Improving demand forecasts of seasonal products using weather variables

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Abstract

- **Purpose**: Analyze of several winter sporting goods and equipment operations related data and how weather conditions affect demand prediction accuracy.
- **Design/methodology/approach**: Analyze of longitudinal data of products' orders matched with location specific weather data using Generalized Additive Models and Bootstrap methods. The underlying hypothesis is that taking into account weather conditions data improves demand forecasting accuracy.
- **Findings**: The fact of including weather conditions data in the task of predicting demand ameliorates forecasting accuracy in general. Further, several levels of enhancing are observed.
- **Research limitations**: Lack of generalization due to the fact that the study concerns Switzerland and leisure goods.
- **Practical implications**: For weather related products such as sporting goods and equipment, demand is obviously affected by weather conditions. Therefore previous and current weather conditions data should be included in the demand forecasting calculations.
- **Keywords**: Demand forecasting, seasonality, weather, GAM, Bootstrap

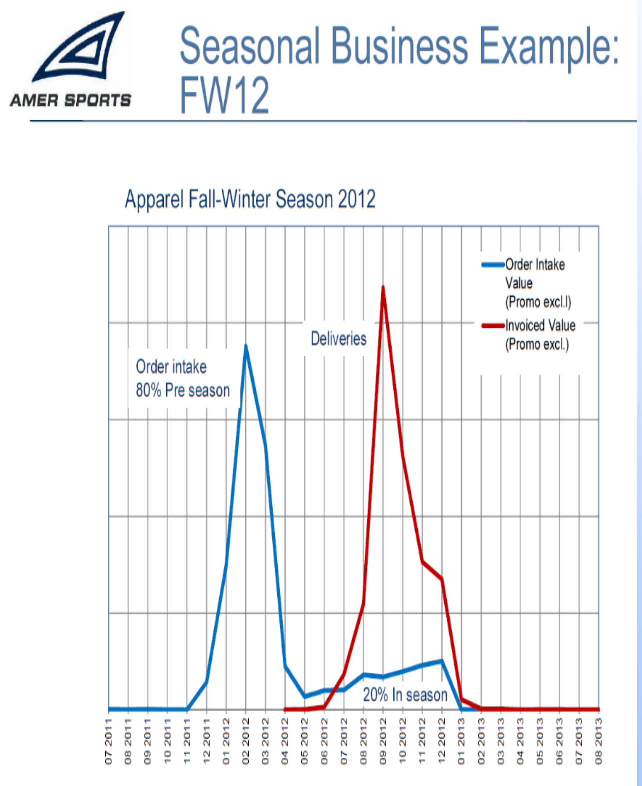
Introduction

For many products, weather represents an important determinant of demand. Especially for products with high seasonality and long lead time in sourcing and delivery, because these latter characteristics make the operations of the company extremely vulnerable from the point of view of financial results. In this project, I consider several seasonal products operations related data and analyze how weather conditions affect demand forecasting accuracy. These products, mainly ski sport goods, are fully seasonal, meaning that all the decisions concerning production volumes have to be made well before, even 8 months, the demand arrives.

Aim: provide a proof of demand accuracy improvement based on generalized additive models (GAM).

To do so, we use real transactional business data of ski sport goods collected from 2005 to 2012, aggregated geographically according to the postal code. These operations and supply chain related transactions data concern two brands, namely Atomic and Salomon which are owned Amer Sports. This data will be matched with another longitudinal data set external to business processes, namely location based weather conditions (temperature, quantity of snow/rain, length of sunshine per day).

