Demand Forecast for Short Life Cycle Products

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OUTLINE

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THE SHORT LIFE CYCLE PRODUCT

An environment of high competition and constant innovation.

As a consequence: Shorter life cycles

4/7/2014
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SHORT LIFE CYCLE PRODUCTS TIME SERIES

Characteristics

1. Non-linear, non-stationary and transient time series
2. Lack or scarcity of information
3. Short time series

Traditional forecasting methods are inadequate
The effect of the use of cumulative or noncumulative data in forecasting
OVERVIEW

Clustering of time series
Existence of non-bell-shaped patterns of short life cycle products demand
**Research Hypothesis**

- Forecast by using cumulative demand/sales data improve the forecast performance
- Forecasts based on data obtained by means of cluster analysis improve forecast performance
- The use of machine learning models in the forecasting process improve the forecast performance
## Literature Review

<table>
<thead>
<tr>
<th>Diffusion models</th>
<th>Similarity based models</th>
<th>Machine learning models</th>
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<tbody>
<tr>
<td>Tseng &amp; Hu (2009)</td>
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<td>Wu &amp; Aytac (2008), Wu et al., (2009)</td>
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<td>Zhu &amp; Toneman (2004)</td>
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LIMITATIONS OF CURRENT METHODS

Current forecasting methods for SLCPs have limitations in the following aspects

• Inability of forecast along the complete life cycle
• No appropriate model
• Ineffective use of time series of old SLCPs
General objective

Propose a forecasting method based on machine learning models to forecast the demand of short life cycle products.
OBJECTIVES

Specific objectives

• Develop a clustering method for short life cycle products time series to extract relevant information for the forecast process.
• Design the forecasting method for the demand of short life cycle products using machine learning techniques.
• Evaluate the performance of forecast models using appropriate metrics and statistical tests.
We have considered different clustering Algorithms:

- Fuzzy $c$-means
- Fuzzy Short Time series FSTS
- Fuzzy Maximum Likelihood Estimation

Each clustering algorithm starts using the initialization process Kauffman
MACHINE LEARNING: REGRESSION MODELS

Linear pattern

Linear learning machines:
Multiple linear regression (MLR)

Non-linear pattern

Nonlinear learning machines:
Support Vector Regression ($\varepsilon$-SVR)
Artificial Neural Networks (ANN)
THE NEURAL NETWORK MODEL

We consider the feedforward multilayer neural network, with Levenberg-Marquardt with Bayesian regularization training algorithm. The learning rate was set to 0.01 and the number of iterations was set to 300. The parameters to tune are the following:

1. Number of hidden layers
2. Number of neurons per hidden layer
THE SUPPORT VECTOR REGRESSION MODEL

In this work we consider the $\varepsilon$-SVR problem with a Gaussian Kernel.

Minimize:

$$\frac{1}{2} \| w \|^2 + C \sum_{i=1}^{n} (\xi_i + \xi_i^*).$$

Subject to:

$$y_i - w' y_i - w_0 \leq \varepsilon + \xi_i,$$
$$w' y_i + w_0 - y_i \leq \varepsilon + \xi_i^*,$$
$$\xi_i, \xi_i^* \geq 0.$$
TUNING PARAMETERS

Machine learning models such as ε-SVR and ANN requires to tuning some set of parameters.

In this work the tuning process is carried out according to the generalization regression error criterion. Such error is estimated by means of a 5-fold-cross-validation procedure.

The idea is to determine the set of parameters that minimizes the generalization regression error.
RESPONSE SURFACE METHODOLOGY (RSM) FOR TUNING PARAMETERS

We use response surface methodology (RSM) and design of experiments (DOE) for tuning parameters. In this process a selective sample of parameters (experimental design) is obtained and for each element of the sample the validation error is calculated.
Experimental Factors

- **Forecasting method**
  - MLR
  - SVR
  - ANN

- **Clustering usage**
  - Yes
  - No

- **Type of data**
  - Cumulative
  - Non-cumulative

FCM, FMLE, FSTS
THE FORECASTING FRAMEWORK

Collect and analyze data

Cumulative data

Classification process

Clustering procedure

Training learning machines

Non-cumulative data

Evaluate forecasts

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We consider the following dataset of time series

• Demand/sales dataset of text and scholar products (RD1)
• Citation of papers dataset (RD2)
• Patent to patent citations dataset (RD3)
• Synthetic dataset (SD1)
THE DATASETS OF TIME SERIES

RD1

RD2

RD3

SD1

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THE RESULTS

A picture of the forecast of each regression method for selected time series of the datasets.

RD1

SD1

RD2

RD3
The Results

The effect of using cumulative data

Relative increase in error and process time due to the use of cumulative data

The use of cumulative data does not improve the forecast performance.

According to the Kruskal-Wallis test there is enough statistical evidence, with a confidence level of 95% or greater, that the use of cumulative data does not improve the performance of the forecast.
The effect of using clustering algorithms

According to the Kruskal-Wallis test there is not statistical evidence, with a confidence level of 95% or greater, that the use of clustering algorithms improve the forecast performance.
## The Results

Summary evaluation of the hypothesis

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Regression method</th>
<th>Use of cumulative data</th>
<th>Use of clustering</th>
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<tr>
<td>RD1</td>
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In general, nonlinear regression methods improve the forecast performance, but this improvement is not statistically significant in most of the datasets.
THE RESULTS

The relative error per period.

- The error is relatively large at the beginning of the time series.
- The error is less when the sales peak is reached.
- The error tends to increase at the end of the product life cycle.
CONCLUSIONS

• The use of cumulative data does not improve the forecasting performance.

• The use of clustering has no significant effect on the forecast performance.

• Regression methods, MLR, ANN, SVR do not differ significantly in forecasts.

• Given the above results, the most efficient method of forecasting is the MLR.
Questions?
Thanks!