EFFECTIVE DEMAND FORECASTING IN INTERNATIONAL FLOWS DATA PHARMACEUTICAL GOODS USING AI: A CASE STUDY

Noureddine Mohtaram, Jérôme Verny, Elsa Corbin, Ghoul, D., Eric Lambourdière, Jérémy Patrix

18-20 mai 2022 - Clermont-Ferrand 14èmes Rencontres de l'AIRL-SCM

LA LOGISTIQUE ET LE SUPPLY CHAIN MANAGEMENT A LA CROISEE DES CHEMINS

EFFECTIVE DEMAND FORECASTING IN INTERNATIONAL FLOWS DATA PHARMACEUTICAL GOODS USING AI: A CASE STUDY

Noureddine Mohtaram, HighLab, Highsys, Paris, mohtaram.noureddine@gmail.com

Jérôme Verny, MOBIS, Neoma BS, Rouen, jerome.verny@neoma-bs.fr

Elsa Corbin, Université des Antilles (Pôle Martinique), elsa.corbin@univ-antilles.fr

Eric Lambourdiere, MIS, Université de Picardie, eric.lambourdiere@univ-antilles.fr

Jérémy Patrix, Opal Research, Rouen, jeremy.patrix@gmail.com

Abstract. Pharmaceutical products are subject to a high degree of demand variation in the industrial market. We have seen that the global spread of the COVID-19 pandemic has had a devastating impact on such supply chains. In this paper, we describe the integrated procedure for market demand forecasting and purchase order generation in the pharmaceutical demands on a national level. Thereafter, we process and analyze data on international flows of labeled pharmaceutical goods to extract knowledge and forecast. We undertake cross-national analysis to forecast demand for over 240 countries around the world. In this study, we rely on an OEC data source "The Observatory of Economic Complexity" to visualize, understand and interact with the historic international trade data. The objective of this paper is to predict future demands from the quantity of previous features by considering the effects of external factors by employing several existing machine learning approaches applied on pharmaceutical import/export data. Forecasting scenarios for demand calculations such as LSTM, CNN, multiple linear regressions and other models are tested. The given application illustrates the effectiveness of these approaches. Their performance measures in both cross validation and overfitting learning modes are studied experimentally, and their practical implications are discussed.

Keywords: demand forecasting, cross-country, pharmaceutical industry, deep learning.

1. INTRODUCTION

The global pharmaceutical market reached 1.2 trillion during 2018, an increase of 100 billion compared to 2017, and the US alone holds over 45% of the global pharmaceutical market. In this study we want to predict the top10 pharmaceutical countries - it is necessary to ensure the efficiency of the supply chain: governments and the pharmaceutical industry pay a lot of attention to demand forecasting methods (Kiely (2004), Merkuryeva, Valberga and Smirnov (2019)). Jain (2003), based on a survey of the pharmaceutical industry, the most popular forecasting models such as basic exponential smoothing, moving averages and regression were listed. Weller and Crone (2012) conducted a survey of 200 companies and confirmed that univariate statistical methods have retained their dominant position in the pharmaceutical and other industries. Chase (2016) summarized that while companies can use a variety of software to aid demand forecasting, moving average, basic exponential smoothing and simple regression models remain the most popular forecasting methods. Other work on supply chain efficiency relies on Blockchain technology. Guangyuan, Zhe, Wenjun and Baykal-Gursoy (2021), Paul, Chowdhury, Moktadir and Lau (2021) identify and analyze the supply chain recovery challenges related to the COVID-19 pandemic in the textile and clothing industry, to help practitioners formulate strategies and reimagine value chains in the wake of the pandemic. In Tirivangani, Alpo, Kibuule, Gaeseb and Adenuga (2021) attempted to document the salient points that can help pharmaceutical and government institutions deal with the disruption of the pharmaceutical supply chain during future pandemics.

The pharmaceutical industry is known to be one of the strongest R&D industries researching how the supply chain technology can provide high margins on sales of original products by reducing all the costs. Therefore, a significant increase in the number of generic companies focusing on the development of effective, efficient and low-cost supply chains is forcing the pharmaceutical industry to turn to the challenges of forecasting future demand, confirming the importance of supply chain efficiency for the future development of the industry.

In this work, we will focus on the pharmaceutical industry because many pharmaceutical companies are integrating artificial intelligence after data analytics to support drug and advanced logistics development. There is a lot of AI technology involved in the supply chain department (from production to delivery). However, as you have already guessed, we will focus on AI models and the different uses that come by applying these on international pharmaceutical flows data.

2. DATA COLLECTION AND PRE-PROCESSING

The OEC[1] (Observatory of Economic Complexity) is our data collection source for visualizing, understanding and interacting with the historical data of international trade. Collaborating with almost all states, the OEC is therefore considered appropriate for exploring the latest trade data (at least one year behind real time). For years, the database has been collected, filtered and preprocessed by our own tools to summarize the historical information since 1998 (to keep the statistical links in the evolution of product category names).

As example, the Figure 1 is a screenshot of a dynamic data visualization (video). Using a processing on our collected data, this dynamic graph "bar chart race" shows the evolution year by year ranking the 10 countries that France imports the most pharmaceutical products.

