JADS DD-SCM-Intel 2018

Assignment 4/WU-2 small: Improving ordering decisions by predictive analytics

Vrs. 2018, November 29

Introduction

In computer practical 1 and 3, you have developed a simulation model to evaluate (and optimize) the performance of a base stock policy for a fresh food product at a retail outlet. For details on the assumptions of the inventory systems that we consider, we refer to the related practical instructions. Deviations in assumptions are reported in the text below.

In this assignment you will compare two approaches for ordering:

1. Apply a base stock policy (BSP) where the order-up-to level S is recomputed every day by forecasting the next day(s) demand by a moving average approach using two data points related to the last two weekdays,
2. Apply BSP, as in approach 1, but forecast demand by some machine learning algorithm (your choice) that takes weather information into account.

The performance of the two approaches is defined by the average daily costs, % waste, % shortage over the observation period (excluding warming up), where % waste = total waste/total ordered, and % shortage = total demand not met/total demand (=1-beta).

Simulation model

In previous computer practicals you were supposed to construct a simulation model in Python that mimics the inventory dynamics of a perishable product at a retailer. You are now provided with a Matlab file (see Blackboard) to check, and if needed correct, your Python model. We shortly explain the processes included in the simulation model, and you have to think how to modify for this assignment.

Demand forecasting and forecasting error

After the problem data and some initialization of statistics, the core of the simulation start with setting (non-stationary) order up to level S_t. Initially these were weekday dependent, but these need to be updated every day. The following rule of thumb is used: $S_t = \mu_{R+L}(t) + z\, \sigma_{R+L}(t)$, where $\mu_{R+L}(t)$ is a forecast of the expected demand on day t and t+1, $\sigma_{R+L}(t)$ is the forecast error, and z is a safety factor that defines the safety stock $ss = z\, \sigma_{R+L}(t)$.

Initially, we have assumed the retailer knowns the mean and standard deviation of the (theoretical) demand distribution. In that case $\mu_{R+L}(t)$ and $\sigma_{R+L}(t)$ are set to the (theoretical) mean and standard deviation of the demand on day t and day t+1. As demand is Poisson distributed $\sigma_{R+L}(t) = \sqrt{\mu_{R+L}(t)}$. In practice and in this assignment, the retailer needs to estimate these values. So prior to setting the order quantity, Q_t, he will forecast the demand.

In approach 1, the retailer uses a moving average approach: he looks at the historic demand on the same weekdays in the last two weeks: so on Monday the retailer estimates $\mu_{R+L}(t)$ by the average of the (realized) demand on the last two Mondays ($d(t-7)$ and $d(t-14)$) and Tuesdays:

$$\mu_{R+L}(t) = [\ (d_{t-14}+d_{t-13}) + (d_{t-7}+d_{t-6})\ ]\ /\ 2.$$

During the first 14 days this estimate cannot be computed by a lack of a history of demand realization. Hence the forecast is set differently, e.g. $\mu_{R+L}(1)=0$, and $\mu_{R+L}(t>1)=d(t\text{-}1)$. As these estimates may be poor, we do not like the performance measures to be affected: so we include a warming up period of at least 14 days.

A perfect forecast would precisely predict the real demand $d(t)+d(t+1)$. A perfect forecast has forecast error of 0. Due to demand uncertainty usually the forecast is not perfect and some forecast error $\sigma_{R+L}(t)>0$ applies. The forecast error should be estimated by studying the root of the sum of squared difference between the realized demand and the forecasted value: $\sigma_{\mathrm{R+L}}(t) = \hat{\sigma}_{R+L}(t) = \sqrt{\frac{\sum_{i=1}^{t-2}\left((d_i+d_{i+1})-\hat{\mu}_{R+L}(t)\right)^2}{t-3}}$. Note, in this downsized assignment a *correct evaluation of the forecast error is part of the assignment*, in contrast to the original much bigger assignment.

In approach 2, the retailer uses a data science/machine learning approach that takes as input the historic demand and weather data as well as the weather forecasts for today and tomorrow.

Setting an order quantity

Both approach 1 and 2, assume orders are set by a base stock policy (BSP), hence:

$Q_t = S_t - I_t$, where $S_t = \mu_{\mathrm{R+L}}(t) + z\,\sigma_{\mathrm{R+L}}(t)$, and I_t is the total number of products in stock (summed over the different expiration dates: $I_t = I_{t,1}+\ldots+I_{t,m}$). In this assignment we consider a food product with a fixed shelf life of m=5 days. Initially you may fix the safety factor z to 2. An interesting optional bonus question is to optimize the value of z for each approach.

Demand generation

Initially, demand was randomly drawn from a Poisson distribution. In this assignment, demand $d(t)$ reveals by reading $d(t)$ from a data set. Note: demand reveals after setting the order quantity $Q(t)$, thus $d(t)$ is not known yet and needs to be forecasted.

