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Correlated daily time series and forecasting in the M4 competition

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Abstract

We participated in the M4 competition for time series forecasting and describe here our methods for forecasting daily time series. We used an ensemble of five statistical forecasting methods and a method that we refer to as the correlator. Our retrospective analysis using the ground truth values published by the M4 organisers after the competition demonstrates that the correlator was responsible for most of our gains over the naive constant forecasting method. We identify data leakage as one reason for its success, partly due to test data selected from different time intervals, and partly due to quality issues in the original time series. We suggest that future forecasting competitions should provide actual dates for the time series so that some of those leakages could be avoided by the participants.

Keywords: Forecasting competitions, time series, correlation, data leakage, ensembling

1. Introduction

The task in the M4 time series forecasting competition was to provide forecasts for 100,000 numeric time series with different frequencies and origins (Makridakis et al., 2018). Participants of the competition were free to choose their methods differently depending on the type of time series and in the following we will describe how we compiled our forecasts on the 4227 time series from the Daily category. Each of those time series contained a numeric value for each day over a time interval ranging from 93 to 9919 days, and the task was to forecast the values for the next 14 days.

We participated in the M4 competition as a team of 24 students and 1 instructor and our submission was created in a dedicated M4 seminar at the

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University of Tartu. We formed subteams to try out different approaches and evaluated these in an internal competition where we withheld the last available 14 days as an internal validation set. Our final submission was obtained by choosing a different ensemble of models for each category of time series: Hourly, Daily, Weekly, Monthly, Quarterly, Yearly. Forecasting the Daily time series was done using an ensemble of 5 statistical methods and one correlation-based method, which we refer to as the correlator. After the organisers of the M4 competition published the full time series we performed an analysis revealing that the key to the good performance of our submission was the correlator.

In Section 2 we will describe our methods used for forecasting the Daily time series in the M4 competition. In Section 3 we evaluate the methods separately on the official M4 test data and demonstrate the role of the correlator in the final performance of our submission. In Section 4 we discuss the reasons behind the success of the correlator and its implications for forecasting competitions.

2. Methods

Our forecasts for the Daily time series in the M4 competition were obtained with two methods. For a subset of the 4227 time series a forecasting method which we refer to as the correlator was used. This method compares the time series in a given dataset between themselves to find highly correlated segments and uses this information to produce the forecasts. The method is used only on those time series for which the correlation is larger than a given threshold. The method is described in detail in Section 2.2.

On the rest of the time series, that is for the time series for which the correlator did not find high correlations, an ensemble of five models was used to produce the forecasts. The ensemble is described in detail in Section 2.1.

The methods were selected based on their performance on the holdout validation dataset that we had separated from the training data. From each training time series, we removed the last 14 time points and these removed values formed the validation data. After this, we were able to evaluate any method by calculating its performance measure on the validation set.

As a post-processing step, all the negative predicted values were replaced by zeros. This was done because the original dataset did not contain any negative values and thus avoiding forecasting negative values was deemed beneficial.

2.1. Ensembling model

Our ensembling method used five models:

• Naive model, which makes a constant forecast equal to the last observed value in the time series;

• an ETS model (see Appendix B for details);

• two ARIMA models (see Appendix B for details);
- a custom model based on time series decomposition (see Appendix C for details).

These five methods were chosen based on empirical results on the holdout validation data. In addition we considered Holt-Winters (Hyndman et al., 2002), BATS (Livera et al., 2011), LSTM networks (Kong et al., 2019) and a combination of ARIMA and a neural network (Zhang, 2003). On each time series, we trained each of the chosen methods to obtain five models. The ensemble forecast was obtained by taking the median of the five single method based forecasts for each time point in the forecasting horizon. Flowchart of the method can be seen in Figure 1.