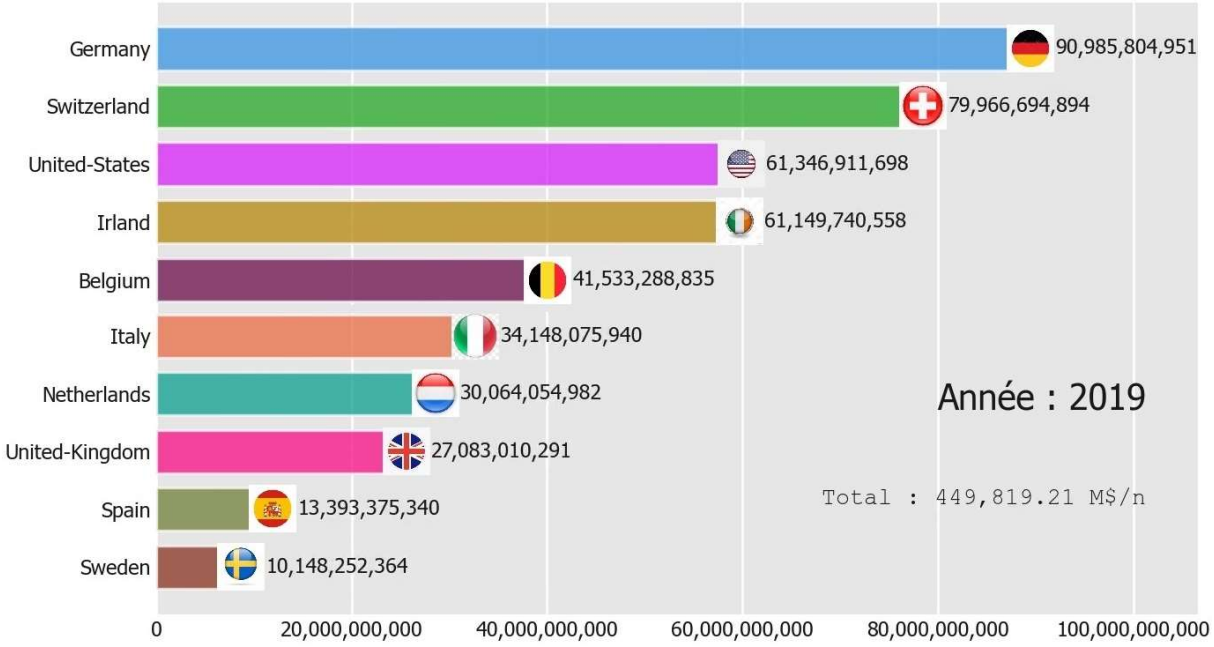


Figure 1: Evolution of pharmaceutical products imports in France: Top 10-countries. These values displayed are dynamic in our video, not the real total values. For example, in 2018, this top 10 represents 19 billion euros or 92% of the total.

For many years among media, many experts have been circulating the information:

- "*80% of the raw materials for the active components of a medicine come from China or Asia*" as PolePharma (Europe's leading pharmaceutical cluster) warned again on social media in early 2020,

[1] https://oec.world/

- "*Active substances in the required quantity and quality are now 80% produced in India, China and South-East Asian countries*" according to the National Pharmaceutical Association in 2018,
- "*80% of the active ingredients that have fallen into the public domain are produced outside Europe, compared to 20% 30 years ago*" more recently by economists,
- "*India and China, which in 2012 accounted for between 60% and 80% of the active ingredients produced in the world by volume (less than 20% 20 years ago)*" by the Academy of Medicine,
- "*80% of the active pharmaceutical substances used in Europe were manufactured outside the European Economic Area in 2012*" by the EMA (European Medicines Agency), adding the IGAS figure that China had 5,000 active substance manufacturers. This concentrated 40-50% of the production of synthetic intermediates used in the production of active substances used in the composition of generics on the European market.

Whatever the media, the first source that calculated this statistic seems never to be cited (including the one from 2012 above). Yet every time France has a drug shortage, we have none of these experts reminding us that China and India are not in the top 10 countries that France imports (such as demonstrated in the Figure 1), while the shortage maybe produced / amplified by companies of intermediary countries that puts imported stocks for its own nation first (sometimes legally obliged) or for economic interests (to the highest bidder), such as we heard in news reports in the early months of the COVID-19 epidemic (such as the misappropriation of imported orders on airport tarmacs).

year	origin	Territoire d'origine	dest	Territoire de destination	Dist_VO (km)	hs92	Nom du produit	export_val	import_val
1995	afg	Afghanistan	chn	Chine	4110	3003	Unpackaged Medicaments	0.0	148895.0
1995	afg	Afghanistan	blx	Belgique-Luxembourg	5362	3004	Packaged Medicaments	0.0	31082.0
1995	afg	Afghanistan	che	Suisse	5120	3004	Packaged Medicaments	0.0	155005.0
1995	afg	Afghanistan	chn	Chine	4110	3004	Packaged Medicaments	0.0	1538216.0
1995	afg	Afghanistan	deu	Allemagne	4938	3004	Packaged Medicaments	0.0	115000.0

year	origin	dest	Dist_VO (km)	hs92	hs92_product_name	export_val	import_val
1995	fra	and	2628	3001	Glands and Other Organs	1203.00	0.00
1995	fra	arg	10801	3001	Glands and Other Organs	135647.80	2114378.90
1995	fra	aus	15793	3001	Glands and Other Organs	357434.56	129999.00
1995	fra	aut	3110	3001	Glands and Other Organs	973082.86	0.00
1995	fra	blx	2550	3001	Glands and Other Organs	7153759.72	1607207.89

```
df['hs92_product_name'].value_counts()
Packaged Medicaments       4388
Human or Animal Blood      4304
Special Pharmaceuticals    3578
Bandages                   3131
Unpackaged Medicaments     2923
Glands and Other Organs    1694
```

Figure 2: Three examples of tables. From 1995 to 2019, (1) we processed the first table of all collected data (one row foreach origin, destination, HS92 product category names, amount of export and import values) (2) to merge in the second table the rows of imports values about 20,018 categorized imports of France, and (3) to summarize

its element number per category. (3) In the third table, we summarized them for each year and states in order to obtain the top 10 states from which France imports the most pharmaceutical products by value ($) such as seen in the "bar chart race" of the Figure 1: Germany, Switzerland, USA, Ireland, Belgium, Italy, Netherlands, UK, Spain and Sweden.