Demand is met

We assume all consumer take the oldest products from stock and thus that new products are brought from the back room to the shelves immediately when the last product is taken from the shelf. Thus the retailer makes sure that all consumers will take the oldest items from stock, and no shortages will happen as long as products are available in the back room. Let $B(t,r)$ denote the number of products with remaining shelf life r that is taken from the shelf on day t to meet the consumer demand.

Update inventory levels: move to next day

$B(t,r)$ products with remaining shelf life r are taken from the shelf, thus $I(t,r) - B(t,r)$ products leave behind, which are carried over to the next day: $I(t+1,r-1) = I(t,r) - B(t,r)$ (for r>1). At the end of the day $I(t,1) - B(t,1)$ product turn into waste. And at the start of the next day, before opening new fresh products are added to stock: $I(t+1,m) = Q(t)$.

Update statistics/Compute performance measures

% waste = total waste/total ordered, and % shortage = total demand not met/total demand (=1-beta)

Data

Instead of sampling the demand the simulation model reads the demand from a (text) file (see blackboard). Next to demand data we also provide you, for approach 2, with weather data over January 6, 2014 to December 31, 2017. (source: http://projects.knmi.nl/klimatologie/daggegevens/selectie.cgi).

You are supposed to split the data into two sets:

1. training dataset of three years: January 6, 2014 till December 31, 2016,
2. test dataset of the year 2017.

We have kept behind another test dataset (of January 1, 2018 to November 1, 2018), which we may use when grading your solution. The weather data is available for location De Bilt, you may assume the retail store of interest is in that area.

In approach 2, you need to estimate demand using weather forecasts. We assume the weather forecasts are perfect (exact) for the next two days, i.e. the weather forecast for the day t and t+1 is equal to the realized weather available in the file. The weather forecast for the days after tomorrow are not available and are not to be used in this assignment. Your simulation starts on Monday January 6, 2014, with no products in stock, and it should include a warming-up period of 14 days. In when training performance metrics are computed for Monday January 20, 2014 until December 31, 2016). For testing the performance is evaluated over January 15, 2017 until December 31, 2017.

What to hand-in?

Python files/ Jupyter notebooks:

> All models should be self-contained (e.g. executables or Jupyter notebooks), with clear instructions on how to run them, and perform inference based on new data. Furthermore, in case there are pre-processing steps involved, they have to be automatically applied to new data. Keep in mind that pre-processing has to be performed on training data only, and the same parameters have to be applied to test data, so as to avoid information leakage.

Report: Next to handing in the model files, you should hand in a report in WORD/pdf, that includes:

1. Intro to the assignment,
2. Data analysis: what insights do you get from analysing the demand and weather data?
3. Description of the machine learning algorithm for demand forecasting as part of approach 2, including validation results for approach 2 on the data set 2014-2016 (training dataset).
4. Comparison of the performance of the two forecasting approaches by simulation using the data for 2017 (test data): what would be the average weekly costs, % waste and % shortage over 2017 for the two approaches.
5. BONUS = optional (prescriptive analytics):
   include the results for optimizing the value of the safety factor z for each approach
   a. explain how you did the optimization (e.g. choose the best values of z in {1, 1.2,..., 2.8, 3}), by simulation using the training data.
   b. fix the value of z for each approach and compare the average costs level, % waste, and % shortage using the test data of 2017.
6. Appendix: instructions on how to evaluate your pre-trained model using the provided test set and our second test set (with data of 2018). In particular, specify how we should call your model for approach 2 from any other python simulation program.

Assessment criteria:

1. Quality (clear, complete, and concise) of report (including the appendix with instructions).
2. Descripion/explannation of the machine learning model as part of approach 2: it should not read as a Blackbox; if you use a toolbox explain how it is configured and motivate/explain the choices made in choosing the approach as well as in setting the parameter values. Furthermore, all pre-processing steps as well as the training procedure, have to be reported.
3. Performance of the machine learning approaches. We have kept behind another test dataset (of January 1 to November 1, 2018), which we may use when grading your solution. Therefore, avoid using (i.e. overfitting to) the test set that we have provided.
4. Answering the BONUS question on optimizing the safety factor *z* may raise your grade by a maximum of 1 point out of 10.

Due date :
December 10, 2018 by email to Rene.Haijema@wur.nl

Hints:

After modifying the code such that the mean demand is estimated using a moving average approach, you should get (for approach 1) the following performance over 2014-2016 with a safety factor of 2 and a shelf life of 5 days: an average costs in the order of 293 per day, about 21% waste and around 36% and the (long-run) average fill rate around 80% or 92% (depending on the definition used). Your results may differ (hopefully only slightly), due to alternative modelling assumptions.