2.2. Correlator

The idea behind the correlator is to look for highly correlating patterns between different time series at different times. If such a correlation is found between the last 14 days of the current time series and some other 14 day period that continues for at least 14 days in the training set, then the correlator uses these subsequent 14 days to produce a forecast for the current series. The practical applications of this idea are limited, because it relies on the existence of correlating patterns between different times in different time series. However, as we show and discuss in the following sections, this idea worked surprisingly well in the M4 competition.

There are 4227 time series in the Daily category with varying lengths and starting times. Let us denote the $j$-th time series of the Daily dataset as $y^j$.
and its data points as \(y^j_1, y^j_2, \ldots, y^j_{n_j}\) where \(n_j\) denotes the length of the \(j\)-th time series. Further, for convenience we will use notation \([i_1 : i_2]\) for interval indexing, that is we denote data points of time series \(y\) from index \(i_1\) until index \(i_2\) as \(y[i_1 : i_2] := (y_{i_1}, \ldots, y_{i_2})\).

To produce forecasts for the \(j\)-th time series \(y^j_1, \ldots, y^j_{n_j}\), the correlator first takes its last 14 values \(y^j_{[n_j-13:n_j]}\) and calculates Pearson correlation coefficient between this vector of 14 values and all the non-terminal segments of the same length across all time-series, where by non-terminal we mean segments which have at least 14 subsequent data points. We denote the Pearson correlation coefficient between the end segment of the \(j\)-th time series and a segment of the \(k\)-th time series \(y^k_1, \ldots, y^k_{n_k}\) ending at \(\tau \in \{14, \ldots, n_k - 14\}\) as follows

\[
r_{jk}(\tau) := \text{pearson}(y^j_{[n_j-13:n_j]}, y^k_{[\tau-13: \tau]}),
\]

where for any length \(n\) and for any vectors \(a = (a_1, \ldots, a_n)\) and \(b = (b_1, \ldots, b_n)\) of real numbers, \(\text{pearson}(a, b)\) is the Pearson correlation coefficient

\[
\text{pearson}(a, b) = \frac{\sum_{i=1}^{n} (a_i - \text{mean}(a))(b_i - \text{mean}(b))}{\text{std}(a) \cdot \text{std}(b)},
\]

where

\[
\text{mean}(a) = \frac{1}{n} \sum_{i=1}^{n} a_i, \quad \text{std}(a) = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (a_i - \text{mean}(a))^2}.
\]

Next, we find for each time series \(y^j_1, \ldots, y^j_{n_j}\) the values \(k\) and \(\tau\) which maximise \(r_{jk}(\tau)\). In other words, the end segment of a time series \(y\) is compared to all given time series and a time series \(y^k\) is found with a segment that is most similar to the end segment of time series \(y\) and continues for at least 14 data points. The next 14 data points \(y^k_{[\tau+1: \tau+14]}\) from time series \(y^k\) are then scaled and translated using a function \(f\) defined as

\[
f(x) = \left(x - \text{mean} \left( y^k_{[\tau-13: \tau]} \right) \right) \frac{\text{std} \left( y^j_{[n_j-13:n_j]} \right)}{\text{std} \left( y^k_{[\tau-13: \tau]} \right)} + \text{mean} \left( y^j_{[n_j-13:n_j]} \right),
\]

where \(x\) is a real number. Function \(f\) maps values \(y^k_{[\tau-13: \tau]}\) approximately to values \(y^j_{[n_j-13:n_j]}\). The obtained result is considered as the forecast for the time series \(y^j\). We denote this result as \(\hat{y}^j_{n_j+1} := f(y^k_{\tau+1}), \ldots, \hat{y}^j_{n_j+14} := f(y^k_{\tau+14})\).

The resulting forecast from the correlator is used as the actual forecast only if two conditions are met. The first condition that must hold is that the correlation must be at least 0.9999, that is

\[
r_{jk}(\tau) \geq 0.9999.
\]
This condition was used to avoid spurious correlations. As the segment over which the correlation is calculated is only 14 data points long, a high threshold had to be used.