Among the data (such as in the tables), the attribute of each territory is coded in the ISO 3166-1 alpha-3standardaccording to the COMTRADE[2] structure, which is important to know since the values (in $) of imports and exports also include often the values of their island territories / insular states. For example: data from *Guadeloupe* (glp), *Martinique* (mtq), *French Guiana* (guf), *Reunion* (reu) and *Mayotte* (myt) are aggregated in the data for *France* (fra); *Puerto Rico* (pir) and *US Virgin Islands* (vir) into *United States* (usa); *Faroe Islands* (fro) into *Denmark* (dnk); *Channel Islands* (ggy and jey) and *Isle of Man* (imn) into *United Kingdom* (gbr); *Svalbard and Jan Mayen* (sjm) into *Norway* (nor); *Taiwan* (twn) into *China* (chn); etc. From 1995 to 2019, few data are missing for: *Botswana* (bwa), *Lesotho* (Iso), *Namibia* (nam), *Eswatini* (ex-*Swaziland*) (swn), *Liechtenstein* (lie) and *Monaco* (mco). But this does not affect the results of this study.

Such as in the tables, the *Harmonized System* from 1992 (HS92) classification code has a detailed and hierarchical nomenclature: 2 digits for chapter, 4 digits for category, 6 digits for subcategory, and 8 digits for legal level (rarely available) and 10 digits for statistical level (rarely available). We have collected three datasets of HS92 according to 2,4 and 6 digits: the more digits, the more refined the classifications (e.g., several 6-digit subcategories are included in one 4-digit category, and included in one 2-digit chapter).

A total of 944,346 rows partitioned into ten classes (labeled "medical products, territory of origin and territory of destination") were collected over the reference period, from 1998 to 2019, among five HS92 categories: (3001) *glands and other organs*, (3003) *unpackaged medicaments*, (3004) *packaged medicaments*, () *special pharmaceuticals*, () *bandages*, and () *human or animal blood*. Their quantity was large enough that we could not collect them manually: by using an *API*, we developed a *Python*-based web crawler to automatically download the data given in *JSON* format and to store it in *CSV* files. These contents were analyzed, the classes and other information were stored in a database that we built using *Mathematica* and processed with *Python* scripts.

Rather than polemicize, this study is part of a larger analysis project whose objective in this paper is to study forecast models to predict 2020 more accurately and compare the performance

[2] http://comtrade.un.org/ normalized by the *BACI International Trade Database*

of each model when machine / deep learning is done on such data from 1998 to 2019. After this study, we will compare our 2020 forecasted results with the2020 real data that we will collect once they come online in 2022. They have been available since the end of 2021, but the more 240 states that provided them (or the OEC) has not yet had time to translate the imported / exported values into the common currency (dollars) of this open data.

3. PHARMACY SUPPLY CHAIN

This study examines the international pharmaceutical supply chain over the last twenty years and focuses on the import French market.

This industrial market is dedicating huge investments in creating an environment where import-export of pharmaceutical products can flow without barriers. The pharmaceutical supply chain consists of three key players: suppliers, distributors and customers, as illustrated in Figure 1. Pharmacies and complex organizations, whose services include pharmacy, laboratory, surgery, dietetics, administration and others, are the main suppliers of drugs and other health-related products. Distributors deliver finished products to retailers, hospitals or pharmacies.

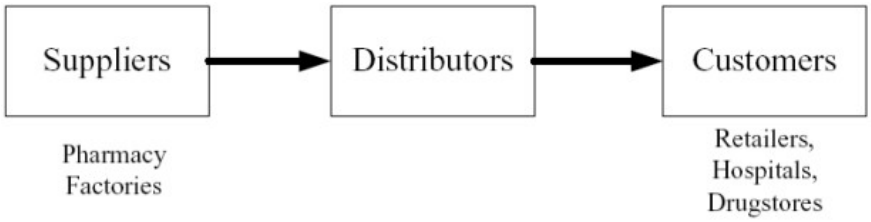


Figure 3: Supply chain of the pharmaceutical industry

The pharmaceutical service represents a significant portion of hospital operating expenses. Several researchers have pointed out that inventory costs in the health sector are substantial and are estimated to be between 15% and 20% of total revenues Kelle, Woosley and Schneider (2012). Any measure to control spending in this area, including the entire supply chain, particularly the logistics of these components, can have a significant impact on the overall efficiency of the organization.

4. APPLICATION CONTEXTE OF AI IN PHARMACEUTICAL INDUSTRY

The main reasons supply chain managers invest in AI technology is to improve their optimization process, which leads to increased profits and margins. If we look at AI success

stories in the supply chain space, we will find examples of direct or indirect cost reductions. Take the case of the e-commerce sector: they invest heavily in fully automated distribution centers to increase their shipping capacity, using AI such as applied computer vision, real-time object detection, … combined to their data warehouse. Indeed, shipping capacity is directly related to the profits that such a company can make.

With forecasting can be done by known algorithms, organizations are trying to be automated and improved through machine learning models, which allows companies to include external factors in their demand planning. By leveraging such accurate data, they are now able to improve their raw material sourcing, manage suppliers and optimize delivery according to forecasts.

When a new disease is spreading, they can have better anticipation by starting the R&D process to find its cure, leading to potential new benefits as explained previously. Technically speaking, it will essentially be algorithms that will analyze a massive amount of data from various sources (government, media, social media, etc.) combined with machine learning scripts to decipher events and provide a reasonable output.

