - NonSeasonal	ESD	no	Smoothing parameter = 0.6, 0.17, 0.8, S(0) = first historical data point
678	Exponential Smoothing - Damped - F6 - Seasonal	ESD	yes	Smoothing parameter = 0.6, 0.17, 0.8, S(0) = first historical data point
679	Exponential Smoothing - Damped - F8 - NonSeasonal	ESD	no	Smoothing parameter = 0.8, 0.2, 0.8, S(0) = first historical data point
680	Exponential Smoothing - Damped - F8 - Seasonal	ESD	yes	Smoothing parameter = 0.8, 0.2, 0.8, S(0) = first historical data point
681	Exponential Smoothing - Damped - L2 - NonSeasonal	ESD	no	Smoothing parameter = 0.2, 0.1, 0.8, S(0) = the level for the model of the linear regression
682	Exponential Smoothing - Damped - L2 - Seasonal	ESD	yes	Smoothing parameter = 0.2, 0.1, 0.8, S(0) = the level for the model of the linear regression
683	Exponential Smoothing - Damped - L4 - NonSeasonal	ESD	no	Smoothing parameter = 0.4, 0.13, 0.8, S(0) = the level for the model of the linear regression
684	Exponential Smoothing - Damped - L4 - Seasonal	ESD	yes	Smoothing parameter = 0.4, 0.13, 0.8, S(0) = the level for the model of the linear regression
685	Exponential Smoothing - Damped - L5 - NonSeasonal	ESD	no	Smoothing parameter = 0.5, 0.15, 0.8, S(0) = the level for the model of the linear regression
686	Exponential Smoothing - Damped - L5 - Seasonal	ESD	yes	Smoothing parameter = 0.5, 0.15, 0.8, S(0) = the level for the model of the linear regression
687	Exponential Smoothing - Damped - L6 - NonSeasonal	ESD	no	Smoothing parameter = 0.6, 0.17, 0.8, S(0) = the level for the model of the linear regression

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688	Exponential Smoothing - Damped - L6 - Seasonal	ESD	yes	Smoothing parameter = 0.6, 0.17, 0.8, S(0) = the level for the model of the linear regression
689	Exponential Smoothing - Damped - L8 - NonSeasonal	ESD	no	Smoothing parameter = 0.8, 0.2, 0.8, S(0) = the level for the model of the linear regression
690	Exponential Smoothing - Damped - L8 - Seasonal	ESD	yes	Smoothing parameter = 0.8, 0.2, 0.8, S(0) = the level for the model of the linear regression
801	Theta 2.00 - Exponential Smoothing - Simple - A2 - NonSeasonal	TH	no	Theta = 2.00, Smoothing parameter = 0.2, S(0) = average of all historical data
802	Theta 2.00 - Exponential Smoothing - Simple - A2 - Seasonal	TH	yes	Theta = 2.00, Smoothing parameter = 0.2, S(0) = average of all historical data
803	Theta 2.00 - Exponential Smoothing - Simple - A4 - NonSeasonal	TH	no	Theta = 2.00, Smoothing parameter = 0.4, S(0) = average of all historical data
804	Theta 2.00 - Exponential Smoothing - Simple - A4 - Seasonal	TH	yes	Theta = 2.00, Smoothing parameter = 0.4, S(0) = average of all historical data
805	Theta 2.00 - Exponential Smoothing - Simple - A5 - NonSeasonal	TH	no	Theta = 2.00, Smoothing parameter = 0.5, S(0) = average of all historical data
806	Theta 2.00 - Exponential Smoothing - Simple - A5 - Seasonal	TH	yes	Theta = 2.00, Smoothing parameter = 0.5, S(0) = average of all historical data
807	Theta 2.00 - Exponential Smoothing - Simple - A6 - NonSeasonal	TH	no	Theta = 2.00, Smoothing parameter = 0.6, S(0) = average of all historical data
808	Theta 2.00 - Exponential Smoothing - Simple - A6 - Seasonal	TH	yes	Theta = 2.00, Smoothing parameter = 0.6, S(0) = average of all historical data
809	Theta 2.00 - Exponential Smoothing - Simple - A8 - NonSeasonal	TH	no	Theta = 2.00, Smoothing parameter = 0.8, S(0) = average of all historical data
810	Theta 2.00 - Exponential Smoothing - Simple - A8 - Seasonal	TH	yes	Theta = 2.00, Smoothing parameter = 0.8, S(0) = average of all historical data
811	Theta 2.00 - Exponential Smoothing - Simple - M2 - NonSeasonal	TH	no	Theta = 2.00, Smoothing parameter = 0.2, S(0) = mean of first 4 historical data
812	Theta 2.00 - Exponential Smoothing - Simple - M2 - Seasonal	TH	yes	Theta = 2.00, Smoothing parameter = 0.2, S(0) = mean of first 4 historical data
813	Theta 2.00 - Exponential Smoothing - Simple - M4 - NonSeasonal	TH	no	Theta = 2.00, Smoothing parameter = 0.4, S(0) = mean of first 4 historical data
814	Theta 2.00 - Exponential Smoothing - Simple - M4 - Seasonal	TH	yes	Theta = 2.00, Smoothing parameter = 0.4, S(0) = mean of first 4 historical data
815	Theta 2.00 - Exponential Smoothing - Simple - M5 - NonSeasonal	TH	no	Theta = 2.00, Smoothing parameter = 0.5, S(0) = mean of first 4 historical data
816	Theta 2.00 - Exponential Smoothing - Simple - M5 - Seasonal	TH	yes	Theta = 2.00, Smoothing parameter = 0.5, S(0) = mean of first 4 historical data