The second condition is

$$\text{std} \left( \hat{y}_j^{\ell} \left[ n_j+1:n_j+14 \right] \right) \leq 2.5 \cdot \text{std} \left( y_j^{\ell} \left[ n_j-13:n_j \right] \right) \quad (6)$$

which means that the standard deviation of the forecast $\hat{y}_j^{\ell} \left[ n_j+1:n_j+14 \right]$ must not exceed 2.5 times the standard deviation of the end segment of the time series $y_j^{\ell}$. Without this condition, the forecast can have a sudden change in standard deviation compared to the end segment of the time series, e.g. the forecast can contain large jumps. Therefore, the correlator skips forecasts that do not satisfy Equation (6) to find forecasts more similar to the end segment of current time series.

If the Equation (6) does not hold, new values $k'$ and $\tau'$ are found such that they maximise $r_{jk'}(\tau')$ and differ from the previously found $k$ and $\tau$. This is iterated until suitable values are found or no suitable values exist, in which case the correlator is not used. The flowchart of the correlator can be seen in Figure 2.

The only changeable parameters for this method are the number of values used from the end of the time series, in this work 14, the correlation cut-off threshold in (5) and the multiplier for standard deviation comparison in (6). All of these were chosen in this work based on empirical results on the validation dataset. However, our retrospective analysis showed that the threshold of 0.9999 was not optimal and Equation (6) was not needed (see Table 2).

2.3. Differences from submission

After the submission of our forecasts to the M4 competition, we found two bugs in our implementation of the correlator. Therefore, the method used for producing the submission has two differences from the description given in Section 2.2.

First, in the original submission, the correlator was used only on time series D1-D2138 and not used on any of the time series D2139-D4227. This was probably caused by an unseen memory error when applying the correlator. We will refer to this error as Bug 1.

The second difference is that instead of Equation (6), due to human error the condition

$$\text{std} \left( \hat{y}_j^{\ell} \left[ n_j+1:n_j+14 \right] \right) \leq 2.5 \cdot \text{std} \left( y_j^{k} \left[ \tau-13:\tau \right] \right) \quad (7)$$

was used instead. We will refer to this error as Bug 2.

3. Results

In this section we present the performance of all models presented in Section 2.1 individually and compare these to the performances of the ensemble
with and without the correlator to determine which part of our method was most successful. We also compare the performance of the correlator with different parameter values. Tables 1, 2 and 3 show the post-submission analysis of the data, using the actual test set that was made public by the organisers after the competition.

In our experiments, we use the correlator’s parameter values mentioned in Section 2.2 if not stated otherwise. The results were evaluated using MASE, sMAPE and the overall weighted average (OWA) of the relative MASE and the relative sMAPE (M4Team, 2018). Relative MASE and relative sMAPE are obtained by dividing MASE and sMAPE of the forecast by MASE and sMAPE of naive forecast respectively, and OWA is the mean of the obtained values. Therefore, OWA of less than 1 is better than Naive and more than one is worse than Naive. In the following, the presented values of MASE, sMAPE and OWA are the average values over the considered forecasts.

Table 1: OWA for single models, ensemble and benchmark method Comb on Daily dataset. Benchmark method Comb is the arithmetic average of the Simple, Holt and Damped exponential smoothing models that is also used by Makridakis et al. (2018). We evaluated the performance of Comb using its implementation available in the M4 code repository1.