Batch Analysis: one of the mains challenges for the pharmaceuticals industry is to maintain at 0 default the production quality. Knowing that there can be up to 27 intermediaries between a supplier of an active substance and a pharmacist, each step is protected with a transfer of responsibility: each supplier delegates responsibility for the product to the customer (hence the difficulty of courts to condemn when all the legal steps and audits have been respected while a pharmaceutical product has generated health problems). Thus, private audits (between supplier and client) and public audits (authorities) are carried out to refuse an order which does not respect the quality specifications (which has generally been paid 30% on order and will await receipt of a delivery to pay the 70%). When this happens, the least careful production companies will sometimes find another buyer rather than try to recycle it: this is how it encourages online fraud of counterfeit medicines (as well as when the producer loses his contract when his factory is already ready to continue production). To accelerate these audit processes, companies create AI to analyze each batch allowing production and quality to increase their efficiency and reduce defect through data analysis.

The pharmaceutical supply chain is facing one of its most critical tests as a result of the current COVID-19 pandemic, and many companies are struggling. We all have been and still concerned by the recent COVID-19 pandemic. However, with one specificity for the pharmaceuticals industries: they simply can’t stop producing, shipping and distribute their products. In a sanitary crisis like this, they become or reinforce they position as an ally of the government.

In the following part, we will determine how the AI has the potential to fill the technology chasm for this industry but also what challenges the companies will be facing in investing in it. We will also determine if the COVID 19 can act as a catalyst or obstacles for the upcoming industry revolution. We have seen through our interviews and research that the pharmaceuticals companies tend to have a certain delay in their technology maturity for their supply chain or other non-core business activities. The main reason is that the core business of a pharmaceuticals company is to research, develop, create and sell new drugs. In this area, they have invested a lot, for example during the covid-19 crisis, some companies were running AI software to help determine the right genomes and run test faster on prototypes allowing them to get faster to the right drugs.

5. MACHINE LEARNING APPLICATION IN THE PHARMACEUTICAL INDUSTRY

5.1 Long-range Forecasting methods

Achieving an accurate long-range forecast is a challenge many companies face due to the uncertainty in anticipating demand several years out. Since companies make strategic decisions based on these forecasts – such as long-term investments and supply and capacity planning – it is critical that the long-range forecast be as accurate as possible. While traditional statistical methods have been extensively used in demand forecasting, due to technological developments, machine learning has shown improvements in forecasting, especially in short-term forecasting. Could deep learning be applied to improve long-range forecasting?

We developed forecasts by comparing four (machine and deep) learning algorithms: RF (random forest), ANN (artificial neural network), LR (linear regression), and SVM (support vector machine). However, we needed to determine which features are critical for predicting long-term demand for certain drugs. In addition, we expect the performance of the machine learning models to differ significantly depending on the availability of data, the forecasting horizon, and the individual product.

Data management is the biggest challenge in order to apply machine learning approaches to forecasting. Since these approaches for long-term forecasting have not shown conclusive historical results (based on the state of the art) and since the creation of a data management program requires a significant initial investment, then a detailed cost-benefit analysis and an

internal discussion between developers, data scientists and their managers are highly recommended before attempting to develop such applications (and their required databases).

Learning types	Data processing tasks	Distinction norm	Learning algorithm
Supervised learning	Classification / Regression / Estimation	Computational classifiers Statistical classifiers	Support Vector Machine Naïve Bayes Hidden Markov model Bayesian networks Neural networks
Unsupervised learning	Clustering / Prediction	Parametric Non-parametric	K-means Gaussian mixture model Dirichlet process mixture model
Deep learning	Classification / Prediction	Model-based	Convolutional Neural Network Recurrent Neural Network Long Short-Term Memory

Table 1: Comparison of machine and deep learning methods

It is difficult to achieve a high degree of accuracy in forecasting because forecasts are made under the assumption that current trends in the forecast model will continue into the future, but it is quite possible that these trends will change due to many unexpected events over a long period of time, such as the Covid-19 pandemic.

5.2 Time series and regression methods

Different regression models on time series are often used Mangai, Kasinathan, Alagarsamy and Sankar (2014) such as moving average, exponential smoothing, Holt-Winters and ARIMA methods. In time series forecasting models, the classical approach is to collect historical data, to analyze the underlying characteristics of the data, and to use the model to predict the forecast future Mangai et al. (2014). The above table summarizes the definitions and parameters of the machine learning approaches that are used in the field of time series demand forecasting.

5.3 Deep Learning

DL is an evolved approach of machine learning that can analyze the features, correlation, and complex interactions between features of a problem from samples of a dataset and learn a model, which in our case can be used for demand forecasting. The machine learning applies

deep neural network architectures to resolve various complex problems. Deep learning has become a very popular research topic among researchers and has yielded impressive results in image processing, computer vision, natural language processing, bioinformatics, and many other fields.

In general, DL is an implementation of artificial neural networks. Although, more the deep neural network is sophisticated and more it is can analyze and compose more complex features and interactions than a traditional neural network. But this requires higher computing power and large amounts of data for training. However, with the recent improvements in GPUs (graphical processing units) and parallel architectures have made it possible to achieve deep neural networks. DL uses successive layers of neurons, where each layer extracts more complex and abstract features from the output of previous layers. Thus, a DL can automatically perform feature extraction without any preprocessing steps such as in the aeras of visual object recognition, speech recognition and genomics.

5.4 Artificial neural network

ANN is a technology used for classification, prediction, clustering, and pattern alerting Haykin and Network (2004). The power to learn from examples is probably the most important property of neural networks in applications, and can be used to train a neural network with the memory of the past responses of a complex system Wei, Zhang and Li (1997). To develop a functional model of the neuron, there are three basic components. First, its synapses are modeled as weights, where each value represents the strength of the connection between an input and a neuron. Negative weight values reflect prohibitive connections, while positive values denote excited connections. Secondly, two components model the actual activity within the neuron cell. An adder adds up all the inputs modified by their respective weights. This activity is called linear combination. Finally, an activation function controls the amplitude of the neuron's output. An acceptable range of output is usually between 0.0 and 1.0, or from -1.0 to 1.0 Jang (1993).