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817	Theta 2.00 - Exponential Smoothing - Simple - M6 - NonSeasonal	TH	no	Theta = 2.00, Smoothing parameter = 0.6, S(0) = mean of first 4 historical data
818	Theta 2.00 - Exponential Smoothing - Simple - M6 - Seasonal	TH	yes	Theta = 2.00, Smoothing parameter = 0.6, S(0) = mean of first 4 historical data
819	Theta 2.00 - Exponential Smoothing - Simple - M8 - NonSeasonal	TH	no	Theta = 2.00, Smoothing parameter = 0.8, S(0) = mean of first 4 historical data
820	Theta 2.00 - Exponential Smoothing - Simple - M8 - Seasonal	TH	yes	Theta = 2.00, Smoothing parameter = 0.8, S(0) = mean of first 4 historical data
821	Theta 2.00 - Exponential Smoothing - Simple - F2 - NonSeasonal	TH	no	Theta = 2.00, Smoothing parameter = 0.2, S(0) = first historical data point
822	Theta 2.00 - Exponential Smoothing - Simple - F2 - Seasonal	TH	yes	Theta = 2.00, Smoothing parameter = 0.2, S(0) = first historical data point
823	Theta 2.00 - Exponential Smoothing - Simple - F4 - NonSeasonal	TH	no	Theta = 2.00, Smoothing parameter = 0.4, S(0) = first historical data point
824	Theta 2.00 - Exponential Smoothing - Simple - F4 - Seasonal	TH	yes	Theta = 2.00, Smoothing parameter = 0.4, S(0) = first historical data point
825	Theta 2.00 - Exponential Smoothing - Simple - F5 - NonSeasonal	TH	no	Theta = 2.00, Smoothing parameter = 0.5, S(0) = first historical data point
826	Theta 2.00 - Exponential Smoothing - Simple - F5 - Seasonal	TH	yes	Theta = 2.00, Smoothing parameter = 0.5, S(0) = first historical data point
827	Theta 2.00 - Exponential Smoothing - Simple - F6 - NonSeasonal	TH	no	Theta = 2.00, Smoothing parameter = 0.6, S(0) = first historical data point
828	Theta 2.00 - Exponential Smoothing - Simple - F6 - Seasonal	TH	yes	Theta = 2.00, Smoothing parameter = 0.6, S(0) = first historical data point
829	Theta 2.00 - Exponential Smoothing - Simple - F8 - NonSeasonal	TH	no	Theta = 2.00, Smoothing parameter = 0.8, S(0) = first historical data point
830	Theta 2.00 - Exponential Smoothing - Simple - F8 - Seasonal	TH	yes	Theta = 2.00, Smoothing parameter = 0.8, S(0) = first historical data point
831	Theta 2.00 - Exponential Smoothing - Simple - L2 - NonSeasonal	TH	no	Theta = 2.00, Smoothing parameter = 0.2, S(0) = the level for the model of the linear regression
832	Theta 2.00 - Exponential Smoothing - Simple - L2 - Seasonal	TH	yes	Theta = 2.00, Smoothing parameter = 0.2, S(0) = the level for the model of the linear regression
833	Theta 2.00 - Exponential Smoothing - Simple - L4 - NonSeasonal	TH	no	Theta = 2.00, Smoothing parameter = 0.4, S(0) = the level for the model of the linear regression

