Deep Transfer Learning for Installed Base Life-Cycle Evolution Forecast

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Abstract: In Healthcare industry, companies are reducing their environmental impact by implementing a closed loop supply chain (CLSC) in which products can be de-installed and bought back for reconditioning or parts reuse. In this supply chain, it is necessary to implement the appropriate strategies to ensure a sustainable parts management system knowing that the installed base (IB) evolution and the products design changes are highly impacting factors. Since strategic CLSC decisions are taken early in the part and/or product life-cycles, usually there is not enough data to predict the IB information. Therefore, We build a Deep Transfer learning framework to forecast the products IB evolution from the beginning to the end-of-life (EOL) using data of different generations from the same product family. We provide a use case from a Healthcare company showing the performance of different deep learning models on a long horizon.

1 INTRODUCTION

In Healthcare industry, optimizing spare parts consumption and production is crucial to establish a circular economic strategy and to attain the carbon emissions neutrality by the year 2050 (European-Commission, 2020). Companies are changing their approaches to be more environmental friendly and are working on different levels of their supply chains to reduce their impact. Typically, they employ a closed-loop supply chain (CLSC) in which there is more profit to the company and to the environment.

In a CLSC, a product-service system (PSS) is implemented, which means that products are delivered along with different types of services. Companies design a products' return scheme, provide maintenance service contracts, and have more interactions with the customers to fulfil their needs and reduce their environmental impact during the product use phase (Mont, 2002).

Spare parts consumption is mainly governed by installed base (IB) information like the number of products in use, their location, and their ages. Therefore, predicting the IB information evolution from the beginning of life to the end-of-life (EOL) is necessary for long-term spare parts demand forecasting. Existing methods in the literature focusing on the IB prediction use experts knowledge, statistical methods, Consumer/market research and the handled data is usually from pre-sales or from other products historical sales (Machuca et al., 2014). These methods perform poorly when there is not enough historical data, especially for new products. It is also important to acknowledge that the products sales depend on their types, their use, and in the case of healthcare industry, the location of the customer.

In this paper, we build a model to predict the IB information of Healthcare products during different phases of their life-cycles. We provide a Transfer Deep learning framework trained on data from previous generations of the same product family installed in the same region. We compare four deep learning models namely RNN, LSTM, a combination of RNN and LSTM, and GRU. We show that GRU and RNN are the better performing models on the used data.

2 LITERATURE REVIEW

In this section, we study the IB information forecast methods and the use of machine learning and deep learning models for this aim.

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When predicting the installed base evolution, we assume that it will change over time. It increases during the product's growth phase, reaches a peak during the maturity phase, and decreases during the EOL phase (Van der Auweraer et al., 2019). The forecast model should capture the pattern of the installed base in different life-cycle stages. Hu and Li (2023) employs Bayesian netwrok (BN) to predict products demand. The authors conduct numerical experiments on six data-sets and compare the BN to ARIMA method and PSO algorithm to show that the method provides a good prediction for products demand. Machine learning models were in recent years used to predict the IB sales. These models can detect the correlation between the IB information and the non-linear trends in consumption. In this vein, (Bandara et al., 2019) exploits the non-linear patterns of product sales in an e-commerce using a Long-Short-Term model to generate sales forecast. (Salinas et al., 2020) proposes DeepAR, a model based on an auto-regressive recurrent neural network model to calculate time series future probability distribution. Smyl (2020) proposes a hybrid method that exploits exponential smoothing and neural networks for time series forecasting. However, these models do not address the issue of missing data for new products.

A similar domain to the products IB evolution prediction with the lack of historical data, is new products sales forecast. This is a complex problem since the predictions can be very far from the reality. In practice, decision makers use previous products information on which they base their strategic moves. For new products that are very different from the past ones, the risk of great error is particularly high (Thomas et al., 2007). This is a subject that has been widely addressed in the literature. In this case, usually there is not enough data to provide prediction and forecasters have either very little historical information or none. Therefore, they need to rely on other types of information. Four types of prediction models can be implemented to forecast new products sales namely judgmental forecast using experts knowledge, Consumer/market research, cause/effect models, time-series and explanatory models, and Artificial intelligence (Machuca et al., 2014). (Ching-Chin et al., 2010) designed a procedure called NFSP for this purpose using similar product sales, pre-sales data and/or product classification information. The authors suggest employing the best model among classic forecast methods like Moving Average (MA) and Exponential Smoothing, and Heuristic methods like Sales Index (SI), Taylor Series (TS), and Diffusion Model (DF). Baardman et al. (2017) Proposes a model for clustering other products and fitting linear regression with LASSO regularization to these clusters simultaneously to predict new products in the same cluster. Other regression analysis techniques like Nonlinear regression and Logistic regression are also used (Thomas et al., 2007). The use of machine learning methods in this research area is limited as machine learning models require a big set of data to be accurate. To deal with the lack of historical data problem, (Karb et al., 2020) used a Transfer learning approach from similar products in the food industry using a neural network.

