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Citation for final published version:

Nikolopoulos, Konstantinos and Petropoulos, Fotios 2016. Misbehaving, misdesigning and miscommunicating. *Foresight: The International Journal of Applied Forecasting* 41 , pp. 18-19.

Publishers page:

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Misbehaving, misdesigning and miscommunicating

Kostas Nikolopoulos and Fotios Petropoulos

There are two kinds of sins: sins of omission and sins of commission. In this short commentary, we will try to fold out some of the sins that FSS users fall into. Also, we point out some misdesign issues of current forecasting support systems. Finally, we commeny on the miscommunication of forecast uncertainty from both users and systems' perspective.

USERS' SINS

Users' misbehaviour is usually linked with their need to justify their own roles and salaries. For example, while most forecasting software provide optimisation procedures for at least some key parameters of the available forecasting methods, users tend to unnecessarily change the suggested by the software optimal values so that it seems that they are involved in the forecasting process. However, in some cases they even lack the knowledge of the impact of different parameter values on the produced (suboptimal) forecasts.

The same behaviour is observed in the case of automatic method selection approaches which are often considered as black boxes being 'too complex'. Users prefer to have the sense of ownership on the produced forecasts. Even if there is evidence that judgmental model selection can be of value if performed properly, users tend to virtually create limited pools of methods by consistently selecting amongst one or two simple methods that can easily understand and feel familiar with.

Tinkering of parameters and bypassing the system's recommendations provide the excuses managers use to justify their role in the forecasting process.

Users are not always trained forecasters/demand planners (see also the discussion by Fildes and Goodwin, 2007). Anecdotal evidence suggests that it is not uncommon to find that demand planners' positions are occupied by people that do not possess the necessary skillsets and have been in such positions "accidentally". To that respect, the professional training that is offered from various institutions and universities is of tremendous value.

Also, users are purposely but erroneously misuse their forecasting systems in order to secure bonuses. Examples of such behaviours usually lie in the category of judgmental adjustments. Managers in different positions (operations, production, marketing, finance) frequently are judged by different key performance indicators and their cost functions are sometimes asymmetric, meaning differential costs for errors of over and underforecasting. The danger is that the result is unwarranted adjustments of the statistical forecasts in the direction that will better ensure individual performance bonuses. (See also the article by Paul Goodwin in this issue). The problem is that the profitability of company as a whole is jeopardised.

A potential solution for this behaviour is, unfortunately, 'police enforcement'. Systems could provide mechanisms under which different sets of forecasts (statistical, budget, marketing, finance, operational, final) are stored, aligned with users/managers and benchmarked separately. While each set of forecasts can be the base for a different scenario, from a research viewpoint an interesting question is the optimal reconciliation of such forecasts.

VENDOR'S SINS

Scott Armstrong (2001) has attempted to gather best principles and practices in forecasting and more recently has developed a “golden rule checklist” (Armstrong and colleagues, 2015) of 28 operational guidelines for conservative forecasting. Most forecasting systems fail to support the application of such forecasting principles, despite the considerable empirical evidence for their value.

One could argue that such principles/rules are not always universally applicable. For example, judgmental adjustments to statistical forecasts may reduce accuracy and introduce biases, however, they might prove to be beneficial in cases where soft information is not captured in any other way. As such, a ‘horses for courses’ approach would be of value: what is suitable for one person or situation might be unsuitable for another. In the same way that different forecasting methods are suitable for different types of data, forecasting principles and operational guidelines can significantly help in improving performance if applied properly. A forecasting system that would include such principles and also guidance towards their application would be in an advantageous position to produce accurate forecasts.

“Software companies have been slow to adopt methods that have been shown to improve accuracy” (Armstrong and Fildes, 2006). While this quote is already 10 years old, we can still see that software vendors continue to deliberately omit robust forecasting methods. The same methodological issue has been further discussed in a recent *Foresight* article (Petropoulos, 2015). Noteworthy examples of non-adopted forecasting methods include the Theta method, the winner of M3-Competition, and Syntetos and Boylan approximation, a bias-correction of the Croston’s method for intermittent demand data. We expect that the inclusion of such methods would significantly increase the performance of the automatic selection methodologies offered by the different forecasting software. On a brighter note, we are happy to see large software vendors expanding their pool of available methods (see for example the new features of Microsoft Excel 2016). In any case, much more progress remains to be done.

MISCOMMUNICATION BY USERS AND VENDORS

Here, we refer to the problem of miscommunicating the uncertainty around forecasts. Both users and software tend to rely on the point forecasts and not the prediction intervals that show the likely range of error in the point forecasts. These intervals are frequently wide (large range of potential error) and forecasters avoid communicating this result if they feel that they might appear incompetent in producing forecasts and supporting respective decisions.

Similarly, software vendors avoid presenting such information in the fear that this might decrease the value of their product. In fact, presenting the uncertainty around the provided forecasts adds considerable value to the forecasting process, while it can prove useful in effective worst/best case scenario planning.

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