ID	Forecasting Method	Category	Apply Seasonality	Comments
834	Theta 2.00 - Exponential Smoothing - Simple - L4 - Seasonal	TH	yes	Theta = 2.00, Smoothing parameter = 0.4, S(0) = the level for the model of the linear regression
835	Theta 2.00 - Exponential Smoothing - Simple - L5 - NonSeasonal	TH	no	Theta = 2.00, Smoothing parameter = 0.5, S(0) = the level for the model of the linear regression
836	Theta 2.00 - Exponential Smoothing - Simple - L5 - Seasonal	TH	yes	Theta = 2.00, Smoothing parameter = 0.5, S(0) = the level for the model of the linear regression
837	Theta 2.00 - Exponential Smoothing - Simple - L6 - NonSeasonal	TH	no	Theta = 2.00, Smoothing parameter = 0.6, S(0) = the level for the model of the linear regression
838	Theta 2.00 - Exponential Smoothing - Simple - L6 - Seasonal	TH	yes	Theta = 2.00, Smoothing parameter = 0.6, S(0) = the level for the model of the linear regression
839	Theta 2.00 - Exponential Smoothing - Simple - L8 - NonSeasonal	TH	no	Theta = 2.00, Smoothing parameter = 0.8, S(0) = the level for the model of the linear regression
840	Theta 2.00 - Exponential Smoothing - Simple - L8 - Seasonal	TH	yes	Theta = 2.00, Smoothing parameter = 0.8, S(0) = the level for the model of the linear regression
851	Theta 1.50 - Exponential Smoothing - Simple - A2 - NonSeasonal	TH	no	Theta = 1.50, Smoothing parameter = 0.2, S(0) = average of all historical data
852	Theta 1.50 - Exponential Smoothing - Simple - A2 - Seasonal	TH	yes	Theta = 1.50, Smoothing parameter = 0.2, S(0) = average of all historical data
853	Theta 1.50 - Exponential Smoothing - Simple - A4 - NonSeasonal	TH	no	Theta = 1.50, Smoothing parameter = 0.4, S(0) = average of all historical data
854	Theta 1.50 - Exponential Smoothing - Simple - A4 - Seasonal	TH	yes	Theta = 1.50, Smoothing parameter = 0.4, S(0) = average of all historical data
855	Theta 1.50 - Exponential Smoothing - Simple - A5 - NonSeasonal	TH	no	Theta = 1.50, Smoothing parameter = 0.5, S(0) = average of all historical data
856	Theta 1.50 - Exponential Smoothing - Simple - A5 - Seasonal	TH	yes	Theta = 1.50, Smoothing parameter = 0.5, S(0) = average of all historical data
857	Theta 1.50 - Exponential Smoothing - Simple - A6 - NonSeasonal	TH	no	Theta = 1.50, Smoothing parameter = 0.6, S(0) = average of all historical data
858	Theta 1.50 - Exponential Smoothing - Simple - A6 - Seasonal	TH	yes	Theta = 1.50, Smoothing parameter = 0.6, S(0) = average of all historical data
859	Theta 1.50 - Exponential Smoothing - Simple - A8 - NonSeasonal	TH	no	Theta = 1.50, Smoothing parameter = 0.8, S(0) = average of all historical data

ID	Forecasting Method	Category	Apply Seasonality	Comments
860	Theta 1.50 - Exponential Smoothing - Simple - A8 - Seasonal	TH	yes	Theta = 1.50, Smoothing parameter = 0.8, S(0) = average of all historical data
861	Theta 1.50 - Exponential Smoothing - Simple - M2 - NonSeasonal	TH	no	Theta = 1.50, Smoothing parameter = 0.2, S(0) = mean of first 4 historical data
862	Theta 1.50 - Exponential Smoothing - Simple - M2 - Seasonal	TH	yes	Theta = 1.50, Smoothing parameter = 0.2, S(0) = mean of first 4 historical data
863	Theta 1.50 - Exponential Smoothing - Simple - M4 - NonSeasonal	TH	no	Theta = 1.50, Smoothing parameter = 0.4, S(0) = mean of first 4 historical data
864	Theta 1.50 - Exponential Smoothing - Simple - M4 - Seasonal	TH	yes	Theta = 1.50, Smoothing parameter = 0.4, S(0) = mean of first 4 historical data
865	Theta 1.50 - Exponential Smoothing - Simple - M5 - NonSeasonal	TH	no	Theta = 1.50, Smoothing parameter = 0.5, S(0) = mean of first 4 historical data
866	Theta 1.50 - Exponential Smoothing - Simple - M5 - Seasonal	TH	yes	Theta = 1.50, Smoothing parameter = 0.5, S(0) = mean of first 4 historical data
867	Theta 1.50 - Exponential Smoothing - Simple - M6 - NonSeasonal	TH	no	Theta = 1.50, Smoothing parameter = 0.6, S(0) = mean of first 4 historical data
868	Theta 1.50 - Exponential Smoothing - Simple - M6 - Seasonal	TH	yes	Theta = 1.50, Smoothing parameter = 0.6, S(0) = mean of first 4 historical data
869	Theta 1.50 - Exponential Smoothing - Simple - M8 - NonSeasonal	TH	no	Theta = 1.50, Smoothing parameter = 0.8, S(0) = mean of first 4 historical data
870	Theta 1.50 - Exponential Smoothing - Simple - M8 - Seasonal	TH	yes	Theta = 1.50, Smoothing parameter = 0.8, S(0) = mean of first 4 historical data
871	Theta 1.50 - Exponential Smoothing - Simple - F2 - NonSeasonal	TH	no	Theta = 1.50, Smoothing parameter = 0.2, S(0) = first historical data point
872	Theta 1.50 - Exponential Smoothing - Simple - F2 - Seasonal	TH	yes	Theta = 1.50, Smoothing parameter = 0.2, S(0) = first historical data point
873	Theta 1.50 - Exponential Smoothing - Simple - F4 - NonSeasonal	TH	no	Theta = 1.50, Smoothing parameter = 0.4, S(0) = first historical data point
874	Theta 1.50 - Exponential Smoothing - Simple - F4 - Seasonal	TH	yes	Theta = 1.50, Smoothing parameter = 0.4, S(0) = first historical data point
875	Theta 1.50 - Exponential Smoothing - Simple - F5 - NonSeasonal	TH	no	Theta = 1.50, Smoothing parameter = 0.5, S(0) = first historical data point
876	Theta 1.50 - Exponential Smoothing - Simple - F5 - Seasonal	TH	yes	Theta = 1.50, Smoothing parameter = 0.5, S(0) = first historical data point
877	Theta 1.50 - Exponential Smoothing - Simple - F6 - NonSeasonal	TH	no	Theta = 1.50, Smoothing parameter = 0.6, S(0) = first historical data point
878	Theta 1.50 - Exponential Smoothing - Simple - F6 - Seasonal	TH	yes	Theta = 1.50, Smoothing parameter = 0.6, S(0) = first historical data point

