BIGcoldTRUCKS: a BIG data dashboard for the management of COLD chain logistics in refrigerated TRUCKS

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***Abstract*—The technological development of the food industry is bringing new opportunities for the optimization of cold chain logistics. Many businesses of all sizes have been capturing their trips' data and they are ready to apply Big Data analytics and use Big Data tools in order to extract knowledge and patterns that can be useful for decision-making and therefore provide added value to their business. In this line, we developed a shiny dynamic dashboard that provides a friendly user interface to the business in order to visualize and understand their data in the form of rankings, trips duration, demand seasonality, and geographic representation of the trips. The dashboard connects seamlessly with two Big Data tools, elasticSearch and the DEEP training facility from the European Open Science Hub (EOSC). More specifically, those tools were used for data indexing and demand estimation of products using cloud computing respectively. Thanks to the interconnection of these tools, we are able to enhance the dynamic dashboard with Big Data Analytics in the form of multivariate demand prediction of the products using a Long Short Term Memory Network and ease query time and computation, creating real value for the cold chain logistics industry. The development of this solution was done with the support of the EOSC-Digital Innovation Hub initiative through a business pilot.**

The dashboard functionalities were implemented using a real-case dataset which cannot be shown for privacy reasons. In its place, we have simulated a meat-based products database for the purpose of this paper.

***Index Terms*—smart logistics, elasticSearch, cold chain, smart transportation, Big Data**

I. Introduction

Due to the development of ICT and IoT, the food transportation sector has evolved over the last years to a point in which vehicles are more efficient, connected, and monitored. Real-time information and the interconnectivity of things, supplemented with novel technologies can revolutionise and improve the way food logistics is carried out. This paradigm allows the analysis of supply chain data to improve decision-making. However, currently, there is a lack of use of the monitored data with the goal of optimising the cold chain when transporting perishable products and the impact of other related variables such as the grouping of goods, type length of the trip duration, or conditions to be maintained in the products has not been studied. This can be addressed through Big Data analytics tools, given the great amounts of data of a different type that are generated.

Our work intends to create value for cold chain logistics through Big Data analytics. Cold chain logistics are the technology and processes that allow for the safe transport of temperature-sensitive such as food, beverages, and biopharmaceutical products along the supply chain. The study of the characteristics of the trips and products will have as a goal to make the chain more efficient: save petrol and reduce food waste. Our goal is twofold. First, we seek the development of a system that can analyse historical data in order to extract existent patterns in the transportation of perishable goods and identify malpractice. Then, we want to provide real-time predictions to support decision-making in relation to demand estimation. This can be used to optimize the transportation of goods.

This work presents the scientific outcomes of a project that was a pilot of European Open Science Cloud (EOSC) - Digital Innovation Hub (DIH). The EOSC DIH provided support to our project after being selected as one of their pilots in a competitive call in which we were awarded a 10k voucher. They helped us in identifying the Big Data technologies that could serve our purpose within the services that were offered by the EOSC, including support from scientific institutions.

As a pilot in EOSC DIH, we have adopted and adapted the Big Data technologies and services that they provide for performing descriptive and predictive analytics on several aspects of perishable goods supply trips. On the one hand, we have developed a dynamic dashboard in order to explore what happened and why. On the other hand, we have developed deep learning models for demand prediction in order to anticipate sales and avoid waste and losses. The predictive analysis is based on the daily estimate of product demand by using a Multivariate Long-Short Term Memory (LSTM) recurrent neural network. For visualization and development purposes, we are using a simulated database of a meat products producer, since the real data is confidential. In that sense, we are presenting a general tool that connects with Big Data services and can add value to any cold chain logistics use case: biological samples (healthcare or pharmaceutical uses) transportation, fish transportation, and other perishable food and products. The dynamic dashboard was deployed with the R package Shiny and for dissemination purposes, we made it available[1].