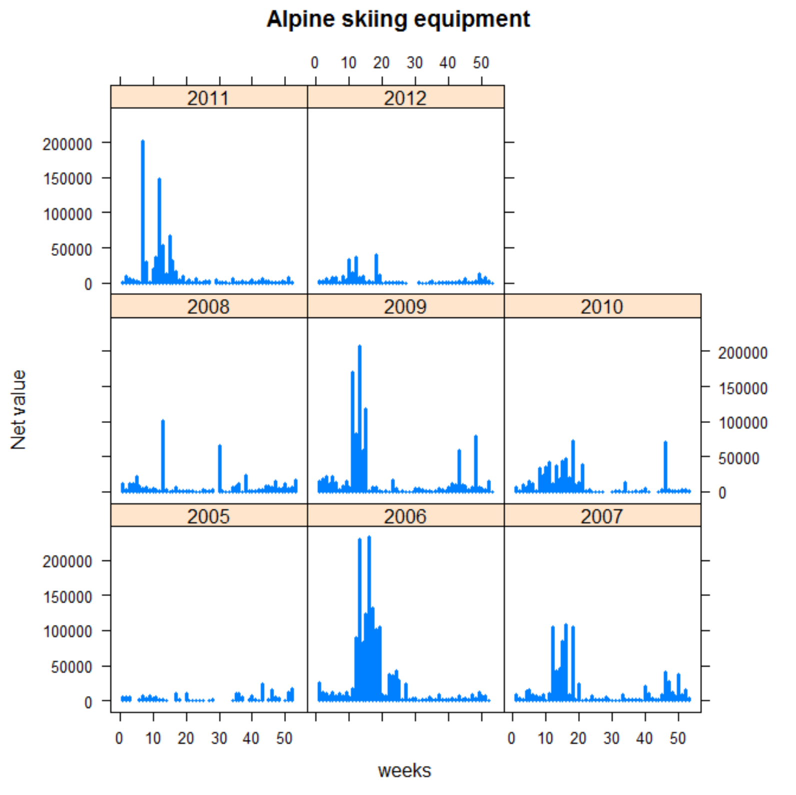
The main purpose is to statistically explain the effects of fluctuations in weather on demand forecasting accuracy. This information can be used, for instance, to integrate the impact of weather variability in the decision making processes, in order to better anticipate demand variability.



Data

- **Operational related data:** the alpine skiing equipment in both brands Salomon and Atomic of Amer Sports.
- **Weather data:**
  - **Snow**: thickness of snow measured at 05:40 am (cm)
  - **Temperature**: temperature at 2 meters above ground, which is the deviations from the daily maximum in relation to the "norm 6190" (norm 1961-1990), (°C).
  - **Fresh snow**: thickness of fresh snow, sum of the day (24 hours), measured at 05:40 am (cm)
  - **Rain**: sum of the day (24 hours), (mm)
  - **Sun**: sunshine duration to daily maximums (%)

Alpine skiing equipment's orders' volume distribution according to years



Methodology: GAM

- **Generalized additive models (GAM)** are used to explain the mean of order net value μ using the set of covariates (operational and weather variables). GAMs are generalized linear models (GLM) in which the response variable (g(μ)) depend linearly on unknown smooth functions of some covariates (Guisan et al., 2002; Hastie and Tibshirani, 1986, 1990).

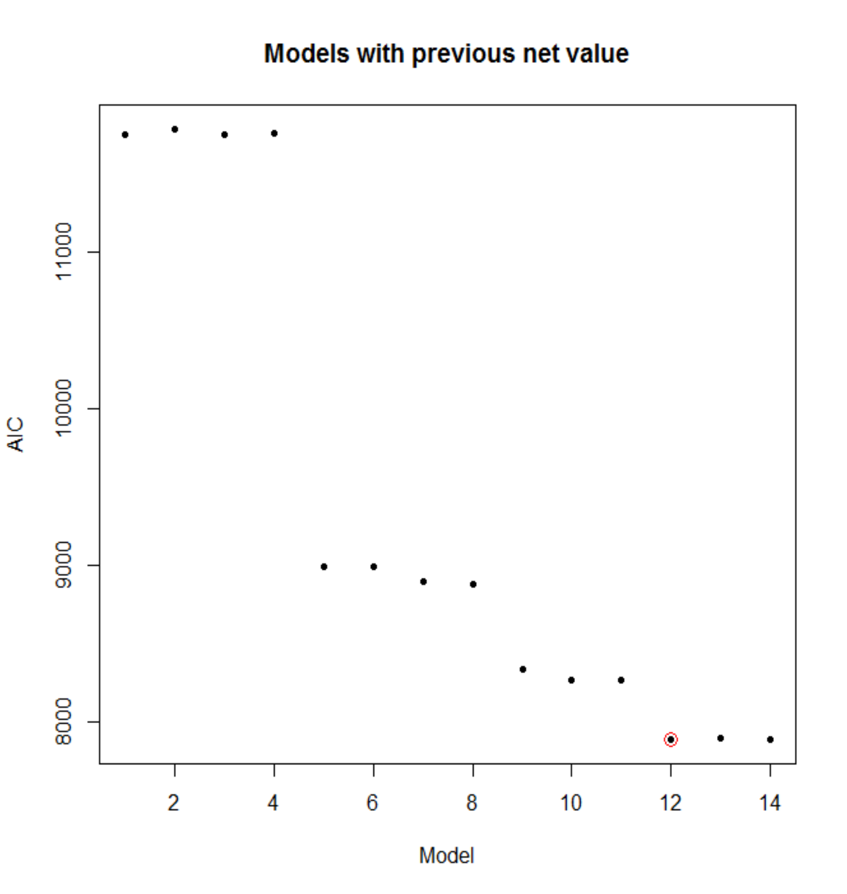
$$g(\mu) = \beta_0 + \beta_{1*} f_1(x_1) + \beta_{2*} f_2(x_2) + \ldots + \beta_{m*} f_m(x_m)$$