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879	Theta 1.50 - Exponential Smoothing - Simple - F8 - NonSeasonal	TH	no	Theta = 1.50, Smoothing parameter = 0.8, S(0) = first historical data point
880	Theta 1.50 - Exponential Smoothing - Simple - F8 - Seasonal	TH	yes	Theta = 1.50, Smoothing parameter = 0.8, S(0) = first historical data point
881	Theta 1.50 - Exponential Smoothing - Simple - L2 - NonSeasonal	TH	no	Theta = 1.50, Smoothing parameter = 0.2, S(0) = the level for the model of the linear regression
882	Theta 1.50 - Exponential Smoothing - Simple - L2 - Seasonal	TH	yes	Theta = 1.50, Smoothing parameter = 0.2, S(0) = the level for the model of the linear regression
883	Theta 1.50 - Exponential Smoothing - Simple - L4 - NonSeasonal	TH	no	Theta = 1.50, Smoothing parameter = 0.4, S(0) = the level for the model of the linear regression
884	Theta 1.50 - Exponential Smoothing - Simple - L4 - Seasonal	TH	yes	Theta = 1.50, Smoothing parameter = 0.4, S(0) = the level for the model of the linear regression
885	Theta 1.50 - Exponential Smoothing - Simple - L5 - NonSeasonal	TH	no	Theta = 1.50, Smoothing parameter = 0.5, S(0) = the level for the model of the linear regression
886	Theta 1.50 - Exponential Smoothing - Simple - L5 - Seasonal	TH	yes	Theta = 1.50, Smoothing parameter = 0.5, S(0) = the level for the model of the linear regression
887	Theta 1.50 - Exponential Smoothing - Simple - L6 - NonSeasonal	TH	no	Theta = 1.50, Smoothing parameter = 0.6, S(0) = the level for the model of the linear regression
888	Theta 1.50 - Exponential Smoothing - Simple - L6 - Seasonal	TH	yes	Theta = 1.50, Smoothing parameter = 0.6, S(0) = the level for the model of the linear regression
889	Theta 1.50 - Exponential Smoothing - Simple - L8 - NonSeasonal	TH	no	Theta = 1.50, Smoothing parameter = 0.8, S(0) = the level for the model of the linear regression
890	Theta 1.50 - Exponential Smoothing - Simple - L8 - Seasonal	TH	yes	Theta = 1.50, Smoothing parameter = 0.8, S(0) = the level for the model of the linear regression
901	Theta 0.75 - Exponential Smoothing - Simple - A2 - NonSeasonal	TH	no	Theta = 0.75, Smoothing parameter = 0.2, S(0) = average of all historical data
902	Theta 0.75 - Exponential Smoothing - Simple - A2 - Seasonal	TH	yes	Theta = 0.75, Smoothing parameter = 0.2, S(0) = average of all historical data
903	Theta 0.75 - Exponential Smoothing - Simple - A4 - NonSeasonal	TH	no	Theta = 0.75, Smoothing parameter = 0.4, S(0) = average of all historical data

