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Research Article

Ata method's performance in the M4 competition

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Abstract

Like the previous M competitions, M4 competition resulted in great contributions to the field of forecasting. Ata method which is a new forecasting method alternative to exponential smoothing, competed in this competition with five different models. The results obtained from these five models are discussed in detail in this paper. According to various error metrics, the models perform better than their exponential smoothing based counters. Despite their simplicity, they are ranked satisfactorily high compared to the other methods. In addition, the forecasting accuracy of simple combinations of these Ata models and ARIMA are given for the M4 competition data set. The combinations work significantly better than models that are much more complex. Therefore, besides the fact that Ata models perform well alone, Ata should be considered as a candidate for being included in combinations of forecasts.

Mathematics Subject Classification (2020). 62M10

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1. Introduction

Efforts for better forecasting and the competitions in which the outcomes of these efforts are tested and measured will never cease. Better forecasting is crucial to every science and business field. The most important platforms in which the performance of the studies for accurate forecasting is measured are the M-competitions [2]. The most recent of these competitions, M4, has ended [5]. The aim of the M4 competition, like the competitions held before it, was to "learn how to improve the forecasting accuracy, and how such learning can be applied to advance the theory and practice of forecasting and are there any new methods that could really make a difference?".

M competitions are very important and prestigious platforms for forecasting researchers since they provide researchers and developers of new forecasting methods opportunities to test and prove themselves. Another benefit of these competitions is that they usually lead to both the destruction of many taboos known in the forecasting literature and discovery of new methods that help increase forecasting accuracy.

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In the M4 competition, the number of data from the previous M3 [6] competition was increased from 3,000 to 100,000. There were numerous applications (248), but only 49 of the applicants were able to provide forecasts for the entire 100,000 series. With the addition of 10 benchmarks and 2 standard methods, 61 methods were considered [4]. Only 17 out of 49 valid applications outperformed the com benchmark set by the competition committee. Of these 17 successful methods, 12 are combinations of known statistical methods obtained by using different weighting techniques. The winner of the competition, Slavek's work is a hybrid method that combines ML (Machine Learning) and Holt-Winters using RNN (Recurrent Neural Network). The remaining 4 methods are statistical methods, but 3 of the 4 statistical methods are different versions of the Theta method, the winner of the M3 competition. 2 of the 3 different versions of the Theta method were prepared by researchers that were on the competition committee. The other statistical method Forecast Pro, which also participated in the M3 competition, is a commercial software that uses known statistical methods. In short, there has been no mention of a new method that stood out in terms of forecasting performance in the literature reporting the results of the M4 competition. On the contrary, the winner of the M3 competition, Theta method, attracted much attention, even though later it was shown to be a special case of the ES (Exponential Smoothing) [3]. Many studies were conducted on the Theta method and it was chosen as a benchmark for the M4 competition. As a result three different versions of Theta were ranked amongst the first 17 and it has been used in almost all of the 12 successful combination approaches.

The results of the M4 competition were examined in detail in a very short time by the organizing committee of the competition, but one issue escaped their attention. This issue can easily be seen when Table 1 is studied. Ata method participated in the competition with five versions, namely the models numbered 009, 252, 253, 255 and 256, and these versions were ranked 51-55 with respect to OWA (Ordered Weighted Averaging) [8] when all the 100,000 data sets were considered. However, when the daily data sets were excluded, versions of Ata method scored better than all the benchmarks in addition to ES and ARIMA (Autoregressive Integrated Moving Average) for all other data types. This is particularly important since Ata method is a new statistical method, that is fast and 100% replicable. So, what happened that caused this new method to perform so poorly on the daily data when it was performing so well on the other data types? It was simply an error of only reading a sub-sample of each daily data set from the .csv file. The daily data consisted of very long data sets and they were given in multiple rows in the .csv file prepared by the competition committee and there were no warnings that informed the researchers about this case special to the daily data. In order to obtain forecasts for versions of Ata, the data sets were read into a separate computer program from the .csv file and since incomplete data sets were transferred the methods actually predicted parts of the in-sample by mistake. Other methods did not suffer from this issue since they used the readily given data sets in the M4comp2018 R package. This error has been reported to the competition committee immediately after the competition results were announced

In short, even though numerous papers have been published that discuss and examine the findings of the M4 competition, none has mentioned this new, simple, 100& replicable and fast statistical method that actually performed astonishingly when the correct forecasts are considered for the daily data. The method and its actual performance in the M4 competition will be given in this paper so that the forecasting community will become aware of the fact that there is a new simple and fast way to obtain accurate forecasts.