II. Related Work

The logistics of perishable items include resource planning, warehouse management, transportation management, predictive maintenance, and data security. Especially in the case of food logistics, the farm to fork strategy, at the heart of the European Green Deal, consists of the re-design of those steps, including waste prevention, and sustainable consumption, making them optimal and smarter [1].

Smart supply chain management means "having the right product item in the right quantity at the right time at the right place for the right price in the right condition to the right customer" [2]. However, due to the complexity, uncertainty, poor coordination, insufficient information and other factors involved in the supply management, there are supply-demand mismatch problems such as overstocking, under-stocking and late delivery which have long been popular research topics over the last few decades in the business management literature [3]. Nowadays, supply systems are becoming more complex, costly, uncertain and easily affected by the outer environment. To deal effectively with the increasing challenges due to globalization and increasing demand of the customer, supply chains must become a lot smarter [4].

IoT is a technological revolution in computing and communications, which leads to the vision of communication at any time and anywhere, through any media. IoT allows digital and physical entities to be interlinked together so that it can provide a whole new class of applications. RFID tags can be used to categorize, identify and manage the flow of products in an industrial context[5]. For example, Walmart is using RFID to enhance the security and safety of food products [6], vibrational spectroscopy is efficient method spectroscopy for both the assessment of food quality and food authenticity [7]. With the help of biosensors/wireless mechanisms, food contamination problems can be recognized very effectively and thereby improving the quality of the mechanism of food products. Biosensors play an important role in detection of food pathogens [8]. In [9] a novel architecture for the automation of the supervision, monitoring and tracking of rolling cargo based on auto-ID technologies (Barcode, QRCode, and magnetic ID cards) was designed.

Traceability is mainly used for the prevention or reduction of food hazards. In this process, the products are traced at each level for determining any contamination in food products [6]. Artificial intelligence is significant to use during intelligence in the food sorting stage of the production line in the food industry. This may involve the integration of expert system knowledge and database in executing artificial intelligence-based activities to help managers to secure the safety of food products [10].

A Cloud-Enhanced System Architecture for Logistics Tracking Services is presented in [11]. They combine IoT, SaaS cloud architecture and big data analytics technologies for setting up efficient real-time monitoring of customers cargoes. They use HBase is used for storing. To supervise the delivery of containers in the ship transportation industry, unique identifiers codes are written on the container. To overcome the high computation time of text detection, characters extraction and text recognition, [12] uses Hadoop MapReduce. The container's code is captured using cameras and stored on Hadoop distributed system file (HDFS). After that greying colour image steps are applied. Next, the image is decomposed into blocks that are separately analysed on different machines using MapReduce to extract the text regions. They separate code characters from the text regions and apply Optical Character Recognition (OCR). Finally, they are merged and the text is recognised.

After an extensive review of the state-of-the-art on this topic, we realise that there is not an advanced system based on Big Data tools for the improvements of logistics in the cold chains. There exist works pointing out the necessity and relevancy that those systems could have in the food logistics optimization [13]. With this work, we have started testing the application of Big Data technologies using real data from a business.

III. Dashboard

A. The dataset

The dataset is composed of 2 years of data from trucks that transport perishable products between locations in Europe. Each row contains information about a product that belongs to a trip between two points. The columns that we used to develop our services are

- Load, Delivery and the Dispatch date
- License plate
- Load and Dispatch country
- Number of palets
- Product
- Product code