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904	Theta 0.75 - Exponential Smoothing - Simple - A4 - Seasonal	TH	yes	Theta = 0.75, Smoothing parameter = 0.4, S(0) = average of all historical data
905	Theta 0.75 - Exponential Smoothing - Simple - A5 - NonSeasonal	TH	no	Theta = 0.75, Smoothing parameter = 0.5, S(0) = average of all historical data
906	Theta 0.75 - Exponential Smoothing - Simple - A5 - Seasonal	TH	yes	Theta = 0.75, Smoothing parameter = 0.5, S(0) = average of all historical data
907	Theta 0.75 - Exponential Smoothing - Simple - A6 - NonSeasonal	TH	no	Theta = 0.75, Smoothing parameter = 0.6, S(0) = average of all historical data
908	Theta 0.75 - Exponential Smoothing - Simple - A6 - Seasonal	TH	yes	Theta = 0.75, Smoothing parameter = 0.6, S(0) = average of all historical data
909	Theta 0.75 - Exponential Smoothing - Simple - A8 - NonSeasonal	TH	no	Theta = 0.75, Smoothing parameter = 0.8, S(0) = average of all historical data
910	Theta 0.75 - Exponential Smoothing - Simple - A8 - Seasonal	TH	yes	Theta = 0.75, Smoothing parameter = 0.8, S(0) = average of all historical data
911	Theta 0.75 - Exponential Smoothing - Simple - M2 - NonSeasonal	TH	no	Theta = 0.75, Smoothing parameter = 0.2, S(0) = mean of first 4 historical data
912	Theta 0.75 - Exponential Smoothing - Simple - M2 - Seasonal	TH	yes	Theta = 0.75, Smoothing parameter = 0.2, S(0) = mean of first 4 historical data
913	Theta 0.75 - Exponential Smoothing - Simple - M4 - NonSeasonal	TH	no	Theta = 0.75, Smoothing parameter = 0.4, S(0) = mean of first 4 historical data
914	Theta 0.75 - Exponential Smoothing - Simple - M4 - Seasonal	TH	yes	Theta = 0.75, Smoothing parameter = 0.4, S(0) = mean of first 4 historical data
915	Theta 0.75 - Exponential Smoothing - Simple - M5 - NonSeasonal	TH	no	Theta = 0.75, Smoothing parameter = 0.5, S(0) = mean of first 4 historical data
916	Theta 0.75 - Exponential Smoothing - Simple - M5 - Seasonal	TH	yes	Theta = 0.75, Smoothing parameter = 0.5, S(0) = mean of first 4 historical data
917	Theta 0.75 - Exponential Smoothing - Simple - M6 - NonSeasonal	TH	no	Theta = 0.75, Smoothing parameter = 0.6, S(0) = mean of first 4 historical data
918	Theta 0.75 - Exponential Smoothing - Simple - M6 - Seasonal	TH	yes	Theta = 0.75, Smoothing parameter = 0.6, S(0) = mean of first 4 historical data
919	Theta 0.75 - Exponential Smoothing - Simple - M8 - NonSeasonal	TH	no	Theta = 0.75, Smoothing parameter = 0.8, S(0) = mean of first 4 historical data
920	Theta 0.75 - Exponential Smoothing - Simple - M8 - Seasonal	TH	yes	Theta = 0.75, Smoothing parameter = 0.8, S(0) = mean of first 4 historical data
921	Theta 0.75 - Exponential Smoothing - Simple - F2 - NonSeasonal	TH	no	Theta = 0.75, Smoothing parameter = 0.2, S(0) = first historical data point
922	Theta 0.75 - Exponential Smoothing - Simple - F2 - Seasonal	TH	yes	Theta = 0.75, Smoothing parameter = 0.2, S(0) = first historical data point