A variety of studies have addressed the problem of new product sales. These works use pre-sales data, market research, or other product history. In the context of our research, there is numerous products for which the IB can be very different depending on their type or family and on their location. Therefore, we propose an approach based on Transfer learning to predict the IB information during a product life-cycle. We start by a classification of the products according to their family or usage and their location. Our contribution to the literature is in the use of transfer learning to study the patterns of previous product generations and to provide a long horizon forecast for different IB information of the targeted product in Healthcare industry. We evaluate different deep learning models and discuss their performance on a use case from GEHealthCare.

3 PROPOSED APPROACH

In this section, we present a novel forecasting approach to predict the products IB information. Firstly, we provide an overview of the method and then we show more details of its composing elements. We start by collecting data and creating features that describe the IB. We use Transfer learning with four deep learning models namely Long-Short-Term Memory (LSTM), simple Recurrent Neural Networks (RNN), Gated Recurrent Unists (GRU), a combination of RNN and LSTM. Then, we compare between these models on a use case from GEHealthCare.

3.1 Data Collection and Features Engineering

We collect data of products IB from the same family and the same region. This first classification of products is important since the products installation, the customers needs, the regulations, and the collected data are different from one region to another and from one product family to another. The purpose is to study the historical IB patterns for the past generations of a

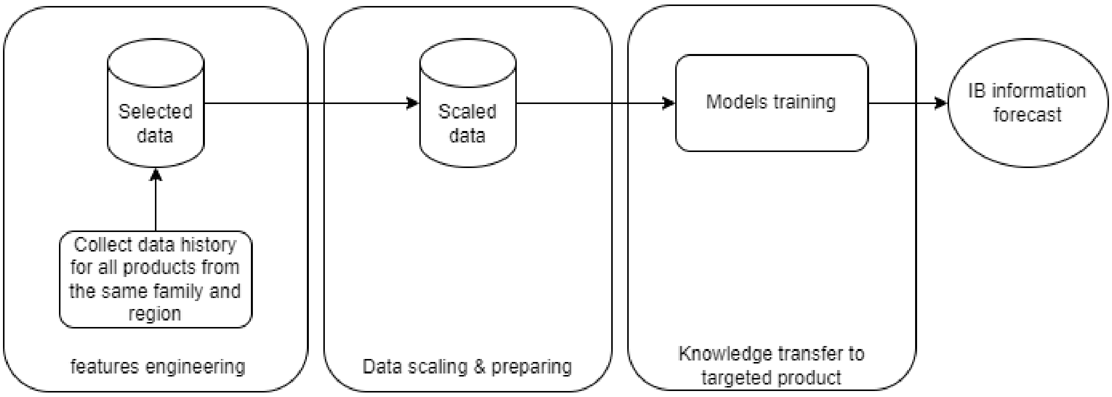

Figure 1: Deep Transfer learning Framework.

product family or type to predict the IB evolution for the newest generation. The collected data contains snapshots of the IB status updated each week starting from the first installed product of the oldest generation up until the latest one. We use it to create features that can help us model the IB evolution over the years. The created features are the IB count, the average IB age, and the new installations count.

3.2 Deep Transfer Learning Framework

We build a Deep Transfer learning framework to predict the selected IB information. The framework is illustrated in Figure 1. The first step is Features engineering where we collect historical data for all products. Then, a classification is applied based on the product family and the region where these products are installed. The second step is Data scaling and preparing. In this step, we clean the selected data by removing noise, standardizing data, and imputing the missing values using the Multivariate Imputation by Chained Equations (MICE) algorithm. In the following step, we build a time-series Transfer Deep learning model for each feature. We train the models on data for all products from the same family and region as the targeted product. Then, we transfer the learnt knowledge to predict the features evolution on the targeted product from the beginning to the end of its life-cycle.

4 GE HealthCare USE CASE

In this section, we show results from numerical experiments on a product in GE HealthCare. We have chosen to work with a family of products that had multiple changes in products generations over the years. In Figure 2, we show the IB count, the new installations count, and the de-installations count of the studied products. We observe that the IB count for each of them is impacted by the installations at the beginning of its life and the de-installation at the EOL. In this industry, it becomes more complex to predict the IB information at the EOL since de-installed products can be re-injected into the IB in a different region and at a different customer.