2. Materials and methods

Ata method that participated in the M4 competition in five different forms can be generalized in damped additive and damped multiplicative forms. Let X_t, $t = 1, \ldots, n$ be a time series. Then the additive damped form of Ata denoted by $Ata^{add}(p,q,\phi)$ can be written as:

$$S_t = \begin{cases} \left(\frac{p}{t}\right) X_t + \left(\frac{t-p}{t}\right)(S_{t-1} + \phi T_{t-1}) & t > p \\ X_t & t \le p \end{cases}$$
$$T_t = \begin{cases} \left(\frac{q}{t}\right)(S_t - S_{t-1}) + \left(\frac{t-q}{t}\right)(\phi T_{t-1}) & t > q \\ X_t - X_{t-1} & t \le q \\ 0 & t = 1 \end{cases} \tag{2.1}$$
$$\hat{X}_t(h) = S_t + (\phi + \phi^2 + \cdots + \phi^h)T_t,$$

where $t > p \ge q$, $p \in \{1,2,\ldots,n\}$, $q \in \{0,1,\ldots,p\}$, $0 \le \phi \le 1$ and $h = 1,2,\ldots$. The multiplicative damped form denoted by $Ata^{mult}(p,q,\phi)$ can be given in a similar fashion as:

$$S_t = \begin{cases} \left(\frac{p}{t}\right) X_t + \left(\frac{t-p}{t}\right)\left(S_{t-1} T_{t-1}^{\phi}\right) & t > p \\ X_t & t \le p \end{cases}$$
$$T_t = \begin{cases} \left(\frac{q}{t}\right)\left(\frac{S_t}{S_{t-1}}\right) + \left(\frac{t-q}{t}\right) T_{t-1}^{\phi} & t > q \\ \frac{X_t}{X_{t-1}} & t \le q \\ 1 & t = 1 \end{cases} \tag{2.2}$$
$$\hat{X}_t(h) = S_t + T_t^{(}\phi + \phi^2 + \cdots + \phi^h),$$

where again $t > p \ge q$, $p \in \{1,2,\ldots,n\}$, $q \in \{0,1,\ldots,p\}$, $0 \le \phi \le 1$ and $h = 1,2,\ldots$. In the sets of equations (2.1) and (2.2), X_t represents the observed time series, T_t is the trend component, S_t is the smoothed value, p, q and ϕ are the level, trend and dampening smoothing parameters respectively. Finally, $\hat{X}_t(h)$ stands for the h step ahead forecast value.

Without dampening effect on the trend component ($\phi = 1$), the additive trended ($Ata^{add}(p,q,1)$) and multiplicative trended ($Ata^{mult}(p,q,1)$) models can be obtained as follows respectively:

$$S_t = \begin{cases} \left(\frac{p}{t}\right) X_t + \left(\frac{t-p}{t}\right)(S_{t-1} + T_{t-1}) & t > p \\ X_t & t \le p \end{cases}$$
$$T_t = \begin{cases} \left(\frac{q}{t}\right)(S_t - S_{t-1}) + \left(\frac{t-q}{t}\right)(T_{t-1}) & t > q \\ X_t - X_{t-1} & t \le q \\ 0 & t = 1 \end{cases} \tag{2.3}$$
$$\hat{X}_t(h) = S_t + hT_t,$$

$$S_t = \begin{cases} \left(\frac{p}{t}\right) X_t + \left(\frac{t-p}{t}\right)(S_{t-1} T_{t-1}) & t > p \\ X_t & t \le p \end{cases}$$
$$T_t = \begin{cases} \left(\frac{q}{t}\right)\left(\frac{S_t}{S_{t-1}}\right) + \left(\frac{t-q}{t}\right) T_{t-1} & t > q \\ \frac{X_t}{X_{t-1}} & t \le q \\ 1 & t = 1 \end{cases} \tag{2.4}$$
$$\hat{X}_t(h) = S_t + T_t^h,$$

where for both (2.3) and (2.4) $t > p \ge q$, $p \in \{1,2,\ldots,n\}$, $q \in \{0,1,\ldots,p\}$ and $h = 1,2,\ldots$.