Other columns that are not used yet but we consider that are important are

- Business department
- Set-point temperature
- Door opening

[1]http://gauss.inf.um.es:8080/bigcoldtrucks/

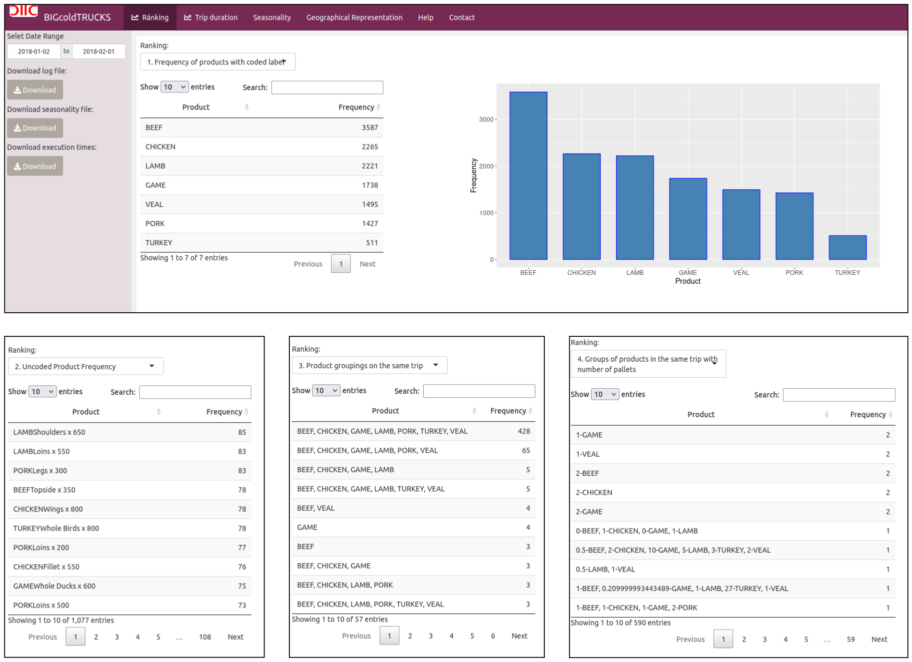

Fig. 1. Whole dashboard for Ranking 1 (upper part) and the tables for Rankings 2-4 (lower part)

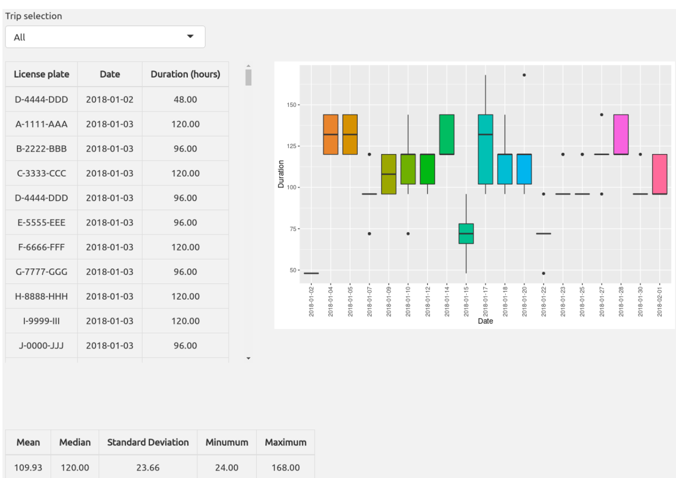

Fig. 2. Trips duration panel information (zoomed)

- Load and dispatch city and region
- Kind of palets

For privacy issues, we have not used the original products of the business we collaborate with. Instead, their databased inspired the simulated one that we are showing, which contains meat-related products.

B. Dashboard configuration

As a starting point, we needed to preprocess the data. We created 4 main tabs: ranking, trip duration, seasonality and geographical representation, which will be described in the following. The dashboard also contains a general tab that is always present and from which the user can select the range of dates for data querying and download some of the tables that will be generated, including a log file that provides errors in the database and the execution times of the different queries and services. The dashboard also counts with a password.

In order to analyse the factors that cause product demand, we created a ranking tab that shows the most frequent transported products and the ones that are frequently transported together.

The frequency of the products demands has been computed in 4 different ways: taking into account the coded product, the whole name of the product (uncoded), the groupings on the same trips and the number of pallets.

