Applied Intelligence IBERIA COE

A Global Hub of Data & Analytics experts

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Context

Understanding situation

4 Datasets

+115K

Historical orders records

+35

European cities within supply chain

+700

Products

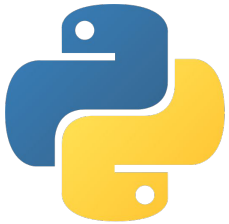
Different factors intervene in delay shipment cost and emission

With delay in shipments, the perception of the company worsens

With data mining we are able to go beyond and **extract value** for our customers to **improve** their **services** and their **supply chain** in order to have less delays with a **better customer experience** and **added value** to **shipping services** through predictive **data-driven modelling**.

Methodology

Tools used



Methodology

Process computed

The process we followed was EDA, Preprocessing, Training and Validation.

1.Data Interpretation

2.Data Preparation

3. Model prediction training & Validation

4. Data insights Business actions & Value proposition

Methodology

1. Data Interpretation

4 Datasets

+115K
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European cities within supply chain

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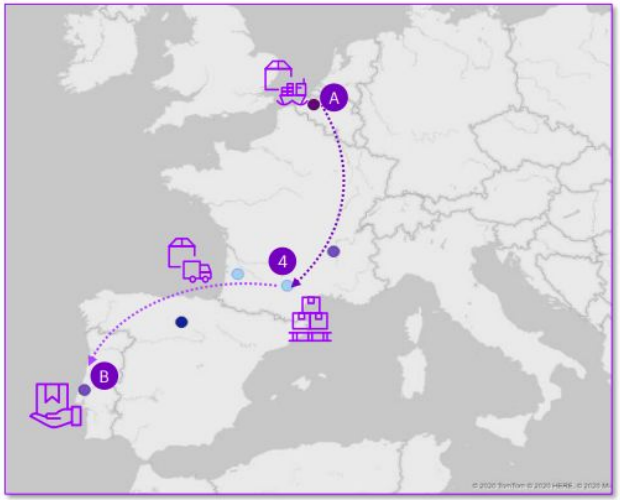
Products

Data correction (missing values and incorrection) has been realized and **interpolated** in order **to understand the customers deliveries** and **observe** the **tendency between delays** or correct shippings