|                | Macro | Micro | Demographic | Industry | Finance | Other | All   |
|----------------|-------|-------|-------------|----------|---------|-------|-------|
| Single model   |       |       |             |          |         |       |       |
| ARIMA 1        | 1.160 | 1.023 | 1.142       | 1.016    | 1.052   | 1.038 | 1.041 |
| ARIMA 2        | 1.123 | 1.009 | 1.144       | 1.031    | 1.035   | 1.051 | 1.033 |
| ETS            | 1.022 | 0.989 | 0.983       | 1.012    | 0.991   | 1.006 | 0.996 |
| Custom method  | 1.336 | 1.360 | 1.050       | 1.342    | 1.380   | 1.304 | 1.354 |
| Naive          | 1.001 | 1.000 | 1.000       | 1.000    | 1.000   | 1.000 | 1.000 |
| Ensemble       |       |       |             |          |         |       |       |
| No correlator  | 1.020 | 0.990 | 0.999       | 1.008    | 0.967   | 1.011 | 0.995 |
| Correlator with Bug 1 and 2 | 0.805 | 0.785 | 0.849       | 1.007    | 0.995   | 1.011 | 0.930 |
| Correlator with Bug 2 | 0.805 | 0.785 | 0.849       | 1.007    | 0.944   | 0.981 | 0.908 |
| Correlator     | 0.776 | 0.778 | 0.814       | 1.007    | 0.939   | 0.979 | 0.903 |
| Benchmark Comb | 1.015 | 0.980 | 0.978       | 1.005    | 0.958   | 1.005 | 0.979 |

Table 2: Comparison of correlator’s performance on Daily dataset for different values of STD ratio threshold in Equation (6), dash means that Equation (6) was not used. Correlator MASE, sMAPE and OWA are calculated from the forecasts of the correlator, that is only subset of Daily dataset is considered. Full OWA is calculated from the full dataset using forecasts obtained from the combination of ensemble and correlator.

| STD ratio threshold | Correlation threshold 0.9999 | Correlation threshold 0.999 | Correlation threshold 0.99 |
|---------------------|-------------------------------|----------------------------|----------------------------|
|                     | 2    | 2.5 | 3    | 2    | 2.5 | 3    | 2    | 2.5 | 3    | 2    | 2.5 | 3    | 2    | 2.5 | 3    |
| Correlator used (#) | 480  | 518 | 541  | 566  | 743 | 794  | 827  | 825 | 1764 | 1772 | 1827 | 1867 |
| Correlator used (%) | 11.4 | 12.3 |12.8  |13.4  |17.6 |18.8  |19.6  |20.2 |40.3  |41.9  |43.2  |44.2  |
| Correlator MASE     | 0.191| 0.183|0.186 |0.254 |0.227|0.214 |0.221 |0.275|2.176 |2.134 |2.140 |2.145 |
| Correlator sMAPE    | 0.310| 0.298|0.334 |0.386 |0.299|0.284 |0.306 |0.356|2.485 |2.411 |2.411 |2.408 |
| Correlator OWA      | 0.698| 0.692|0.696 |0.715 |0.609|0.601 |0.604 |0.612|0.729 |0.709 |0.704 |0.699 |
| Full OWA            | 0.913| 0.903|0.897 |0.891 |0.875|0.863 |0.854 |0.848|0.896 |0.878 |0.870 |0.864 |

1https://github.com/M4Competition/M4-methods
Table 3: Performance of correlator on all categories. Correlator MASE, sMAPE and OWA are calculated from the forecasts of the correlator, that is only subset of Daily dataset is considered. Correlator used 14-time-point window for calculating correlations for all categories except for Yearly, for which 13 was used, because some of the time series in Yearly dataset had only 13 data points.

|                          | Hourly | Daily | Weekly | Monthly | Quarterly | Yearly |
|--------------------------|--------|-------|--------|---------|-----------|--------|
| Time series (#)          | 414    | 4227  | 359    | 48000   | 24000     | 23000  |
| Correlator used (#)      | 25     | 518   | 7      | 1357    | 450       | 178    |
| Correlator used (%)      | 6.0    | 12.3  | 1.9    | 2.8     | 1.9       | 0.8    |
| Correlator MASE          | 0.124  | 0.183 | 1.732  | 4.972   | 0.552     | 2.929  |
| Correlator sMAPE         | 0.560  | 0.298 | 0.632  | 8.144   | 1.396     | 5.321  |
| Correlator OWA           | 0.028  | 0.092 | 0.360  | 0.580   | 0.128     | 0.444  |