1) Frequency of products with coded label: shows the number of trips that transport each product, sorted by frequency in descending order and grouping products by their coded label. Therefore we could find here products such as *chicken* or *beef*.
2) Uncoded Product Frequency: it shows information similar to the previous case, only that these products appear uncoded, that is, their full name appears. Therefore we could find here products such as *chicken breast 500 grs* or *chicken thighs 200 grs*.
3) Product groupings on the same trip: this option gives a ranking of those product groups that appear more frequently, using their coded names. For example, *chicken, beef* or *pork, beef, chicken*.
4) Groups of products in the same trip with the number of pallets: this option is similar to the previous one, only in this case the number of pallets for each of the products is specified. For example, *1p-chicken, 3p-beef* or *2p-pork, 5p-beef*.

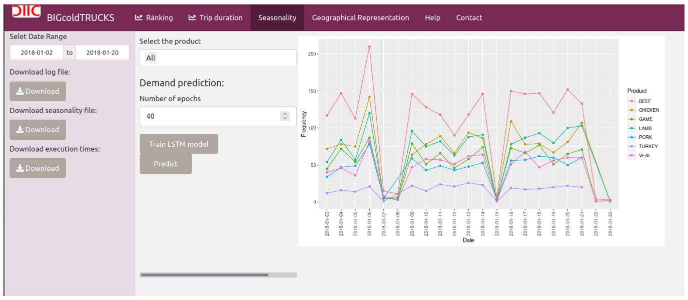

Fig. 3. Whole dashboard with the seasonality panel selected

The tables for all rankings and the barplot for the first one can be seen in Figure 1.

In order to open up the possibilities for trip planning and route optimization, we needed to provide trip duration statistics. This is an important step that can lead to understanding and correcting the facts that imply that trips take longer than expected and learn from them. In the Trip Duration Tab, which can be seen in Figure 2, we find a list of licence plates and duration in hours of each trip; a table with statistics and boxplots summarising the trip durations per day.

This is the first step to the solution of the *travelling salesman problem algorithm* that results in a plan with the shortest path of travel given several stops [14], especially after having populated the database with other sources.

Demand forecasting is a challenging task that can be enhanced by means of Big Data analytics. Product availability is a critical factor for customer satisfaction. An accurate demand forecasting would help ensure that there is the necessary amount of stored goods without excess [15]. With this goal, we have created a seasonality tab that shows the intensity of each product's sell to visualize its seasonality. In Figure 3 we can see the graph and also, some components and buttons that will be used for the next days' demand prediction. Their functionalities will be described in section IV.

Geographic Representation: The origin and destination of the orders are shown as well as the frequency with which the routes are carried out to provide a spatial view of how trips are distributed. The width of the lines shows the frequency of the routes (see Fig. 4).

We have indexed the data using elasticSearch and connected our dashboard to it using the elasticSearchr package. This was a great achievement since this made the dashboard fully operative concerning results' retrieval time. Not only the calculations are automatic but also the indexing of the data.

We have also managed to provide daily and weekly predictions on the demand for each of the products. This is very useful for stock optimisation.

IV. Big Data tools

In order to fasten up the descriptive analysis that is shown in our dashboard, we used the elasticSearch solution for data indexing.

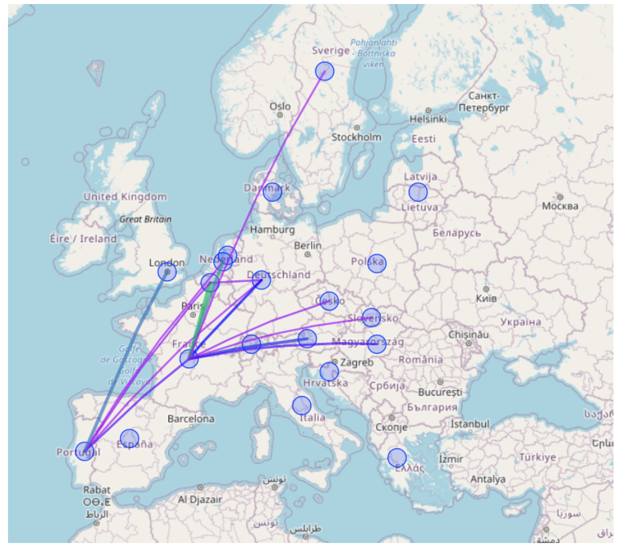

Fig. 4. Geographic representation information (zoomed)