After being trained correctly, ANNs are the most used technique to model the relationship between inputs and outputs of a process (Mok and Kwong (2002); Erkollar, Goztepe and Sahin (2013)). Engineers are using ANNs as signal processing technologies. The general and mathematical structure of this process is illustrated in the following figure. The interval activity

of the neuron can be defined as follows: $v_k = \sum_{j=1}^{p} w_{kj} x_j$. The output of the neuron, y_k, would therefore be outcome of some activation function on the value of v_k.

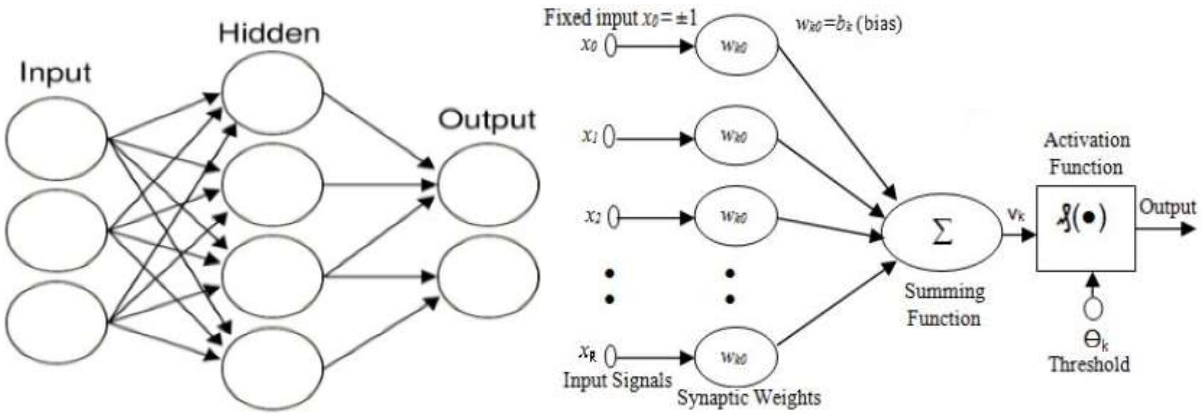


Figure 4: General structure (at the right) and mathematical structure (at the right) of an ANN.

5.5 Support Vector Machine – Regression (SVR)

SVM is a popular classification technique based on a supervised learning model introduced by Vladimir Vapnik. Its background work depends on the early studies of Vapnik and Alexei Chervonenk is on statistical learning theory. While the learning time of the fastest SVMs can be quite slow, their main properties are their high accuracy and their ability to model complex and nonlinear decision boundaries is very strong. They are much less prone to overloading than other methods. Support vectors can also provide a very compact description of the model learned model.

We use the SVR algorithm in our problem, which is a regression implementation of SVM for continuous variable classification problems. This algorithm is used for continuous variable prediction problems as a regression method that safeguards all the main characteristics (maximum margin) as well as for classification problems. The core idea of SVR is the calculation of a linear regression function in a high dimensional feature space. The entry data is mapped by means of a nonlinear function in a high dimensional space. SVR has been applied in several areas, in particular on time series and financial prediction problems, the recognition of handwritten digits, speaker identification, object recognition, convex quadratic programming, and loss function selection are among them Mining (2006). SVR is a continuous variable prediction method like regression. In this study, SVR is used to predict sales demands using the input variables explained in the precedent table.

6. DISCUSSIONS ON MACHINE LEARNING ALGORITHMS

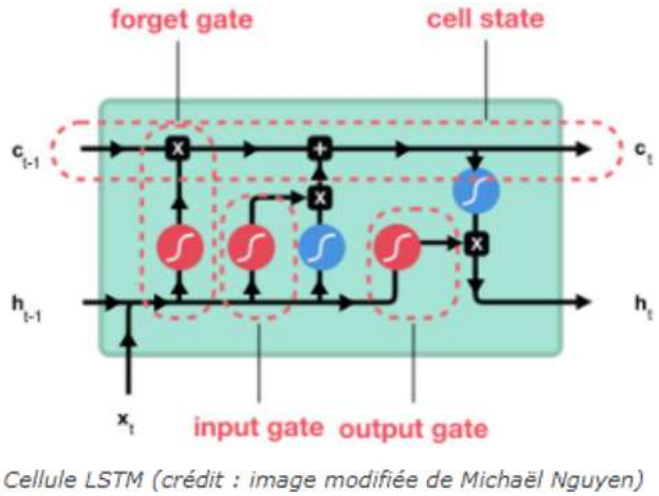
We conducted a case study on the pharmaceutical industry because some pharmaceutical products are increasingly out of stock, even before the covid-19 pandemic. Therefore, it would be interesting to check whether an artificial intelligence model can forecast future disruption risks by analyzing imports and exports between all countries.

6.1 Long Short-Term Memory

LSTM includes cells having three “gates”: computing and regulating the flow of information (by executing specifical actions: forget gate, input gate and output gate), going through two other types of gates named states: hidden state and cell state.

LSTMs are explicitly designed to avoid the long-term dependency problem. Remembering information for long periods of time is practically their default behavior. All recurrent neural networks have the form of a chain of repeating modules of neural network. In standard RNNs, this repeating module will have a very simple structure, such as a single tanh layer. The key to LSTMs is the cell state, the horizontal line running through the top of the diagram. The cell state is kind of like a conveyor belt. It runs straight down the entire chain, with only some minor linear interactions. It’s very easy for information to just flow along it unchanged. We refine these models on the training split with the following hyper parameters:

- Optimizer type: "adam"
- Loss: mean squared error
- Learning rate: 2e-5
- Batch size: 32
- Maximum sequence length: 100
- Epochs: 10



Cellule LSTM (crédit : image modifiée de Michaël Nguyen)

Figure 5: Long Short-Term Memory (LSTM)

The model is evaluated after each epoch, the proof of performance as a function of parameters is shown in the next section. Finally, the accuracy obtained using this set of parameters will be illustrated in the next section.