For non-trended time series data, a simple version of Ata can be obtained by letting $q = 0$ and $\phi = 1$. Then both of the models in (2.1) and (2.2) reduce to $Ata(p, 0, 1)$ as:

$$S_t = \begin{cases} \left(\frac{p}{t}\right) X_t + \left(\frac{t-p}{t}\right) S_{t-1} & t > p \\ X_t & t \le p \end{cases} \tag{2.5}$$
$$\hat{X}_t(h) = S_t,$$

where $p \in \{1, 2, \ldots, n\}$ and $h = 1, 2, \ldots$. There are two special cases of the $Ata(p, 0, 1)$ model given in (2.5). When $p = n$ the model is the equivalent of the naive method, i.e. $\hat{X}_t(h) = S_n = X_n$ and when $p = 1$ then the model uses the arithmetic mean of the past data as a forecast, i.e. $\hat{X}_t(h) = \bar{x} = \frac{\sum_{t=1}^{n} X_t}{n}$. As a result, 7 practical models of Ata can be obtained using the formulas represented in this section and these models were used in the five different approaches that participated in the M4 competition.

Ata method is a pure statistical method where the data does not need to be subjected to any complex transformations or outlier detection before the method is applied. No hold-out strategy is implemented for the method. Seasonality is handled like the other benchmarks by using the classical multiplicative deseasonalization. For the competition, the model parameters are optimized by minimizing the in-sample sMAPE (Symmetric Mean Absolute Percentage Error) values only.

This method was proposed as an alternative to exponential smoothing and it is not a special case of it. The details on the method and how it helps solve some issues that exponential smoothing suffers from can be found in [9–11]. The comparison of forecast accuracy of Ata and ES for simulated data sets with linear and no trend is given in [1] and in this work Ata outperforms ES for both short and long term forecast horizons for data sets with various levels of variability.

In order to test this approach's forecasting performance on real data and compare it to the benchmarks and especially counter ES models, forecasts obtained from five versions of it given the code numbers 009, 252, 253, 255 and 256 were submitted to the M4 competition. The model given the number 253 fits the $Ata(p, 0, 1)$ to all data sets which is the alternative to simple exponential smoothing. Model encoded by 255 fits the $Ata^{add}(p, 1, \phi)$ to the yearly data sets and uses the simple average of the forecasts obtained from the models $Ata^{add}(p, 1, 1)$ and $Ata(p, 0, 1)$ for the other data sets. The model with the code number 256 again fits the $Ata^{add}(p, 1, \phi)$ to the yearly data sets and uses the simple average of the forecasts obtained from $Ata(p, 0, 1)$ and the best of the two models $Ata^{add}(p, 1, 1)$ and $Ata^{mult}(p, 1, 1)$ for the other data sets. The model 252 fits the $Ata^{add}(p, 1, \phi)$ to the yearly data sets and uses the simple average of the forecasts obtained from $Ata^{add}(p, 1, \phi)$, $Ata^{mult}(p, 1, \phi)$,$Ata^{add,lf}(p, 1, \phi)$ and $Ata^{mult,lf}(p, 1, \phi)$ for the other data sets where the additional superscript "lf" stands for the words "level-fixed". For the level-fixed versions, first the level parameter is optimized while holding the higher order parameters at zero, and fixing the level parameter at this optimum value, then the other parameters are optimized. The final model numbered 009 in the competition is a rule based version of Ata. The details on these models can be found in the GitHub repository of the M4 competition [7].

3. Results from the M4 competition

The forecasting performance of the five versions of Ata that competed in the M4 competition are given in the following three tables (Table 1, Table 2 and Table 3) with respect to the error criteria sMAPE, MASE (Mean Absolute Scaled Error) and OWA respectively. These tables only differ from the ones that were represented by the competition committee for the daily data. The sMAPE for the daily data for models 252, 255, 009, 256 and 253 were reported as 37.998, 38.080, 38.011, 38.010 and 38.027; the MASE were 43.273, 43.278,

Table 1. Average forecasting errors for various data types and overall ranks with respect to sMAPE (H:Hybrid, C:Combination, S:Statistical, ML:Machine Learning)