A. elasticSearch

elasticSearch was deployed in the machines of the Poznan Supercomputing and Networking Center[2], which gave us support within the EOSC DIH program.

elasticSearch is a horizontally scalable, distributed database built to handle huge amounts of data volume and to be fault-tolerant, all the while maintaining an API that allows applications from any language or framework access to the database. It is built on APACHE'S LUCENE, and can be thought of as an interface to Lucene designed for Big Data. The complex feature set that Lucene provides for indexing and querying data is directly available through elasticSearch [16].

In elasticSearch, a Document is the unit of search and index. An index consists of one or more Documents, and a Document consists of one or more Fields. In database terminology, a Document corresponds to a table row, and a Field corresponds to a table column. The workflow is as follows:

- Documents of any type and size are uploaded
- They are converted to JSON
- The Tokenizer receives the stream of characters, breaks it inot indiviudal tokens (individual words) and outputs a stream of tokens.
- The words are indexed and mapped so as to group the similar type of words into one mapping type, ensuring a faster retrieval.
- A query is parsed and the searched text from the indexed documents is retrieved.

Since our dashboard is built in the R software [17] by means of the Shiny package [18], we created several functions for creating the queries that are sent to elasticSearch. The choice of Shiny in comparison with other tools such as Tableau was due to its greater visualization and graphs possibilities, the ability to connect to any data source, the availability of

[2]https://www.psnc.pl/

data manipulation and analysis tools, and its flexibility and reproducibility.

In order to connect to elasticSearch from R, we used two packages: *elastic* and *elasticSearchr*. We connected our dashboard to the machine via ssh tunnelling. and we created a process to automatically index the data from R. We called our index “bigCold” , then we were able to locate documents in the elasticSearch cluster as follows:

```
data <- elasticSearchr::elastic(‘‘http://localhost
    :9200”,‘‘bigCold”)
```

In order to obtain the range of dates that are selected by the user, we combine the `range_rule` function within the field “orderDate” that is present in the data.

```
range_rule <- function(field, liminf, limsup) {
  paste0('{"range":{"',field,'":{"gte":"
  ',liminf,'","lte":"',limsup,'"}}}')
}

orderDate_rule <- shiny::reactive({
  F1 = input$Date[1]
  F2 = input$Date[2]
  range_rule("orderDate", F1, F2)
})
```

In that way, `orderDate_rule` is a reactive string that contains the range of dates that the user has selected at the present time and with the following combination of functions we are able to do a search by the date.

```
simple_filter <- function(rule) {
  elasticSearchr::query(rule)
}
orderDateFilter_rule <- shiny::reactive({
  simple_filter({orderDate_rule()})
})

df <- data %search% ({orderDateFilter_rule()} +
    ranking[[option]])
```

In the search that is present in the previous chunk of code, `option` is a number that is chosen through the dashboard to perform one of the 4 kinds of ranking, and `ranking` is a list of strings that contains the desired query according to each of them. All the code is available in an open repository[3].

The computing speed for the retrieval of results was greatly improved in the majority of the descriptive services as portrayed in Table I. For 5 out of 7 queries, we were able to speed up the retrieval time between 51 and 98 % for 1 month of data. For the rankings of grouped products, given the complexity of nested queries with Elastic language, we were not able to improve R’s functionality and we had to keep the original queries using pure R language.