6.2 Example of code python

In the form of python source code, showing the use of the LSTM data and model seems rather daunting. We hope that going through them step by step makes them a bit more accessible.

```
df = pd.read_csv('OEC-4-digit-fra-Medicaments.csv', encoding='latin-1',
df.head()                          parse_dates=['year'], index_col='year')
# Create a new dataframe with only the import value
data = df.filter(['import_val'])
#convert the dataframe to a numpy array
dataset = data.values
#Get the number of rows to train the model on
training_data_len = math.ceil(len(dataset) * .8)
training_data_len
from sklearn.preprocessing import MinMaxScaler
# scale the data
scaler = MinMaxScaler(feature_range=(0,1))
scaled_data = scaler.fit_transform(dataset)
scaled_data
# create the training data set
# create the scaled training data set
train_data = scaled_data[0:training_data_len, :]
#split the data into x_train and y_train data sets
x_train = []
y_train = []
for i in range(100, len(train_data)):
  x_train.append(train_data[i-100:i, 0])
  y_train.append(train_data[i, 0])
  if i <= 101:
    print(x_train)
    print(y_train)
len(x_train)
# convert the x_train and y_train to numpy arrays
x_train, y_train = np.array(x_train), np.array(y_train)
#reshape the data
x_train = np.reshape(x_train, (x_train.shape[0], x_train.shape[1], 1))
x_train.shape
from keras.models import Sequential
from keras.layers import Dense, LSTM
# Build the LSTM model
model = Sequential()
model.add(LSTM(50, return_sequences=True, input_shape = (x_train.shape[1],1)))
model.add(LSTM(50, return_sequences=False))
model.add(Dense(25))
model.add(Dense(1))
#compile the model
model.compile(optimizer='adam', loss='mean squared error')
#train the model
model.fit(x_train,y_train, batch_size=1, epochs=10)
```

```
#Create the testing data set
# Create a new array containing scaled values from index 1995 to 2020
test_data = scaled_data[training_data_len - 100: , :]
#create the data sets x_test and y_test
x_test = []
y_test = dataset[training_data_len:, :]
for i in range(100, len(test_data)):
  x_test.append(test_data[i-100:i, 0])
# Convert the data to numpy array
x_test = np.array(x_test)
# Reshape the data
x_test = np.reshape(x_test, (x_test.shape[0], x_test.shape[1], 1))
# Get the models predicted import values
predictions = model.predict(x_test)
predictions = scaler.inverse_transform(predictions)
# Get the root mean squared error (RMSE)
rmse = np.sqrt(np.mean(predictions - y_test)**2)
rmse
# plot the data
train = data[:training_data_len]
valid = data[training_data_len:]
valid['Predictions'] = predictions
#Visualize the data
plt.figure(figsize=(16,8))
plt.title('Model')
plt.xlabel('Date', fontsize=16)
plt.ylabel('Importation en USD ($)', fontsize=18)
plt.plot(train['import_val'])
plt.plot(valid[['import_val', 'Predictions']])
plt.legend(['Train', 'Val', 'Predictions'], loc='lower right')
plt.show()
```

Figure 6: Code source using python

7. EXPERIMENTATION

The following experimentations has been done using Python v3.7.10, with the libraries of Tensor Flow v2.4.1, Keras v2.4.0, Pandas v1.2.4, Scikit-Learn v0.24.2, Numpy v1.19.5 applied on the dataset of times series such as in Figure 7, but the datasets from Figure 2 too (in order to match the category names with these values). One following section will measure the

performance of our results of trained forecast models according to different number of digits of category names.

date	Afghanistan	Afrique du Sud	Aires	Albanie	Algérie	Allemagne	Andorre	Angola	Anguilla	Antarctique	Antigua-et-Barbuda	Antilles néerlandaises
1995	194229.705882	1.858237e+06	2.199345e+06	140754.529412	5.610820e+06	1.742410e+07	324027.372439	368613.578947	7492.600000	NaN	40752.550000	383486.041667
1996	172559.976667	2.010477e+06	6.787998e+05	193569.195385	3.112079e+06	1.791025e+07	363024.048500	413750.850000	17369.428571	NaN	74173.041667	265216.055556
1997	212957.714286	1.950006e+06	2.219533e+06	133075.805588	3.948619e+06	1.970079e+07	324996.680256	396566.482759	17871.400000	NaN	107748.290323	301806.657143
1998	131085.100000	2.037308e+06	3.157915e+06	195529.647778	4.531331e+06	2.337731e+07	397542.820000	448793.050000	87128.000000	NaN	96521.000000	334711.861538
1999	157795.787879	1.647874e+06	3.065185e+06	234682.426040	4.873843e+06	2.460842e+07	455376.162821	263135.406250	15840.733333	NaN	94538.505682	405989.857143

238 columns

Figure 7: Dataset example of time series. From 1995 to 2019, (1) after processing the data to generate the tables in Figure 2, (2) we used these dataset of time series of imported/exported pharmaceutical products by value ($) to train our AI forecast models.