ID	Forecasting Method	Category	Apply Seasonality	Comments
923	Theta 0.75 - Exponential Smoothing - Simple - F4 - NonSeasonal	TH	no	Theta = 0.75, Smoothing parameter = 0.4, S(0) = first historical data point
924	Theta 0.75 - Exponential Smoothing - Simple - F4 - Seasonal	TH	yes	Theta = 0.75, Smoothing parameter = 0.4, S(0) = first historical data point
925	Theta 0.75 - Exponential Smoothing - Simple - F5 - NonSeasonal	TH	no	Theta = 0.75, Smoothing parameter = 0.5, S(0) = first historical data point
926	Theta 0.75 - Exponential Smoothing - Simple - F5 - Seasonal	TH	yes	Theta = 0.75, Smoothing parameter = 0.5, S(0) = first historical data point
927	Theta 0.75 - Exponential Smoothing - Simple - F6 - NonSeasonal	TH	no	Theta = 0.75, Smoothing parameter = 0.6, S(0) = first historical data point
928	Theta 0.75 - Exponential Smoothing - Simple - F6 - Seasonal	TH	yes	Theta = 0.75, Smoothing parameter = 0.6, S(0) = first historical data point
929	Theta 0.75 - Exponential Smoothing - Simple - F8 - NonSeasonal	TH	no	Theta = 0.75, Smoothing parameter = 0.8, S(0) = first historical data point
930	Theta 0.75 - Exponential Smoothing - Simple - F8 - Seasonal	TH	yes	Theta = 0.75, Smoothing parameter = 0.8, S(0) = first historical data point
931	Theta 0.75 - Exponential Smoothing - Simple - L2 - NonSeasonal	TH	no	Theta = 0.75, Smoothing parameter = 0.2, S(0) = the level for the model of the linear regression
932	Theta 0.75 - Exponential Smoothing - Simple - L2 - Seasonal	TH	yes	Theta = 0.75, Smoothing parameter = 0.2, S(0) = the level for the model of the linear regression
933	Theta 0.75 - Exponential Smoothing - Simple - L4 - NonSeasonal	TH	no	Theta = 0.75, Smoothing parameter = 0.4, S(0) = the level for the model of the linear regression
934	Theta 0.75 - Exponential Smoothing - Simple - L4 - Seasonal	TH	yes	Theta = 0.75, Smoothing parameter = 0.4, S(0) = the level for the model of the linear regression
935	Theta 0.75 - Exponential Smoothing - Simple - L5 - NonSeasonal	TH	no	Theta = 0.75, Smoothing parameter = 0.5, S(0) = the level for the model of the linear regression
936	Theta 0.75 - Exponential Smoothing - Simple - L5 - Seasonal	TH	yes	Theta = 0.75, Smoothing parameter = 0.5, S(0) = the level for the model of the linear regression
937	Theta 0.75 - Exponential Smoothing - Simple - L6 - NonSeasonal	TH	no	Theta = 0.75, Smoothing parameter = 0.6, S(0) = the level for the model of the linear regression
938	Theta 0.75 - Exponential Smoothing - Simple - L6 - Seasonal	TH	yes	Theta = 0.75, Smoothing parameter = 0.6, S(0) = the level for the model of the linear regression

ID	Forecasting Method	Category	Apply Seasonality	Comments
939	Theta 0.75 - Exponential Smoothing - Simple - L8 - NonSeasonal	TH	no	Theta = 0.75, Smoothing parameter = 0.8, S(0) = the level for the model of the linear regression
940	Theta 0.75 - Exponential Smoothing - Simple - L8 - Seasonal	TH	yes	Theta = 0.50, Smoothing parameter = 0.8, S(0) = the level for the model of the linear regression
951	Theta 0.50 - Exponential Smoothing - Simple - A2 - NonSeasonal	TH	no	Theta = 0.50, Smoothing parameter = 0.2, S(0) = average of all historical data
952	Theta 0.50 - Exponential Smoothing - Simple - A2 - Seasonal	TH	yes	Theta = 0.50, Smoothing parameter = 0.2, S(0) = average of all historical data
953	Theta 0.50 - Exponential Smoothing - Simple - A4 - NonSeasonal	TH	no	Theta = 0.50, Smoothing parameter = 0.4, S(0) = average of all historical data
954	Theta 0.50 - Exponential Smoothing - Simple - A4 - Seasonal	TH	yes	Theta = 0.50, Smoothing parameter = 0.4, S(0) = average of all historical data
955	Theta 0.50 - Exponential Smoothing - Simple - A5 - NonSeasonal	TH	no	Theta = 0.50, Smoothing parameter = 0.5, S(0) = average of all historical data
956	Theta 0.50 - Exponential Smoothing - Simple - A5 - Seasonal	TH	yes	Theta = 0.50, Smoothing parameter = 0.5, S(0) = average of all historical data
957	Theta 0.50 - Exponential Smoothing - Simple - A6 - NonSeasonal	TH	no	Theta = 0.50, Smoothing parameter = 0.6, S(0) = average of all historical data
958	Theta 0.50 - Exponential Smoothing - Simple - A6 - Seasonal	TH	yes	Theta = 0.50, Smoothing parameter = 0.6, S(0) = average of all historical data
959	Theta 0.50 - Exponential Smoothing - Simple - A8 - NonSeasonal	TH	no	Theta = 0.50, Smoothing parameter = 0.8, S(0) = average of all historical data
960	Theta 0.50 - Exponential Smoothing - Simple - A8 - Seasonal	TH	yes	Theta = 0.50, Smoothing parameter = 0.8, S(0) = average of all historical data
961	Theta 0.50 - Exponential Smoothing - Simple - M2 - NonSeasonal	TH	no	Theta = 0.50, Smoothing parameter = 0.2, S(0) = mean of first 4 historical data
962	Theta 0.50 - Exponential Smoothing - Simple - M2 - Seasonal	TH	yes	Theta = 0.50, Smoothing parameter = 0.2, S(0) = mean of first 4 historical data
963	Theta 0.50 - Exponential Smoothing - Simple - M4 - NonSeasonal	TH	no	Theta = 0.50, Smoothing parameter = 0.4, S(0) = mean of first 4 historical data
964	Theta 0.50 - Exponential Smoothing - Simple - M4 - Seasonal	TH	yes	Theta = 0.50, Smoothing parameter = 0.4, S(0) = mean of first 4 historical data
965	Theta 0.50 - Exponential Smoothing - Simple - M5 - NonSeasonal	TH	no	Theta = 0.50, Smoothing parameter = 0.5, S(0) = mean of first 4 historical data
966	Theta 0.50 - Exponential Smoothing - Simple - M5 - Seasonal	TH	yes	Theta = 0.50, Smoothing parameter = 0.5, S(0) = mean of first 4 historical data