As can be seen from Table 1, the main improvement over Naive was achieved thanks to using the correlator. From single models, only ETS achieved better performance than Naive with OWA of 0.996. The ensemble of five models only slightly improved the result to 0.995. As can be seen in Table 2, by using the correlator, it would have been possible to obtain an OWA of 0.863. However, our submission achieved only 0.930 due to using a higher correlation threshold (0.9999 instead of 0.999) and the presence of two bugs in the code, as described in Section 2.3. Additional analysis showed that using only one of the two ARIMA models resulted in better OWA: 0.980 when only ARIMA 1 was used and 0.982 when only ARIMA 2 was used.

From Table 2 it can be seen that using the value of 2.5 for the constant in Equation (6) gives the smallest OWA for the correlator’s forecasts (see the row ‘Correlator OWA’ in the table). However, the OWA for the combination of ensemble and correlator is the smallest when Equation (6) is not used at all (see the row ’Full OWA’). Without Equation (6) an OWA of 0.848 could have been achieved by the proposed method.

Finally, Table 3 shows the performance of the correlator on other categories of the M4 dataset. We can see that the correlator was the most successful on Daily and Hourly datasets where it was used on 12% and 6% of the time series respectively and achieved OWA of less than 0.1. On the rest of the categories, the correlator was used on less than 3% of time series and in most cases OWA was considerably larger than on Daily and Hourly datasets. This suggests that the similarities between time series were most exploitable in Daily and Hourly category.

4. Discussion

As can be seen from Table 1, most of the improvement over Naive was achieved thanks to using the correlator. This implies that the Daily dataset contained time series that had highly correlated short segments between each other. However, it turns out that the correlated regions are actually often much
longer. To understand the nature of correlations in this dataset better, we performed the following further analysis.

Similarly to the correlator of Section 2.2, we cross-correlated each time series $y^j$ with every other time series $y^k$ by sliding one time series along the other. However, instead of calculating the Pearson correlation coefficient after each shift between 14 data points we calculated it globally on the whole overlapping region. Formally, this means that for every $\tau \in \{14, \ldots, n_k - 14\}$ we calculated the following correlation:

$$ r'_{jk}(\tau) := \text{pearson} \left( y^j_{[n_j-(\min(n_j,\tau)-1):n_j]} ; y^k_{[\tau-(\min(n_j,\tau)-1):\tau]} \right). $$  \hspace{1cm}(8)

As in Section 2.2, we found for each time series $y^j$ the values $k$ and $\tau$ which maximise $r'_{jk}(\tau)$. As a result, for 1083 time series we found $k$ and $\tau$ with $r'_{jk} \geq 0.995$. Detailed inspection revealed that some of those high correlations were due to a single big jump in both time series which after alignment resulted in a high correlation, even though the regions before the jump and after the jump were not correlated, respectively. We discarded such cases with jumps manually (the detailed list is available in the code repository, see Appendix A).

The remaining set $C$ of 1004 pairs of highly correlated time series ($y^j$, $y^k$) with the respective shifts $\tau$ constitute cases with global correlations, not just a short correlated segment. Note that the length of the overlapping segment between time series $y^j$ and $y^k$ in (8) is $\min(n_j, \tau)$. Figure 3 shows the histogram over the overlap lengths $\min(n_j, \tau)$ of the pairs in set $C$. We can see that the Daily dataset even contains time series that have highly correlated segments with length up to around 4000 data points. However, highly correlated segments of less than 1000 data points are the most frequent. In the following we split the set $C$ of 1004 cases into 4 categories.

T1: **Self-correlations** (cases where $(y^j, y^j) \in C$). These are time series where the end is highly correlated with the beginning. While short self-correlations could be explained by periodicity, our identified cases can have very long repeats, potentially pointing at problems in data, for an example see Figure 4.