Team	Method Type	Yearly	Quarterly	Monthly	Weekly	Daily	Hourly	Total	Rank
Smyl	H	13.176	9.679	12.126	7.817	3.170	9.328	11.374	1
Montero-Manso, et al.	C (S & ML)	13.528	9.733	12.639	7.625	3.097	11.506	11.720	3
Pawlikowski, et al.	C (S)	13.943	9.796	12.747	6.919	2.452	9.611	11.845	5
Jaganathan. & Prakash	C (S & ML)	13.712	9.809	12.487	6.814	3.037	9.934	11.695	2
Fiorucci & Louzada	C (S)	13.673	9.816	12.737	8.627	2.985	15.563	11.836	4
Petropoulos & Svetunkov	C (S)	13.669	9.800	12.888	6.726	2.995	13.167	11.887	6
Shaub	C (S)	13.679	10.378	12.839	7.818	3.222	13.466	12.020	9
Legaki & Koutsouri	S	13.366	10.155	13.002	9.148	3.041	17.567	11.986	8
Doornik, et al.	C(S)	13.910	10.000	12.780	6.728	3.053	8.913	11.924	7
Selamlar (252)	S	13.930	9.960	13.131	8.201	3.003	13.111	12.108	12
Pedregal, et al.	C (S)	13.821	10.093	13.151	8.989	3.026	9.765	12.114	13
Taylan (255)	S	13.930	10.292	12.936	8.540	3.095	12.851	12.098	11
Spiliotis & Assimakopoulos	S	13.804	10.128	13.142	8.990	3.027	17.756	12.148	15
Roubinchtein	C (S)	14.445	10.172	12.911	8.435	3.270	12.871	12.183	17
Ibrahim	S	13.677	10.089	13.321	9.089	3.071	18.093	12.198	18
Yapar, et al.(009)	S	13.981	10.016	13.047	8.540	3.004	12.851	12.093	10
Tartu M4 seminar	C (S& ML)	14.096	11.109	13.290	8.513	2.852	13.851	12.496	23
Waheeb	C (S)	14.783	10.059	12.770	7.076	2.997	12.047	12.146	14
Darin & Stellwagen	S	14.663	10.155	13.058	6.582	3.077	11.683	12.279	19
Dantas & Cyrino Oliveira	C (S)	14.746	10.254	13.462	8.873	3.245	16.941	12.553	25
The M4 Team (Theta)	S	14.593	10.311	13.002	9.093	3.053	18.138	12.309	20
The M4 Team (Com)	S	14.848	10.175	13.434	8.944	2.980	22.053	12.555	27
The M4 Team (Arima)	S	15.168	10.431	13.443	8.653	3.193	12.045	12.661	29
The M4 Team (Damped)	S	15.198	10.237	13.473	8.866	3.064	19.265	12.661	30
The M4 Team (ETS)	S	15.356	10.291	13.525	8.727	3.046	17.307	12.725	31
Yilmaz (256)	S	13.933	10.207	13.085	8.304	3.022	13.399	12.148	16
The M4 Team (Holt)	S	16.354	10.907	14.812	9.708	3.066	29.249	13.775	43
Çetin (253)	S	16.529	10.671	13.409	8.213	3.056	12.771	13.011	35
The M4 Team (SES)	S	16.396	10.600	13.618	9.012	3.045	18.094	13.087	37

43.267, 43.263 and 43.272 and the OWA were 12.840, 12.854, 12.841, 12.840 and 12.845 respectively when the competition ended. When the forecasts are obtained using the same algorithms given in the competition GitHub repository but on the full length daily data set as it was supposed to be, the errors for the daily data sets reduce immensely as given below. These correct results, given in Tables 1, 2 and 3, present new findings about the M4 competition.

According to sMAPE Table 1, 4 of the Ata models are ranked in the first 20. In addition, it can be seen that the model 253, which is the simple version of Ata, performed better than SES (Simple Exponential Smoothing). The model 009 which can be thought as an alternative to ETS (Error Trend Seasonality Forecast) is ranked 10^{th} where ETS is ranked 31^{st}. With respect to MASE and OWA (Table 2 and Table 3) 3 of them are ranked in the first 20. The models 252, 255 and 009 all perform much better than ETS despite the fact that only sMAPE was used for optimizing the Ata approaches for the in-sample data and these approaches only considered limited numbers of candidate models to choose from unlike ETS.