7.1 Results

7.1.1 Cross-validation

To avoid overfitting solutions and to guarantee the standardization of our results, all feature selection and classification experiments were undertaken in a 10-fold repeated cross-validation setting[3]. In 10-factor cross-validation, trainees are randomly split into 10 non-overlapping subsets containing approximately the same number of cases and non-cases. The classification algorithm is trained in nine of these ten subsets of data, and then tested (and independently) in the remainder tenth subset. This procedure is repeated iteratively, so that all tenths of the data are used for both training and testing the algorithm. The entire procedure is repeated 10 times, resulting in a total of 100runs (ten repetitions of ten trainings and tests). The features selected and confirmed in the random sample splits were then fed into the ML classification algorithms. Once again, the data were randomly split using the same cross-validation procedure. For each classification algorithm, the solution was identified in a random sample of 90% of the data and validated in the remaining 10%. This procedure was also repeated 10 times. feature selection

[3] A k-cross validation is a model validation technique used by data scientists for assessing how the results of a trained model will generalize to an independent data set that it never learned before (avoid overfitting when precision criteria is artificially increased by learning and testing the same data). The *k* is the division number of the dataset, of which k-1 parts will be learned and the model performance is measured on the last unlearned part. Then we start again with a next part, and so on until we average the *k* times. This makes the learning and testing period *k* times longer but brings performance measurement statistics closer to reality, by testing and learning all available data.

cross-validation, SVMs, SVM cross-validation, as well as the syntax for calling the average AUC on the SVM cross-validations.

7.1.2 Accuracy metrics

Estimates of predictive accuracy are expressed as mean accuracy. DOR (diagnostic odds ratio) is a metric of the sensitivity versus specificity of a classification system, and infers the accuracy of that system, creating a comparable measure across experiments Bradley (1997). Consistent with literature standards Fawcett (2004), Harrell Jr, Lee and Mark (1996), we consider an average accuracy of 50-60% to indicate random prediction; 60-70% to indicate poor prediction; 70-80% to indicate fair prediction; 80-90% to indicate good prediction; 90-100% to indicate excellent prediction.

7.1.3 Comparing classification algorithms

There were no significant differences between the classification algorithms when applied to the selected features, The respective average accuracy over 100 cross-validation runs were:

- Linear SVM [Precision: 0. 65 - Recall: 0.35]
- Polynomial SVM [Precision: 0.61 - Recall: 0.39]
- LSTM [Precision: 0.56 - Recall: 0.16]
- CNN [Precision: 0.745 - Recall: 0.39]
- ANN [Precision: 0.91 - Recall: 0.43]
- RNN [Precision: 0.64 - Recall: 0.41]

Because SVMs are well suited to data with heterogeneous non-normal distributions heterogeneous distributions consistent with the data types. We proceeded only with linear SVMs for all subsequent evaluations of classification accuracy.

7.2 Validation

The distinct features of this approach are derived from the use of neural networks for a multi-class forecasting problem. The value measurement of medical products is equivalent to classifying all medical products according to the three different norms into three classes of HS92: 2-digits, 4-digits and 6-digits. Several metrics using five-fold cross-validation techniques were examined to evaluate the performance of our approach after the construction of a confusion matrix[4]. Among 944,346 data, 661,042 were used for the learning and 283,304

[4] https://en.wikipedia.org/wiki/Confusion_matrix

for the validation. First, we measured the per-class accuracy and average accuracy of the proposed approach as defined in the following equations:

$$Accuracy_i = \frac{TP_i + TN_i}{TP_i + TN_i + FP_i + FN_i} \quad (1)$$

$$Average\ accuracy = \frac{\sum_{i=1}^{l} \frac{TP_i + TN_i}{TP_i + TN_i + FP_i + FN_i}}{l} \quad (2)$$

$$Precision_i = \frac{TP_i}{TP_i + FP_i} \quad (3)$$

$$Recall_i = \frac{TP_i}{TP_i + FN_i} \quad (4)$$

Where TP_i, TN_i, FP_i and FN_i are for true positives / negatives and false positives / negatives, respectively for class*i*that represents the number of positive examples correctly predicted, and*l*is the number of classes. Although there are differences in the degree of accuracy between the different forecasting periods, this approach is effective in assessing the number of medical products immediately after imports and exports to the country concerned. In addition, it should be noted that the proposed approach provides more accurate and meaningful results. However, the *Precision* indicator is not reliable in our case study because it gives inaccurate results when the dataset is unbalanced Kim, Hong, Kwon and Lee (2017), whereas the *Precision* indicator is a basic metric. For this reason, we calculated *Precision* (positive predictive value), *Recall* (true positive rate or sensitivity) and *DOR* (diagnostic odds ratio) to evaluate the performance of the proposed approach. *Precision* is the number of true positives divided by the number of all positive results, while *Recall* is the number of true positives divided by the number of positive results that should have been returned. *DOR* is a measure of the overall reliability of a classifier and is defined as the ratio of the probability that the classification is positive if the subject is truly positive to the probability that the classification is positive if the subject is truly negative, as shown in equation (5). Here, *Sensitivity* is equivalent to *Recall*, while *Specificity* is the proportion of negatives that are correctly identified. This indicator is independent of prevalence or balanced sets, and ranges from zero to infinity. A *DOR* of exactly one means that the test is equally likely to predict a positive result regardless of the actual condition.

$$DOR_i = \frac{sensitivity \times specificity}{(1 - sensitivity) \times (1 - specificity)} \quad (5)$$

The current study evaluated the implementation of ML methods to predict the rate of imports and exports by country based on information obtained from the history of the past few years. The selection of ML features identified those features that exhausted predictive potential in the dataset. The score was present in more than 95% of the repeated cross-validations, giving an accuracy of 82%. The predictive accuracy of the selected features was equivalent to that obtained using all features. The seven different classification algorithms yielded nearly equal

classification accuracies. The fact that initial information collected, including medical product data, allows for consistent and effective prediction is very promising in the measurement. The prediction accuracy of the prediction accuracy in this study is consistent with the average accuracy obtained.