T2: **Mutual correlations** (cases where $(y^j, y^k) \in C$ and $(y^k, y^j) \in C$ for $j \neq k$). These are pairs of time series where the end of one series correlates with the beginning of the other, and vice versa. For an example, see Figure 5.

T3: **Synchronised correlations** (cases where $j \neq k$ and the correlated region corresponds to the same dates in both time series). In such case using the end of $y^k$ to forecast the continuation of $y^j$ would be using data from the future (forecast earlier dates using data from later dates), which is of course not doable in practical applications and demonstrates data leakage (Kaufman et al., 2012) in the M4 data. For an example, see Figure 6. At the time of competition we could not identify these cases, as the actual starting dates of time series were only published by the M4 organisers after the competition (Makridakis et al., 2018).
T4: **Unsynchronised correlations** (cases where \( j \neq k \) and the correlated region corresponds to different dates in both time series). Depending on which time series is earlier, this might be a leakage or not. The example in Figure 7 shows series that are claimed to start at the same date but become almost perfectly correlated after shifting one of them, possibly suggesting that the start date information might not be correct.

Table 4 shows the number of time series pairs in each of the categories T1, T2, T3 and T4. Note that we made the categories mutually exclusive by excluding those that belong to narrower categories T1 and T2 from the wider categories T3 and T4.

Note that above we have only categorised correlations where one of the segments is at the end and another at the beginning of some time series. Additionally, we identified other more peculiar kinds of correlations, such as the example shown in Figure 8, where one time series can be split into 3 large segments and rearranged almost perfectly into one another time series.

**Figure 3:** Histogram of the lengths of highly correlated regions as identified by our analysis.

**Figure 4:** Time series that repeats itself.

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**Table 4:** Number of time series in categories T1-T4. Table shows how many time series were assigned to one of the categories T1-T4, and the performance of forecasts when using these similarities.

|         | T1 | T2 | T3 | T4 | All |
|---------|----|----|----|----|-----|
| **Time series (#)** | 12 | 202 | 23 | 767 | 1004 |
| MASE    | 1.615 | 0.077 | 0.702 | 0.471 | 0.410 |
| sMAPE   | 1.418 | 0.084 | 0.540 | 0.424 | 0.370 |
| OWA     | 0.482 | 0.030 | 0.202 | 0.166 | 0.144 |

The above results raise the question of whether the success of the correlator in the M4 competition could be fully explained by leakage in forecasting by using
information from the future. Our additional analysis revealed that the correlator used future data in only 26% of the cases where it was applied. Allowing the correlator to use only past values resulted in OWA of 0.895 and 0.917 with correlation thresholds of 0.999 and 0.9999 respectively. These results lead us to the hypothesis that possibly there are further data quality issues, including duplications of data within one time series explaining some of the correlations of type T1, rearrangement errors of time series segments explaining some of T2 cases, and wrong starting dates explaining cases in T4.

Importantly, the evidence we presented here strongly suggests that the success of the correlator in forecasting future from the past was only due to data quality issues in the M4 data, most probably going back to the issues in the databases where the M4 data originate from.

Figure 5: Time series such that the beginning of one is correlated with the ending of the other and vice versa.

Figure 6: Time series that match after standardising.

Figure 7: Time series that are shifted versions of one another.

Figure 8: Time series that can be split into large segments and rearranged into one another.
5. Conclusions

In this article, we have described our method to obtain forecasts for Daily time series within the M4 competition. We used an ensemble of five statistical forecasting methods and a method that we refer to as the correlator. The correlator was applied on a time series only if its last 14 days were found to correlate strongly with another time series. Our retrospective analysis using the full time series published by the M4 organisers after the competition demonstrated that the correlator was responsible for most of our gains over the naive constant forecasting method. We found that in 26% of cases where the correlator was applied it actually used data from the future. However, as the actual starting dates were only published by the M4 organisers after the competition we had no way of filtering those cases out in our submission. To avoid this problem we suggest providing the starting dates explicitly in future competitions. In this analysis we have revealed some potential data quality issues, including potential duplications and rearrangement errors within particular time series and potential errors in starting dates. We cannot rule out the possibility that success of the correlator in forecasting the future from the past was only due to data quality issues in the time series.