Furthermore dummies have been created to **start training** the model



Methodology

1. Data Interpretation

4 Datasets

+115K
Historical orders records

+35
European cities within supply chain

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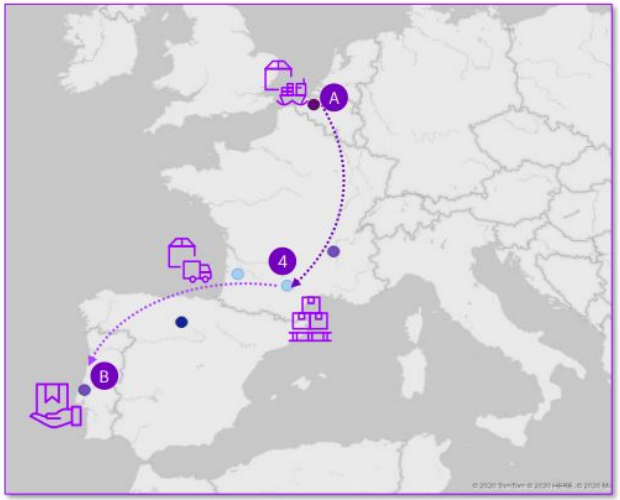
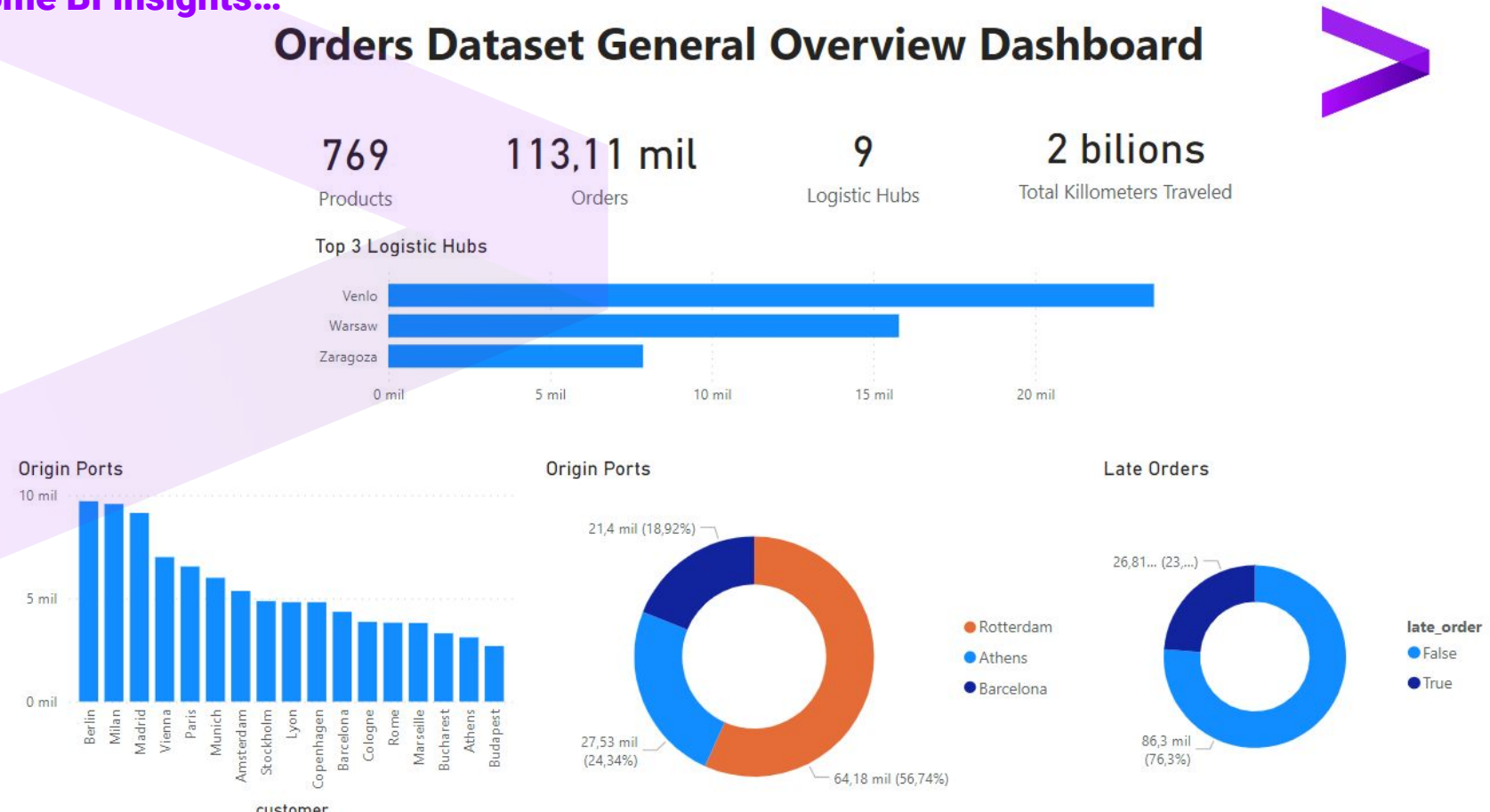
Products

Once deliveries has been aggregated to our prepared dataset for trainning the model, **warehousings** and **final customers** has been **computed** to obtain delivery distances and **predict future data** with a **better performance**



Methodology

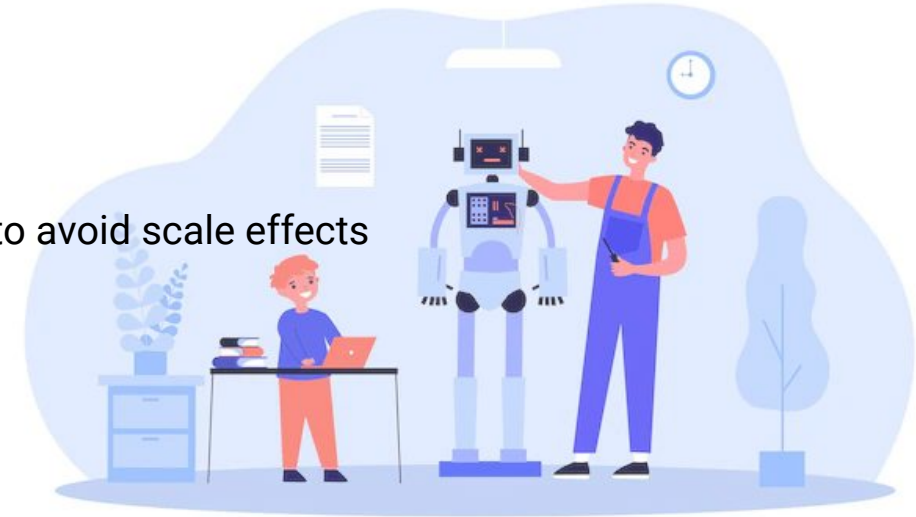
Some BI Insights...



