BIGcoldTRUCKS

BIG data analytics for cold chain logistics optimisation in refrigerated TRUCKS

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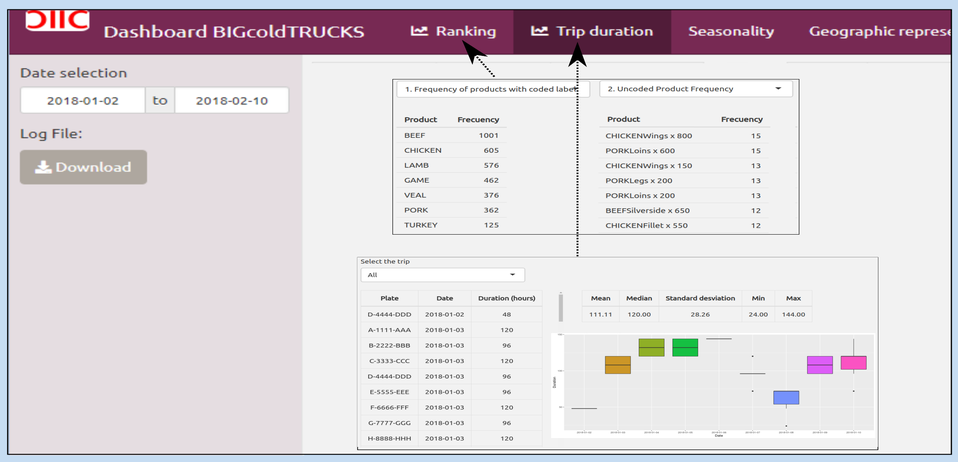
Introduction

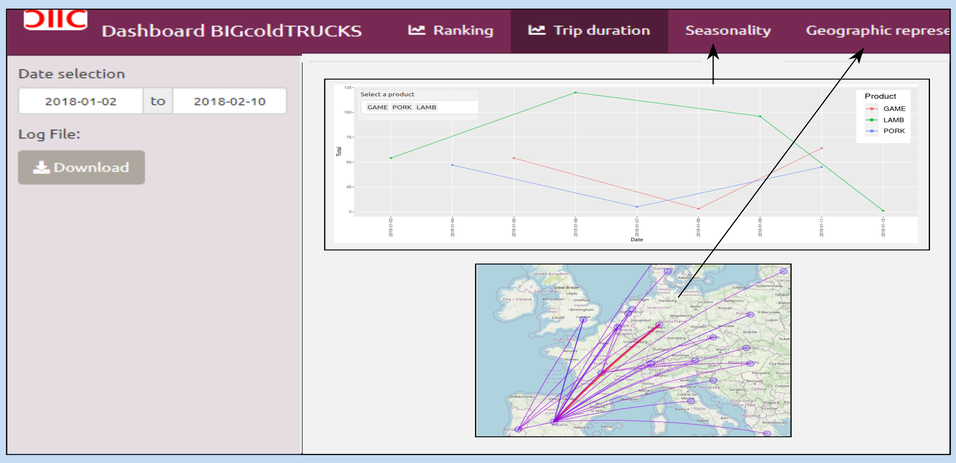
Thanks to the development of IoT, the transportation sector has evolved to a more efficient, connected and monitored environment. This allows the analysis of supply chain data to improve decision-making. As a pilot in EOSC DIH, we are using some digital technologies and services that they provide for performing descriptive and predictive analytics on several aspects of perishable goods supply trips. On the one hand, we have developed a Dashboard in order to explore what happened and why. On the other hand, we are also developing *machine learning* models for demand prediction in order to anticipate and avoid waste and losses. For visualization and development purposes, we are using a simulated database of a meat products' producer. However, our intention is to build a general tool that can be useful for 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[a] and for dissemination purposes, we made it available at `http://gauss.inf.um.es:8080/bigcoldtrucks/`. The predictive analysis is based on the daily estimate of product demand by using ARIMA, the traditional time series method, and the LSTM (Long-Short Term Memory) recurrent neural networks.

[a] https://shiny.rstudio.com/

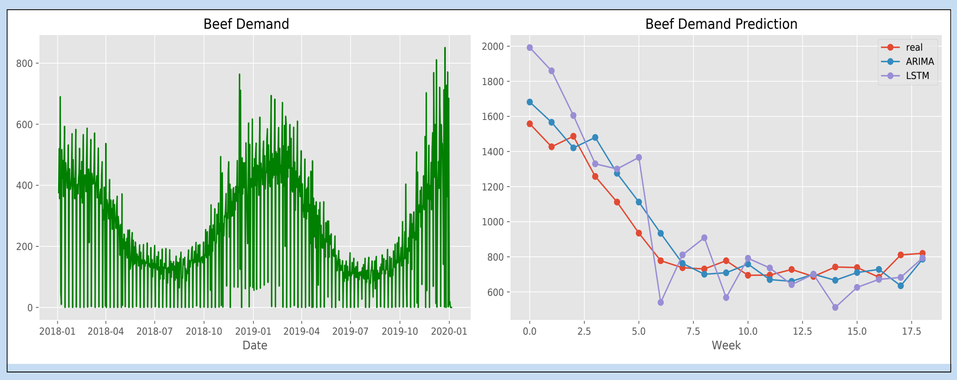
BIGcoldTRUCKS Dashboard

- Ranking: Ranks the products according to their demand in 4 different ways: Frequency of products with coded label, Uncoded product frequency, Product groupings on the same trip and Groups of products in the same trip with number of pallets.
- Trip Duration: a summary of the trips that have been made and the duration of each of them. We find a list of licence plate and duration in hours of each trip; a table with statistics and a boxplot summarising the results.
- Seasonality: Shows the intensity of each product's exports to visualize its seasonality. If we select a product from the drop-down list, a graph will appear on the right side with the evolution of the product's seasonality over time.
- 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 color and thickness of the line represent the number of orders that have taken place between both locations and the exact number is shown when placing the cursor over the line.





Demand prediction using machine learning and indexed database for faster results' retrieval



- Demand Prediction Using the Deep Hybrid Data Cloud [3]: Using historical univariate data we have deployed ARIMA [2] and LSTM [1] predictive models in order to anticipate the weekly demand of the products. For implementing them, we have used the Deep Hybrid Data Cloud e-infrastructure, , in collaboration with the technology experts from EOSC DIH, that provided us access to GPUs computations at scale, a easy implementation of the models through Jupyter notebook[a] and an API to retrieve the results. We plan to connect the Dashboard to this resource.
- The Elastic Solutions [b] for efficient data indexing and Apache Spark[c] for distributed analysis: in order to make the Dashboard fully operative with online data and to provide fast results we considered that the elasticSearch and Kibana solutions can help us in the efficient access of the data and Apache Spark can be used for distribute the data into several nodes.

[a] https://jupyter.org/
[b] https://www.elastic.co
[c] https://spark.apache.org/

References

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[2] Jamal Fattah, Latifa Ezzine, Zineb Aman, Haj Moussami, and Abdeslam Lachhab. Forecasting of demand using arima model. *International Journal of Engineering Business Management*, 10:184797901880867, 10 2018.

[3] Álvaro López García. Deepaas api: A rest api for machine learning and deep learning models. *Journal of Open Source Software*, 4(42):1517, 2019.

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