Measure	Accuracy			Precision		
	2-digits	4-digits	6-digits	2-digits	4-digits	6-digits
ANN	98.02	98.37	82.44	79.11	91.81	47.19
Random forest SVM	96.27	97.54	83.22	65.28	37.87	52.91
CNN	99.06	99.13	88.41	74.28	46.08	51.78
RNN	98.15	99.33	82.81	64.35	36.46	42.78
LSTM	98.89	96.77	69.26	56.54	25.48	51.84
Regression model 1	98.05	96.97	62.76	85.19	51.28	52.87
Regression model 2	98.17	96.39	68.17	67.88	50.74	50.56
Regression model 3	90.11	85.65	55.71	57.86	38.33	49.97
ESM	91.34	86.59	55.92	47.66	50.15	74.47

Measure	Recall			DOR		
	2-digits	4-digits	6-digits	2-digits	4-digits	6-digits
ANN	43.64	1.95	7.08	1435	59.48	4.59
Random forest SVM	35.77	1.08	9.78	1061	61.42	5.47
CNN	39.53	3.86	7.77	1357	72.14	3.9
RNN	41.48	4.44	6.97	1129	66.57	3.7
LSTM	16.64	3.78	30.18	125	9.87	2.68
Regression model 1	3.55	1.45	21.59	76.89	30.79	2.8
Regression model 2	12.14	6.41	26.51	172.90	30.94	3.5
Regression model 3	33.61	3.52	28.73	16.20	3.39	1.4
ESM	25.37	3.99	34.17	28.91	5.74	3.8

Figure 8: Comparison of trained AI models according to four types of ratio measures (Accuracy, Precision, Recall, and DOR merging them) according to three different types (2, 4, and 6 digits, more affined with more digits) of learned HS92 data about international historical imports and exports (from 1995 to 2019).

8. CONCLUSION

Thanks to AI technology not only the industry will be able to quickly move on to a more modern approach in their activity but it will also guide them into an unique spot: they will be able to capitalize on the specificity for their industry to not only increase their margins but operate quicker, faster and better. The only questions that remain unanswered is when these companies will jump on the technology train and begin their transformation.

All these events have impacted the pharmaceuticals industry in a different way, some have touched their core businesses other the way they should organize their activity. However, pharmaceuticals industry can't really change their business models or make their core business evolves, due to regulation the prices are fixed by law, distribution is locked down and new products need to be approved by governmental entities before being allowed on the market. Finally, this work will be further developed using 2020 data including the period of the pandemic to test AI approaches in the context of a health crisis and how these models can improve forecasts. This could be useful to analyze how thecovid-19 pandemic impacted the imports and exports.

Les références bibliographiques :

Bradley, A.P., 1997. The use of the area under the roc curve in the evaluation of machine learning algorithms. *Pattern recognition 30*, 1145–1159.

Chase, C.W., 2016. Next generation demand management: People, process, analytics, and technology. *John Wiley & Sons*.

Erkollar, A., Goztepe, K., Sahin, N., 2013. A study on innovation performance forecasting in advanced military education using neurofuzzy networks. *International Journal of Science and Advanced Technology 3*, 5–12.

Fawcett, T., 2004. Roc graphs: Notes and practical considerations for researchers. *Machine learning 31*, 1–38.

Guangyuan, X., Zhe, D., Wenjun, Y., Baykal-Gursoy, M., 2021. Evaluation of "innovation chain+ supply chain" fusion driven by blockchain technology under typical scenario. *International Journal of Production Economics*, 108284.

Harrell Jr, F.E., Lee, K.L., Mark, D.B., 1996. Multivariable prognostic models: issues in developing models, evaluating assumptions and adequacy, and measuring and reducing errors. *Statistics in medicine 15*, 361–387.

Haykin, S., Network, N., 2004. A comprehensive foundation. *Neural networks* 2, 41.

Jain, C.L., 2003. Business forecasting in the 21st century. *The journal of business forecasting 22*, 3.

Jang, J.S., 1993. Anfis: adaptive-network-based fuzzy inference system. *IEEE transactions on systems, man, and cybernetics 23*, 665–685.

Kelle, P., Woosley, J., Schneider, H., 2012. Pharmaceutical supply chain specifics and inventory solutions for a hospital case. *Operations Research for Health Care 1*, 54–63.

Kiely, D., 2004. The state of pharmaceutical industry supply planning and demand forecasting. *The Journal of Business Forecasting 23*, 20.

Kim, H., Hong, S., Kwon, O., Lee, C., 2017. Concentric diversification based on technological capabilities: Link analysis of products and technologies. *Technological Forecasting and Social Change 118*, 246–257.

Mangai, S.A., Kasinathan, S., Alagarsamy, K., Sankar, B.R., 2014. Hybrid arima-hyfis model for forecasting univariate time series. *International Journal of Computer Applications 91*.

Merkuryeva, G., Valberga, A., Smirnov, A., 2019. Demand forecasting in pharmaceutical supply chains: A case study. *Procedia Computer Science 149*, 3–10.

Mining, W.I.D., 2006. Data mining: Concepts and techniques. *Morgan Kaufinann 10*, 559–569.

Mok, S., Kwong, C.K., 2002. Application of artificial neural network and fuzzy logic in a case-based system for initial process parameter setting of injection molding. *Journal of Intelligent Manufacturing 13*, 165–176.

Paul, S.K., Chowdhury, P., Moktadir, M.A., Lau, K.H., 2021. Supply chain recovery challenges in the wake of covid-19 pandemic. *Journal of business research 136*, 316–329.

Tirivangani, T., Alpo, B., Kibuule, D., Gaeseb, J., Adenuga, B.A., 2021. Impact of covid-19 pandemic on pharmaceutical systems and supply chain – a phenomenological study. *Exploratory Research in Clinical and Social Pharmacy 2*, 100037.

Wei, S., Zhang, J., Li, Z., 1997. A supplier-selecting system using a neural network, in: 1997 *IEEE International Conference on Intelligent Processing Systems* (Cat. No. 97TH8335), IEEE. pp. 468–471.

Weller, M., Crone, S.F., 2012. Supply chain forecasting: Best practices & benchmarking study.