In addition to accuracy, replicability and speed are also very important when selecting a forecasting method. The replicabilities and running times of existing and Ata models are given in Table 4 [4]. From the table it can be seen that all Ata methods are 100% replicable

Table 2. Average forecasting errors for various data types and overall ranks with respect to MASE (H:Hybrid, C:Combination, S:Statistical, ML:Machine Learning)

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Team	Method Type	Yearly	Quarterly	Monthly	Weekly	Daily	Hourly	Total	Rank
Smyl	H	2.980	1.118	0.884	2.356	3.446	0.893	1.536	1
Montero-Manso, et al.	C (S & ML)	3.060	1.111	0.893	2.108	3.344	0.819	1.551	3
Pawlikowski, et al.	C (S)	3.130	1.125	0.905	2.158	2.642	0.873	1.547	2
Jaganathan. & Prakash	C (S & ML)	3.126	1.135	0.895	2.350	3.258	0.976	1.571	6
Fiorucci & Louzada	C (S)	3.046	1.122	0.907	2.368	3.194	1.203	1.554	4
Petropoulos & Svetunkov	C (S)	3.082	1.118	0.913	2.133	3.229	1.458	1.565	5
Shaub	C (S)	3.038	1.198	0.929	2.947	3.479	1.372	1.595	7
Legaki & Koutsouri	S	3.009	1.198	0.966	2.601	3.254	2.557	1.601	8
Doornik, et al.	C (S)	3.262	1.163	0.931	2.302	3.284	0.801	1.627	11
Selamlar (252)	S	3.124	1.155	0.962	2.499	3.246	2.366	1.613	9
Pedregal, et al.	C (S)	3.185	1.164	0.943	2.488	3.232	1.049	1.614	10
Taylan (255)	S	3.117	1.231	0.962	2.578	3.277	2.238	1.631	13
Spiliotis & Assimakopoulos	S	3.184	1.178	0.959	2.488	3.232	1.808	1.628	12
Roubinchtein	C(S)	3.244	1.159	0.921	2.290	3.632	1.129	1.633	15
Ibrahim	S	3.075	1.185	0.977	2.583	3.894	2.388	1.644	16
Yapar, et al. (009)	S	3.115	1.166	1.098	2.578	3.225	2.238	1.678	20
Tartu M4 seminar	C (S & ML)	3.091	1.250	1.002	2.375	3.025	1.058	1.633	14
Waheeb	C (S)	3.400	1.160	1.029	2.180	3.321	0.861	1.706	27
Darin & Stellwagen	S	3.406	1.168	0.924	2.107	4.128	0.856	1.693	25
Dantas & Cyrino Oliveira	C (S)	3.294	1.170	0.952	2.534	3.436	1.598	1.657	17
The M4 Team (Theta)	S	3.382	1.232	0.970	2.637	3.262	2.455	1.696	26
The M4 Team (Com)	S	3.280	1.173	0.966	2.432	3.203	4.582	1.663	18
The M4 Team (Arima)	S	3.402	1.165	0.930	2.556	3.410	0.943	1.666	19
The M4 Team (Damped)	S	3.379	1.173	0.972	2.404	3.236	2.956	1.683	23
The M4 Team (ETS)	S	3.444	1.161	0.948	2.527	3.253	1.824	1.680	21
Yilmaz (256)	S	3.124	1.203	1.182	2.528	3.239	63.805	1.985	44
The M4 Team (Holt)	S	3.550	1.198	1.009	2.420	3.223	9.356	1.772	34
Çetin (253)	S	4.000	1.350	1.009	2.602	3.299	2.163	1.886	40
The M4 Team (SES)	S	3.981	1.340	1.019	2.685	3.281	2.385	1.885	39

and in addition to providing accurate forecasts, their running times are relatively much shorter compared to more complex methods.

These results should motivate users to consider Ata instead of exponential smoothing based forecasting. Another important result from the M4 competition was that combining forecasts improved accuracy. This improvement will become even stronger if the set of initial candidate models are chosen wisely and more meaningful if the combination can be obtained faster as speed is an undeniable factor when choosing a forecasting method due to the need of obtaining forecasts for the streaming and big data sets. The results obtained by using a simple combination of ARIMA and Ata for the M4 competition data set are given in Table 5. For all error metrics considered, Ata approaches provide much better forecasts and since the optimization is much faster than ETS these more satisfying forecasts are obtained much faster.

Just by using the simple combination of Ata and ARIMA, forecasts that are more accurate than most of the methods that competed in the M4 competition and that can compete with the more accurate methods considering the computation complexity and time as important factors can be obtained. The results are given along with the ranks when all the methods are ranked according to OWA in Table 6. The three simple combinations of Ata and ARIMA are ranked in the top 10 when all other methods are considered.