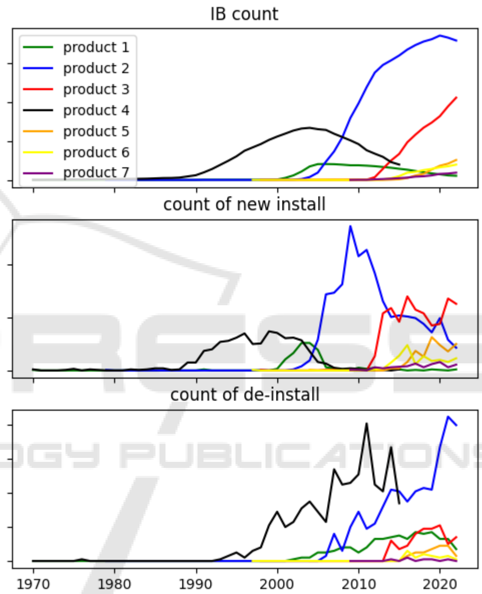

Figure 2: Products IB evoluion.

4.1 Features Engineering

The data we collect is a collection of IB status screenshots updated on a weekly basis from each product generation's beginning of life. Therefore, we need to build informative features of the IB namely the IB count, IB average age, and the Count of new products install. Every product generation has its own life-cycle evolution characteristics namely the maximum count of products, the life-cycle period, the growth and the decline speed, and the maturity period length. The IB count is a result of the new installs of products and products de-installs. However, we need to consider the fact that some de-installed products will also be installed later as a refurbished product. That will make the product life longer and can have an impact on our predictions.

4.2 Results and Discussion

The training data is consisted of information of six other product generations. The models evaluation is conducted one of the newest generations. The product life-cycle is in the growth phase. Looking at its growth compared to the other generations in Figure 2, it has the highest installation speed and count.

We test the proposed framework using four deep learning models namely RNN, LSTM, GRU, and a combination of RNN and LSTM. We use the root mean squared error and the mean absolute error as evaluation metrics. We provide the results in Table 1. Using the RMSE, we see that RNN outperforms the other models for the IB count prediction, while GRU has the best results for the IB average age and the new installations count prediction. Meanwhile, using the MAE, the RNN outperforms the tested models when predicting the new installations.

Table 1: Models results for the IB information forecast.

Model	RMSE			MAE		
Information	IB count	IB Avg age	New install	IB count	IB Avg age	New install
LSTM	113.5	1.8	29.4	89.65	1.44	19.16
RNN	79.45	1.88	27.2	42.18	1.45	13.89
RNN-LSTM	97.9	1.8	27.3	66.5	1.42	16.11
GRU	94.5	1.7	25.88	58.5	1.33	15.42

The model evaluation is conducted on an out of sample data-set. We observe a very close shape to the actual evolution of the IB features. The model is able to predict the growth as well as the decrease in the average age and the number of new installations.

Figures 3 to 5 illustrate the features evolution prediction vs their actual evolution with yearly steps. The models testing is applied on 'product 2'. We observe a close prediction to the actual values. Using this approach, we are able to predict not only the growth, but also the peak and the decline of an installed base information.

5 CONCLUSION & PERSPECTIVE

In this paper, we provided a framework for installed base information prediction on a long horizon in

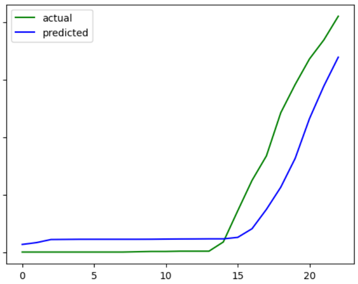

Figure 3: Products IB count prediction.

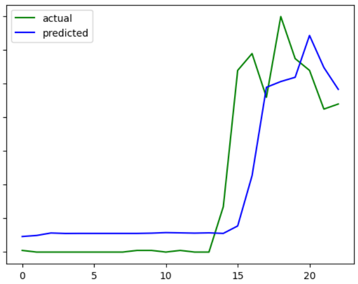

Figure 4: Products IB new install prediction.

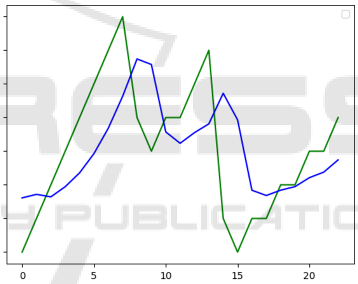

Figure 5: Products IB average age prediction.

Healthcare industry using products classification information. We employed and compared between deep learning models like RNN, LSTM, a combination of both, and GRU to learn the patterns of previous generations from the same product type in the same region. We showed that RNN outperforms the other models for the IB count prediction. We also concluded that, in our use case, the GRU model outperforms the others on the IB average age prediction. This prediction can be used to provide recommendations for decision makers in the Healthcare industry. It can also be used in other industries where the IB is highly impacted by the products families' significant differences and the location of the customers. This work can be improved by using other machine learning models and more data.

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