Where $\mathbf{x_i}$ are covariates, $\boldsymbol{\beta_i}$ the coefficients, $\mathbf{f_i}$ the smooth functions and g the link function

- Covariates: *previous year's order volume*, *order week, order month*, *location*, and current and previous weather variables, namely, *snow, temperature, fresh snow, rain, sun*.

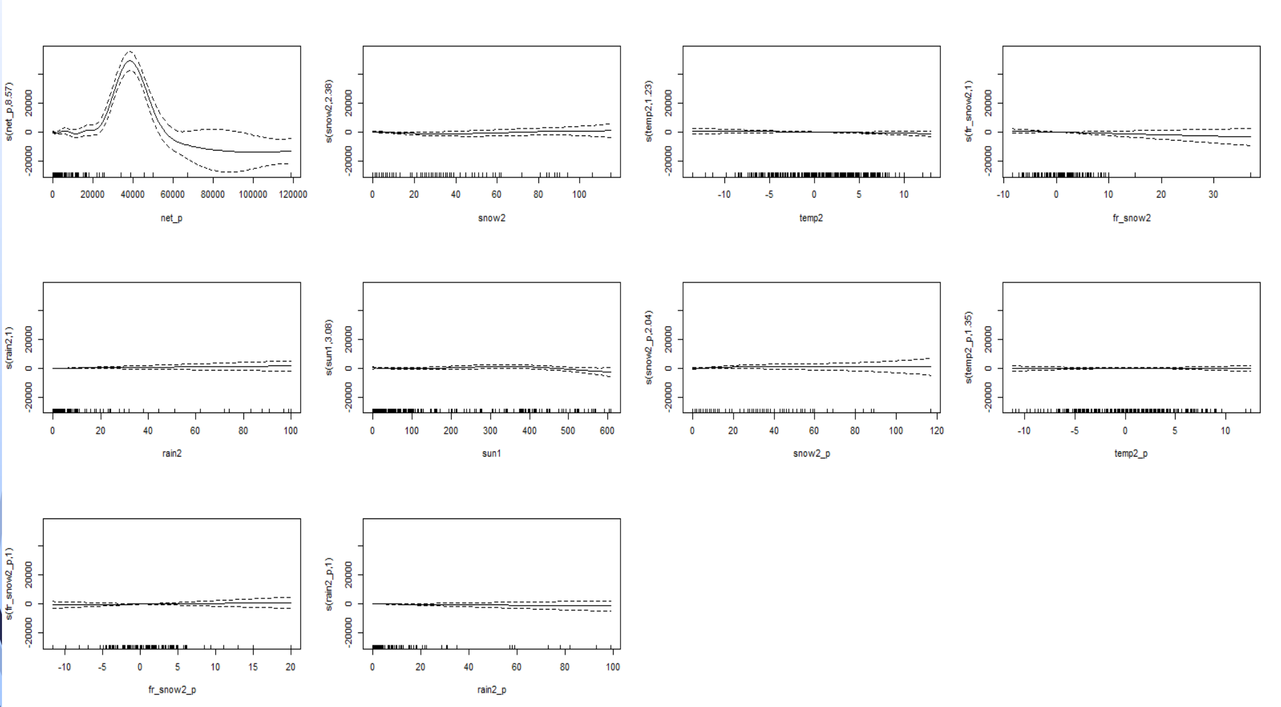
Methodology:GAM

- To find the suitable model, several nested models including different covariates were fitted and compared using the Akaike Information Criterion (AIC, Akaike, 1973; Sakamoto et al. 1988).