Table 3. Average forecasting errors for various data types and overall ranks with respect to OWA (H:Hybrid, C:Combination, S:Statistical, ML:Machine Learning)

Team	Method Type	Yearly	Quarterly	Monthly	Weekly	Daily	Hourly	Total	Rank
Smyl	H	0.778	0.847	0.836	0.851	1.046	0.440	0.821	1
Montero-Manso, et al.	C (S & ML)	0.799	0.847	0.858	0.796	1.019	0.484	0.838	2
Pawlikowski, et al.	C (S)	0.820	0.855	0.867	0.766	0.806	0.444	0.841	3
Jaganathan & Prakash	C (S & ML)	0.813	0.859	0.854	0.795	0.996	0.474	0.842	4
Fiorucci & Louzada	C (S)	0.802	0.855	0.868	0.897	0.977	0.674	0.843	5
Petropoulos & Svetunkov	C (S)	0.806	0.853	0.876	0.751	0.984	0.663	0.848	6
Shaub	C (S)	0.801	0.908	0.882	0.957	1.060	0.653	0.860	7
Legaki & Koutsouri	S	0.788	0.898	0.905	0.968	0.996	1.012	0.861	8
Doornik, et al.	C (S)	0.836	0.878	0.881	0.782	1.002	0.410	0.865	9
Selamlar (252)	S	0.819	0.873	0.908	0.898	0.988	0.851	0.868	10
Pedregal, et al.	C (S)	0.824	0.883	0.899	0.939	0.990	0.485	0.869	11
Taylan (255)	S	0.818	0.916	0.901	0.930	1.008	0.817	0.872	12
Spiliotis & Assimakopoulos	S	0.823	0.889	0.907	0.939	0.990	0.860	0.874	13
Roubinchtein	C (S)	0.850	0.885	0.881	0.873	1.091	0.586	0.876	14
Ibrahim	S	0.805	0.890	0.921	0.961	1.098	0.991	0.880	15
Yapar, et al. (009)	S	0.820	0.880	0.969	0.930	0.985	0.817	0.885	16
Tartu M4 seminar	C (S & ML)	0.820	0.960	0.932	0.892	0.930	0.598	0.888	17
Waheeb	C(S)	0.880	0.880	0.927	0.779	0.999	0.507	0.894	18
Darin & Stellwagen	S	0.877	0.887	0.887	0.739	1.135	0.496	0.895	19
Dantas & Cyrino Oliveira	C (S)	0.866	0.892	0.914	0.941	1.057	0.794	0.896	20
The M4 Team (Theta)	S	0.872	0.917	0.907	0.971	0.999	1.006	0.897	21
The M4 Team (Com)	S	0.867	0.890	0.920	0.926	0.978	1.556	0.898	22
The M4 Team (Arima)	S	0.892	0.898	0.903	0.932	1.044	0.524	0.902	23
The M4 Team (Damped)	S	0.890	0.893	0.924	0.917	0.997	1.141	0.907	25
The M4 Team (ETS)	S	0.903	0.891	0.915	0.931	0.996	0.852	0.908	26
Yilmaz (256)	S	0.819	0.902	1.009	0.908	0.990	13.685	0.967	36
The M4 Team (Holt)	S	0.947	0.932	0.988	0.966	0.995	2.749	0.971	37
Cetin (253)	S	1.009	0.977	0.939	0.917	1.005	0.799	0.973	38
The M4 Team (SES)	S	1.003	0.970	0.951	0.975	1.000	0.990	0.975	39

4. Conclusion

Ata is a new and simple forecasting method that is an alternative to exponential smoothing. Even though its form resembles that of exponential smoothing, its weighting system and parameterization are completely different therefore it is not a special case or derivative of exponential smoothing.These differences allow Ata to behave somewhere between moving averages and exponential smoothing. It can be adapted to all types of time series data much like exponential smoothing in addition to providing more accurate forecasts. Also, Ata can be optimized faster than exponential smoothing since its parameters can take on a limited number of discrete values only.

An interesting result of Ata's weighting system is that when an obtaining a smoothed value at time t for a component, the weight the most recent observed value of that component receives can not go below $\frac{1}{t}$. This happens when the smoothing parameter for that component is equal to 1. In that case, the method behaves like the average method where all the observed values including the most recent one receive equal weights. The biggest weight that the most recent observation can get is 1 and this happens when the smoothing parameter for a component is equal to t. Then, the method behaves like the naive method. In this sense, for different parameter values, Ata covers a wide range of models. Starting from the average method, as the weight that the recent observations receive is increased by increasing the parameter values, it can get equivalent to the naive method.