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Appendix A. Implementation of the algorithm

The code for producing the forecasts using our method can be found in Github repository\(^2\). The detailed instruction on how to run the code is in README.md file in the repository.

Appendix B. ARIMA and ETS models

Two ARIMA models (Box et al., 2015) and an ETS model (Hyndman et al., 2002) were fitted using corresponding functions in the forecast package version 8.3 (Hyndman & Khandakar, 2008) in the R software version 3.2.4. ETS was fitted using function ets with the default parameter settings. ARIMA models were fitted using auto.arima function. In the following we discuss the differences between the two ARIMA models.

The first ARIMA model was obtained using the stepwise algorithm (Hyndman & Khandakar, 2008) with the default settings except the starting values for the order of the autoregressive model and the moving average model which were set to 0. We refer to this method as ARIMA 1.

The second model was obtained using a non-stepwise algorithm that searches through all the (S)ARIMA models with the maximum allowed order for the model set to 8. The fitting of ARIMA models was done using maximum likelihood estimation instead of using approximation with conditional sum of squares as in ARIMA 1 method. We refer to this method as ARIMA 2.

Our retrospective analysis showed that using only one ARIMA model instead of two in the ensemble gave better results as outlined in Section 3. Therefore, since ARIMA 2 is much more computationally expensive, using only ARIMA 1 would have been beneficial.

Appendix C. Custom method

Our custom time series forecasting method\(^3\) is inspired by Forecasting with Decomposition from Hyndman & Athanasopoulos (2014). Our method differs from the method described by Hyndman & Athanasopoulos (2014) in mainly two ways. First, we use the classical decomposition (Macaulay, 1931) instead of STL decomposition (Cleveland et al., 1990) and secondly, we use either linear extrapolation (Shumway & Stoffer, 2017) or past values from the decomposition for forecasting trend and residuals.

In more detail, classical additive decomposition is performed on the time series with frequency set to 2 instead of 1 as in the Daily dataset. This means that a moving average filter with weights (0.25, 0.5, 0.25) is applied to the time series to obtain the trend and then the seasonal component with period 2 is calculated from that, see Hyndman & Athanasopoulos (2014) for details. However, in most

\(^2\)https://github.com/antiingel/correlator

\(^3\)Originally named fearless in our submission
cases the seasonal component is very small relative to other components since the time series does not actually have frequency 2. Therefore, setting frequency to 2 mainly serves to reduce noise in the time series by applying moving average filter. For decomposition `seasonal_decompose` function in `StatsModel` package version 0.8.0 (Seabold & Perktold, 2010) was used.

To predict the trend and the residuals, two approaches for the trend and for the residuals are considered. In total, all four combinations of these approaches are evaluated on the internal validation set and the approach that performs the best according to MASE evaluation measure (Hyndman & Koehler, 2006) is used on the actual dataset. One considered approach is linear extrapolation from the last 14 values, which was performed using `curve_fit` from `Scipy` package version 1.0.1 (Jones et al., 2001–). The other approach is using the previous 14 values of the corresponding component as the forecasts.

Linear functions were chosen for the extrapolation, because the method was mainly developed for Yearly data, in which training samples were limited and in many cases the trend was not changing dramatically. Therefore, the poor performance on Daily dataset was unsurprising. For Yearly dataset our custom method achieved OWA of 0.967. We decided to include the custom method in the Daily ensemble to introduce some variability.

Seasonal component is predicted as seasonal naive, which means that the forecast for current period is the last period’s corresponding value. The final forecast is the sum of the predicted trend, residual and seasonal component. In our original submission, this method was used for all Daily time series except for time series D3160 which had incorrect forecast due to a bug in our code.