ID	Forecasting Method	Category	Apply Seasonality	Comments
967	Theta 0.50 - Exponential Smoothing - Simple - M6 - NonSeasonal	TH	no	Theta = 0.50, Smoothing parameter = 0.6, S(0) = mean of first 4 historical data
968	Theta 0.50 - Exponential Smoothing - Simple - M6 - Seasonal	TH	yes	Theta = 0.50, Smoothing parameter = 0.6, S(0) = mean of first 4 historical data
969	Theta 0.50 - Exponential Smoothing - Simple - M8 - NonSeasonal	TH	no	Theta = 0.50, Smoothing parameter = 0.8, S(0) = mean of first 4 historical data
970	Theta 0.50 - Exponential Smoothing - Simple - M8 - Seasonal	TH	yes	Theta = 0.50, Smoothing parameter = 0.8, S(0) = mean of first 4 historical data
971	Theta 0.50 - Exponential Smoothing - Simple - F2 - NonSeasonal	TH	no	Theta = 0.50, Smoothing parameter = 0.2, S(0) = first historical data point
972	Theta 0.50 - Exponential Smoothing - Simple - F2 - Seasonal	TH	yes	Theta = 0.50, Smoothing parameter = 0.2, S(0) = first historical data point
973	Theta 0.50 - Exponential Smoothing - Simple - F4 - NonSeasonal	TH	no	Theta = 0.50, Smoothing parameter = 0.4, S(0) = first historical data point
974	Theta 0.50 - Exponential Smoothing - Simple - F4 - Seasonal	TH	yes	Theta = 0.50, Smoothing parameter = 0.4, S(0) = first historical data point
975	Theta 0.50 - Exponential Smoothing - Simple - F5 - NonSeasonal	TH	no	Theta = 0.50, Smoothing parameter = 0.5, S(0) = first historical data point
976	Theta 0.50 - Exponential Smoothing - Simple - F5 - Seasonal	TH	yes	Theta = 0.50, Smoothing parameter = 0.5, S(0) = first historical data point
977	Theta 0.50 - Exponential Smoothing - Simple - F6 - NonSeasonal	TH	no	Theta = 0.50, Smoothing parameter = 0.6, S(0) = first historical data point
978	Theta 0.50 - Exponential Smoothing - Simple - F6 - Seasonal	TH	yes	Theta = 0.50, Smoothing parameter = 0.6, S(0) = first historical data point
979	Theta 0.50 - Exponential Smoothing - Simple - F8 - NonSeasonal	TH	no	Theta = 0.50, Smoothing parameter = 0.8, S(0) = first historical data point
980	Theta 0.50 - Exponential Smoothing - Simple - F8 - Seasonal	TH	yes	Theta = 0.50, Smoothing parameter = 0.8, S(0) = first historical data point
981	Theta 0.50 - Exponential Smoothing - Simple - L2 - NonSeasonal	TH	no	Theta = 0.50, Smoothing parameter = 0.2, S(0) = the level for the model of the linear regression
982	Theta 0.50 - Exponential Smoothing - Simple - L2 - Seasonal	TH	yes	Theta = 0.50, Smoothing parameter = 0.2, S(0) = the level for the model of the linear regression
983	Theta 0.50 - Exponential Smoothing - Simple - L4 - NonSeasonal	TH	no	Theta = 0.50, Smoothing parameter = 0.4, S(0) = the level for the model of the linear regression