[3]https://github.com/auroragonzalez/BIGcoldTRUCKSdashboard

TABLE I
RETRIEVAL TIMES (SECONDS) COMPARISON FOR 1 MONTH OF DATA

	R (s)	**Elastic (s)**	**Improvement (%)**
Product’s ranking (coded)	1.107	0.022	98
Product’s ranking (undcoded)	1.03	0.057	94
Grouped Product’s ranking	1.493	2.47	-65
Grouped Product’s with pallets ranking	1.55	4.578	-195
Trip Durations	3.444	1.697	51
Products demand seasonality	1.163	0.051	96
Geographic representation	0.978	0.062	94

B. Demand predictions using High Performance Computing - Deep Hybrid DataCloud

Having improved the process for querying data, we were ready to implement a predictive model in order to estimate the product’s demand for the following day. The model we chose was multivariate LSTM. Neural networks are able to model problems with multiple input variables almost seamlessly. Long Short-Term Memory (LSTM) networks are a type of recurrent neural network capable of learning order dependence in sequence prediction problems. Apart from external variables that are not considered, the demands of a product can be influenced by the demand of others. For that reason, we proposed a multivariate scenario, where all selected products by the user are going to be used to train the LSTM, and a prediction for the next day for all of them will be provided.

On LSTMs, the model is trained using back-propagation, meaning that information about the errors are sent in reverse through the network so that it can alter the weights. This kind of network is well-suited to time series data.

The architecture of an LSTM network has the form of a chain of repeating modules or blocks. Each block has typically a memory cell and 3 gates: an input gate, an output gate, and the so-called forget gate. The memory cell saves the state of the LSTM unit, while the gates are a way to optionally let information through. The gates are composed out of a sigmoid function and a pointwise multiplication operation. The sigmoid function outputs numbers between zero and one so that it controls the extent to which a new value flows into the cell. Similarly, the forget gate and output gate control the extent to which a value remains in the cell and its usage to compute the output activation of the LSTM block, respectively.

In the Dashboard, the following metrics are returned for evaluating the results over the train set: Mean Absolute Error (MAE), Mean Squared Error (MSE), Root MSE (RMSE), Coefficient of Variation of the RMSE (CVRMSE) and Mean Absolute Percentage Error (MAPE). Also, the training set can be downloaded from the left panel in order to use it in other software if desired.

Cloud computing is a paradigm that enables the delivery of computing services over a network, typically the Internet, allowing users to consume resources as a utility without having to build and maintain the necessary computing infrastructures. This allows users to focus on business logic and development tasks, leaving aside the tasks of deployment and architecture management. In this work, we have used the Deep Hybrid DataCloud project to carry out data analysis, allowing us to raise the level of abstraction and gain computational power and capacity.

Deep Hybrid DataCloud is a framework developed in the context of a European H2020 project[4] that provides machine learning as a service to a wide range of users. DEEP focuses on exposing computational resources, such as the one we have used, which is a GPU cluster.

This framework is designed for scientists to develop machine learning and deep learning models in distributed infrastructures and covers the whole development cycle of data analytics problems [19]. We highlight the following modules:

- The DEEP Open Catalogue is a marketplace where users can browse, share, save and download ready-to-use machine learning modules.
- The DEEP learning facility, which coordinates and orchestrates the training, testing and evaluation of models, choosing the appropriate cloud resources for both computation and storage.

  DEEP as a Service solution (DEEPaaS) provides a way to develop and serve a trained model, stored in the catalogue, as a service, for third parties to use the extracted knowledge.

More specifically, we deployed a Jupyter instance in the DEEP CLOUD testbed with a GPU. Again, the EOSC-DIH initiative supported us by helping us contacting the Instituto de Física de Cantabria (IFCA) where the main developers of the platform are based. This served to ease the machine learning models training that was tested for the prediction of the demand of different products. We tested several models and decided to use Long Short Term Memory Networks (LSTMs) for demand prediction.