Table 4. Running times and replicabilities of methods for M4 competition data

Method	Replicability (%)	Running time (min.)
Smyl	98.5	8056.0
Montero-Manso, et al.	99.5	46108.3
Pawlikowski, et al.	99.6	39654.8
Petropoulos & Svetunkov	99.5	4049.5
Shaub	100	8575.0
Legaki & Koutsouri	100	25.0
Doornik, et al.	100	2.1
Selamlar (252)	100	393.5
Pedregal, et al.	100	6742.6
Taylan (255)	100	154.8
Spiliotis & Assimakopoulos	100	3335.9
Roubinchtein	Not replicable	-
Ibrahim	100	109.6
Yapar, et al. (009)	100	63.6
Tartu M4 seminar	Not replicable	-
Waheeb	Not replicable	-
Darin & Stellwagen	Not replicable	-
Dantas & Cyrino Oliveira	Unknown	> 2 months
The M4 Team (Theta)	100	12.7
The M4 Team (Com)	100	33.2
The M4 Team (Arima)	100	3030.9
The M4 Team (Damped)	100	15.3
The M4 Team (ETS)	100	888.8
Yilmaz (256)	100	72.5
The M4 Team (Holt)	100	13.3
Cetin (253)	100	37.2
The M4 Team (SES)	100	8.1

Table 5. Average forecasting errors for various data types and error metrics using simple combinations of forecasts

	Yearly	Quarterly	Monthly	Weekly	Daily	Hourly	Total
				sMAPE			
ETS & ARIMA	14.691	10.027	12.917	8.439	3.076	14.377	12.205
252 & ARIMA	13.857	9.869	12.722	7.458	2.956	12.095	11.864
255 & ARIMA	13.847	9.987	12.653	7.607	2.998	11.942	11.859
009 & ARIMA	13.840	9.897	12.704	7.607	3.002	11.942	11.860
				MASE			
ETS & ARIMA	3.334	1.132	0.909	2.476	3.259	1.249	1.627
252 & ARIMA	3.096	1.123	0.910	2.285	3.241	1.497	1.570
255 & ARIMA	3.093	1.148	0.908	2.345	3.255	1.436	1.575
009 & ARIMA	3.091	1.128	0.979	2.345	3.234	1.436	1.603
				OWA			
ETS & ARIMA	0.869	0.868	0.875	0.906	1.002	0.652	0.875
252 & ARIMA	0.814	0.858	0.869	0.818	0.980	0.642	0.848
255 & ARIMA	0.813	0.872	0.866	0.837	0.989	0.625	0.849
009 & ARIMA	0.812	0.861	0.901	0.837	0.986	0.625	0.856

Table 6. Average forecasting errors (OWA) for various data types along with the ranks

Team	Yearly	Quarterly	Monthly	Weekly	Daily	Hourly	Total	Rank
Smyl	0.778	0.847	0.836	0.851	1.046	0.440	0.821	1
Montero-Manso, et al.	0.799	0.847	0.858	0.796	1.019	0.484	0.838	2
Pawlikowski, et al.	0.820	0.855	0.867	0.766	0.806	0.444	0.841	3
Jaganathan. & Prakash	0.813	0.859	0.854	0.795	0.996	0.474	0.842	4
Fiorucci & Louzada	0.802	0.855	0.868	0.897	0.977	0.674	0.843	5
Petropoulos & Svetunkov	0.806	0.853	0.876	0.751	0.984	0.663	0.848	6
252 & ARIMA	0.814	0.858	0.869	0.818	0.980	0.642	0.848	7
255 & ARIMA	0.813	0.872	0.866	0.837	0.989	0.625	0.849	8
009 & ARIMA	0.812	0.861	0.901	0.837	0.986	0.625	0.856	9
Shaub	0.801	0.908	0.882	0.957	1.060	0.653	0.860	10
Legaki & Koutsouri	0.788	0.898	0.905	0.968	0.996	1.012	0.861	11
Doornik, et al.	0.836	0.878	0.881	0.782	1.002	0.410	0.865	12

To sum up, Ata is a new flexible forecasting framework that performs quite well as shown in this paper. With further research, the forecasting performance and generality of the model can be enhanced and forecasts obtained using Ata will make great contributions to forecasting methods that use combinations of forecasts.

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