ID	Forecasting Method	Category	Apply Seasonality	Comments
984	Theta 0.50 - Exponential Smoothing - Simple - L4 - Seasonal	TH	yes	Theta = 0.50, Smoothing parameter = 0.4, S(0) = the level for the model of the linear regression
985	Theta 0.50 - Exponential Smoothing - Simple - L5 - NonSeasonal	TH	no	Theta = 0.50, Smoothing parameter = 0.5, S(0) = the level for the model of the linear regression
986	Theta 0.50 - Exponential Smoothing - Simple - L5 - Seasonal	TH	yes	Theta = 0.50, Smoothing parameter = 0.5, S(0) = the level for the model of the linear regression
987	Theta 0.50 - Exponential Smoothing - Simple - L6 - NonSeasonal	TH	no	Theta = 0.50, Smoothing parameter = 0.6, S(0) = the level for the model of the linear regression
988	Theta 0.50 - Exponential Smoothing - Simple - L6 - Seasonal	TH	yes	Theta = 0.50, Smoothing parameter = 0.6, S(0) = the level for the model of the linear regression
989	Theta 0.50 - Exponential Smoothing - Simple - L8 - NonSeasonal	TH	no	Theta = 0.50, Smoothing parameter = 0.8, S(0) = the level for the model of the linear regression
990	Theta 0.50 - Exponential Smoothing - Simple - L8 - Seasonal	TH	yes	Theta = 0.50, Smoothing parameter = 0.8, S(0) = the level for the model of the linear regression

8. Averaging Forecasting Methods

The following table contains the Averaging Forecasting Methods that ***AGON*** is using:

- ✓ **ID**: An internal ID of the method, used internally from the ***AGON*** method.
- ✓ **Forecasting Method**: The name of the averaging forecasting method
- ✓ **Category**: The category of the method. For averaging methods is always AVR
- ✓ **Number of methods to use**: An integer (2 or 3), indicating how many simple forecasting method will be used:
  - o **2**: The 2 best performing simple forecasting method will be used.
  - o **3**: The 3 best performing simple forecasting method will be used.
- ✓ **Selection criteria**: How the best simple forecasting methods will be selected
  - o **No extra criteria**: The best according to OWA.
  - o **From different categories**: The best according to OWA, but from different categories.
- ✓ **Weights**: How the weights will be estimated
  - o **Equal**: All simple methods will have the same weight (1/2 for each of the 2 methods, or 1/3 for each of the three methods).
  - o **Estimated**: The weights will be estimated according to the methods OWA. The simple method gets the bigger weight, etc.).

  Of course, the sum of the weights must always be 1.

ID	Forecasting Method	Category	Number of Methods to use	Selection Criteria	Weights
1001	Averaging - Best 2 - Equal Weights	AVR	2	no extra criteria	Equal
1002	Averaging - Best 2 - Estimated Weights	AVR	2	no extra criteria	Estimated
1003	Averaging - Best 3 - Equal Weights	AVR	3	no extra criteria	Equal
1004	Averaging - Best 3 - Estimated Weights	AVR	3	no extra criteria	Estimated
1051	Averaging - Best 2 - DifCat - Equal Weights	AVR	2	From different categories	Equal
1052	Averaging - Best 2 - DifCat - Estimated Weights	AVR	2	From different categories	Estimated
1053	Averaging - Best 3 - DifCat - Equal Weights	AVR	3	From different categories	Equal
1054	Averaging - Best 3 - DifCat- Estimated Weights	AVR	3	From different categories	Estimated

According to the above, we have the following averaging methods:

- **Averaging - Best 2 - Equal Weights**:
  - o We locate the 2 simple forecast methods with the smallest OWA error.

  - We are averaging their forecasts, by using equal weights.
- **Averaging - Best 2 - Estimated Weights**:
  - We locate the 2 simple forecast methods with the smallest OWA error.
  - We are averaging their forecasts, by using unequal weights. Their weights are calculated based on their OWA performance.
- **Averaging - Best 3 - Equal Weights**:
  - We locate the 3 simple forecast methods with the smallest OWA error.
  - We are averaging their forecasts, by using equal weights.
- **Averaging - Best 3 - Estimated Weights**:
  - We locate the 3 simple forecast methods with the smallest OWA error.
  - We are averaging their forecasts, by using unequal weights. Their weights are calculated based on their OWA performance.
- **Averaging - Best 2 - DifCat - Equal Weights**:
  - We locate the 2 simple forecast methods (they must be of a different category) with the smallest OWA error.
  - We are averaging their forecasts, by using equal weights.
- **Averaging - Best 2 - DifCat - Estimated Weights**:
  - We locate the 2 simple forecast methods (they must be of a different category) with the smallest OWA error.
  - We are averaging their forecasts, by using unequal weights. Their weights are calculated based on their OWA performance.
- **Averaging - Best 3 - DifCat - Equal Weights**:
  - We locate the 3 simple forecast methods (they must be of a different category) with the smallest OWA error.
  - We are averaging their forecasts, by using equal weights.
- **Averaging - Best 3 - DifCat- Estimated Weights**:
  - We locate the 3 simple forecast methods (they must be of a different category) with the smallest OWA error.
  - We are averaging their forecasts, by using unequal weights. Their weights are calculated based on their OWA performance.

9. Contact Info

Of course, it is not an easy task to describe all details of a methodology in a description document.

For more information or for any question about the algorithm and how you can reproduce the forecasts, please don't hesitate to contact me:

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