Method Description

General Information

Type of Entry (*Academic, Practitioner, Researcher, Student*)	Software Developer
First Name	Forecast Pro
Last Name	
Country	
Type of Affiliation (*University, Company-Organization, Individual*)	Company
Affiliation	Business Forecast Systems

Team Members (*if applicable*):

1st Member	
First Name	Sarah
Last Name	Darin
Country	USA
Affiliation	Business Forecast Systems / Forecast Pro
2nd Member	
First Name	Eric
Last Name	Stellwagen
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Information about the method utilized

Name of Method	**Forecast Pro**
Type of Method (*Statistical, Machine Learning, Combination, Other*)	**Statistical**
Short Description (up to 200 words)	Forecast Pro is designed to help business people forecast large amounts of data accurately and efficiently. Our approach for the M4 competition was to leverage all the key Forecast Pro software features that are designed specifically for large-scale business forecasting. The core of the Forecast Pro software is our “Expert Selection” algorithm for automated times series forecasting. The majority of M4 time series were forecasted via Expert Selection. However, as is often the case with business data, there are many irregular or unusual series that require review and possibly customization. Forecast Pro is designed to easily identify series that may require a more customized approach. Forecast Pro’s M4 submission uses Expert Selection as a starting point, and then uses filtered reports (primarily exception reports and item reports)

	to identify series that show unusual patterns that may require a customized approach, such as Dynamic Regression. As a final note, business forecasting should integrate domain knowledge as part of the review and customization process. Applying domain knowledge is a critical part of forecasting that could not be utilized in the M4 competition, but it is our recommendation that anybody who chooses to adopt our approach integrates domain knowledge into the process.

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.

Our submission uses Forecast Pro software.

Step 1. Convert ragged right csv files to ragged left and put into Forecast Pro format.

Step 2. Create smaller data files based on length of data to read into Forecast Pro projects. For example, all monthly series that have less than 5 years of data may be included in one project. This was not necessary for weekly or hourly data, as there were a limited number of series within each of these time cycles. Separating data based on length resulted in more manageable projects, and similar series were typically included in the same project.

Step 3. Use Expert Selection with a holdout equal to the forecast horizon for all series in each project.

Step 4. Run the R code provided on GitHub (with some modifications) to calculate SMAPE, MASE and OWA for 8 benchmark statistical methods and Forecast Pro's Expert Selection based on holdout sample.

Step 5. For projects with very long data series (typically > 50 years), use OWA for the project to assess the best time window. To do this we test eliminating perhaps the first 5 years and seeing if there is an impact on the holdout accuracy (based on OWA for each project). We keep doing this until the series are all a reasonable length and/or forecast accuracy is as good or better than using the full dataset.

Step 6. Output Expert Selection SMAPE and series level OWA for each data series for the forecast horizon holdout.

Step 7. Consider alternative forecast approaches which are currently not included in the Expert Selection algorithm. To do this, we apply an alternative approach to all series within a given project. Typically these alternative approaches included Expert Selection with a log transform, dampened exponential smoothing, dampened exponential smoothing with a log transform, a dynamic regression model with Forecast Pro optimized dynamics and a "shift variable" for the more recent data periods and then that same dynamic regression with a logged transform, and often other dynamic regression models that may include other time base dummy variables. For some projects, we considered a Forecast Pro custom component model that is similar to the Naive2 approach, where exponential smoothing with a level smoothing parameter of 1 and seasonal indices are used. The considered approaches varied across projects, based on the structure of the data. For the hourly data, we leveraged 2 Forecast Pro projects, the hourly one and one aggregated to a daily level, to test a top down temporal approach. The adjustment to apply the daily top down forecast to the hourly data was done in R. For each considered approach, we output Forecast Pro forecasts for the holdout period and calculated series level SMAPE and OWA statistics in R
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Step 8. Compare OWA across Expert Selection and the other considered approaches and select the best approach, with some bias towards Expert Selection. For example, if another approach was only slightly better than Expert Selection for the holdout, we selected Expert Selection.

Step 9. Update Forecast Pro project so that the selected approach for each series is applied and generate forecasts for the submission horizon, For the hourly data where the top down approach was selected, we computed the top down forecasts in R and then read in those forecasts as overrides in the Forecast Pro project.

Step 10. Use the Exception Report in Forecast Pro to compare the cumulative forecasts to the cumulative history from the prior period (across the length of the forecast horizon). Sorting by size of the absolute value of the change, we reviewed series with large changes to make sure forecast looks appropriate and adjust as needed (for example, if there is a large percentage increase and there is a log transform applied, remove the transform to dampen the increase a bit). Use outlier detection and correct as necessary. Find periods with 0 forecasts and adjust model (e.g. apply log transform in this case). Create custom models for odd series, as necessary. Similarly, we used the item report to sort by within sample SMAPE,carefully reviewed series with the poorest fit and made adjustments where necessary.

Step 11. Look at PACFS (computed in R) and identify "odd series," for example hourly series that have a high correlation for lag 17. Use Forecast Pro hotlists to import the ids for these series and examine and possibly adjust forecasts in Forecast Pro. Use Forecast Pro advanced diagnostics to examine full PACF and EACF graphs for the series in the hotlist.

Step 12. Output the within sample statistics for Forecast Pro project with selected models and no holdout to the output from all Expert Selection and no holdout. If Expert selection performs better, look at how close the holdout period SMAPE /OWAs are and go back to Expert Selection if the performance is not far off. This is done to avoid overfitting to the holdout sample too much.

Step 13. With this “final” project, go back to holdout period and assess holdout accuracy.

Step 14. Assuming holdout accuracy is still strong, remove holdout period, forecast for submission horizon and output forecasts for submission .