Results

- Plots of smooth funtions

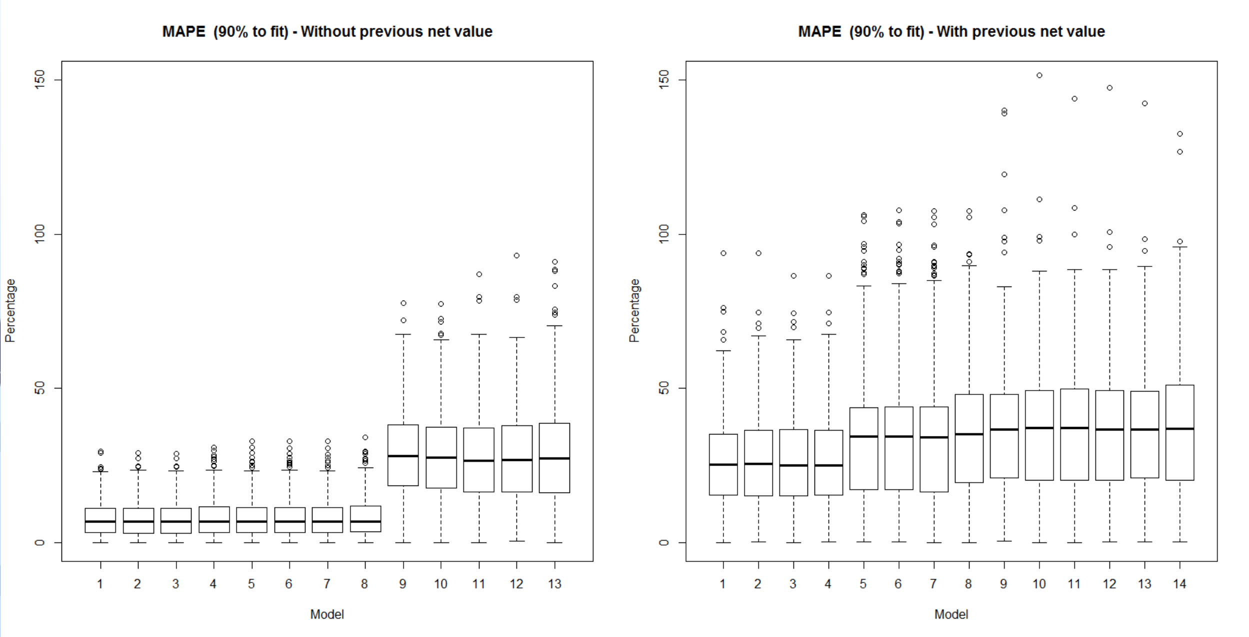


- Table of deviance explained

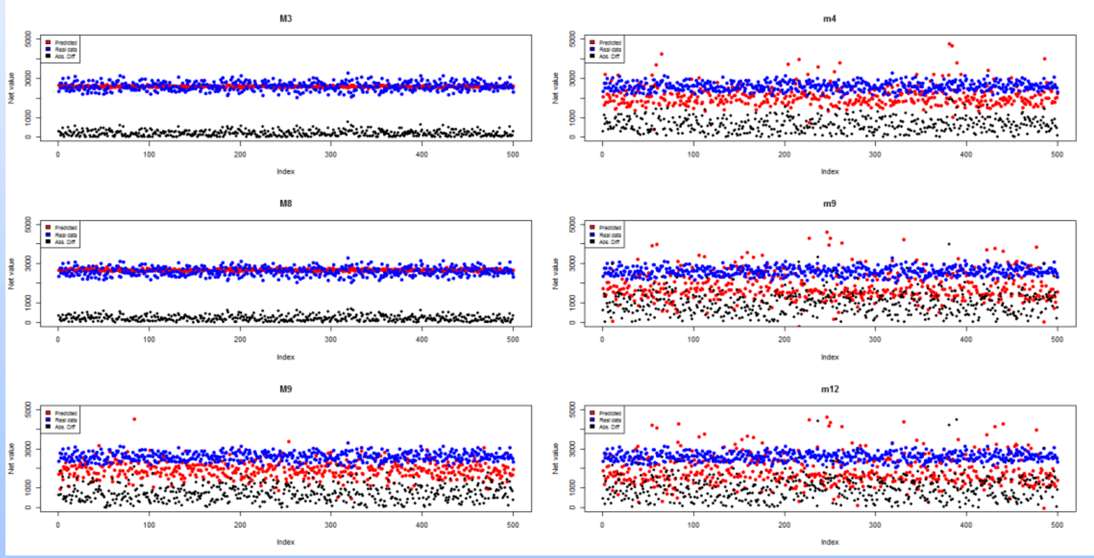
	Amer data	Amer data and previous demand
No Weather data	11%	29%
Current season weather data	13%	61%
Previous and current season weather data	31%	63%

Results

- Mean Absolute percentage errors



- Predictions and absolute errors



Conclusion

- Percentage of deviance explained is significantly improved
- According to the model, the most influent covariates are: previous' year demand, snow and temperature.
- Limitations: Lack of generalization due to the fact that the study concerns Switzerland and leisure goods.
- Further research: work on predictions' variance reduction

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