Once the Jupyter instance was working correctly, we wanted to connect our shiny dashboard to the platform. To do so, we first developed a model using the DEEP Data Science template, that provides the needed structure of a repository so that it works on the system. We created an open GitHub project with the code, requirements and features requested [5]. Once our model was in the right shape, we expose it by running *deepaas-run* in the DEEP as training platform, as can be seen in Figure 5 so that the models are served through the entry point API of the DEEP as a Service (DEEPaaS) API. The outcome of this is shown in Figure 6, where the main functions of our package can be directly used introducing the models' parameters and an URL where the data is stored. Since we have configurated and created the scripts that are needed for the system to run,

[4]https://cordis.europa.eu/project/id/777435/es

[5]https://github.com/auroragonzalez/lstm_test

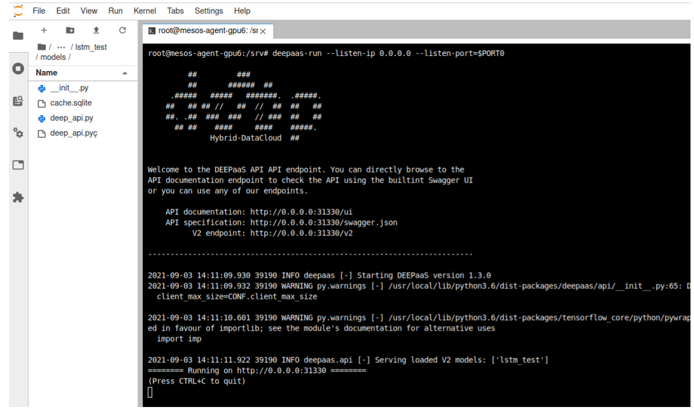

Fig. 5. Deepaas-run terminal

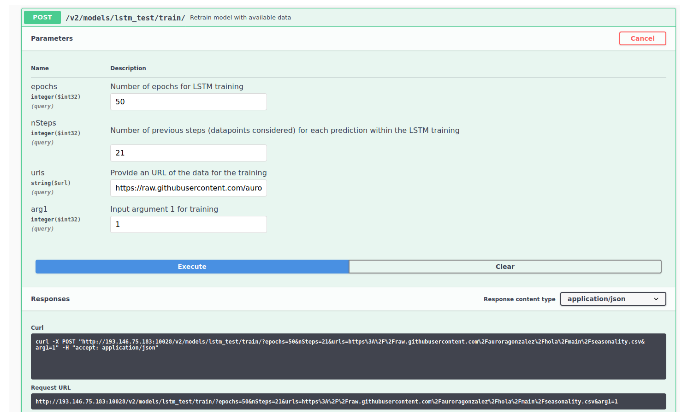

Fig. 6. Entrypoint API

the developed predictive framework can be easily extended with other algorit

These steps that we introduced manually are integrated into our dashboard. In that sense, the input data will correspond to the user selection that is done in the Seasonality panel. As can be seen in Figure 3, there are buttons to train the LSTM and to predict it, as well as a user entrance in order to select the epochs for training the network. The train is done with the data that is selected by the user, and the prediction of the next days' demand for all products is carried out and printed on the screen.

The functionalities that are described in this paper are also depicted in a public video[6].

V. Conclusions and Value

Nowadays, many businesses are concerned about collecting data and make great efforts by deploying sensors. However, they lack solutions that extract information from such data. The transportation sector is not an exception. Our solution provides meaningful knowledge for the logistics business, by giving a better understanding of the trips: product's groupings, duration and product demand seasonality and prediction. Our

[6]https://youtu.be/MBHCX0Fs7bM

solution helps in the identification of malpractice. If any kind of event is identified, for example, product return, they can easily look for reasons and avoid a similar situation in the future.

The Return on Investment is very fast. Our solution is implemented by connecting their database to our dashboard. They will immediately have access to our services. With such value, worker-hours can be reduced and therefore the small expense on our solution is quickly recovered given the gain inefficiency.

Our solution goes beyond the Business Intelligence paradigm since it is capable to analyse data in-depth given its connection to state-of-the-art analytic tools, graphs are of the greatest quality and the functionalities can be customised with little addition of code. It is a flexible, agile solution for more than intelligent, wise logistic businesses. Also, our work is very open, we have provided the code for recreating the dashboard, the code for recreating the algorithm and also recorded a demo and posted it on youtube for disseminating the work.

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