Methodology

2. Data Preparation

- Furthermore dummies variables have been created to **learn** from categorical data
- Dataset has been **splitted*** for designing **train and evaluation sets** that will ensure model's validity
- **Normalization** of data set has been realized to avoid scale effects



*Splitting has been randomized with 80% train & 20% test

Methodology

3. Model prediction training & validation

- We have used a Generalized Linear Model (GLM) for solving this challenge.

  The main reason is that this challenge requires **explainability** and a GLM is a Statistical model that enables us to **explore the reasoning behind the predictions**.

- Dataset has been **splitted*** for designing **train and evaluation sets** that will ensure model's validity

- **Normalization** of data set has been realized to avoid scale effects

Methodology

4. Validation

For validation we have used the proposed ROC Curve and it's AUC. We also provide an accuracy metric for further evaluations.

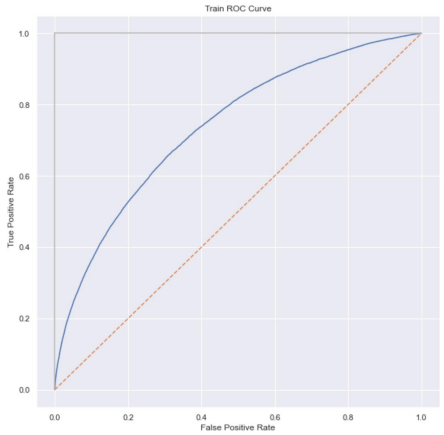
As we can see on the evaluations, the model does not present overfitting.

ROC score

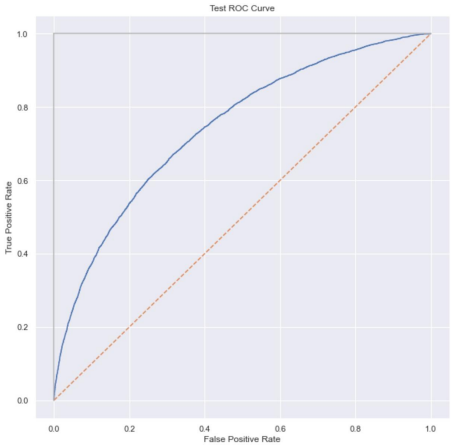
TRAIN AUC SCORE for GLM: 73.83%
TEST AUC SCORE for GLM: 74.28%

Accuracy score

Train Acc: **78.23%**
Test Acc: **78.64%**



Train ROC curve

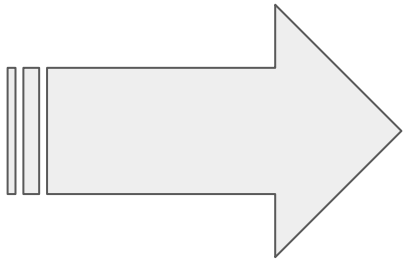


Test ROC curve

Methodology

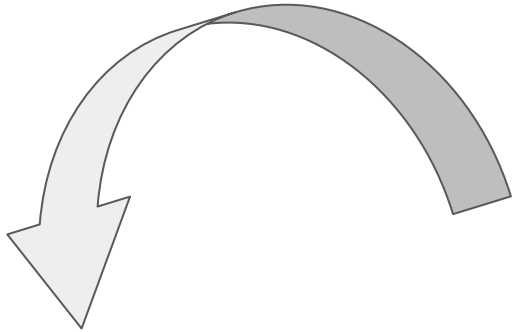
Model explainability

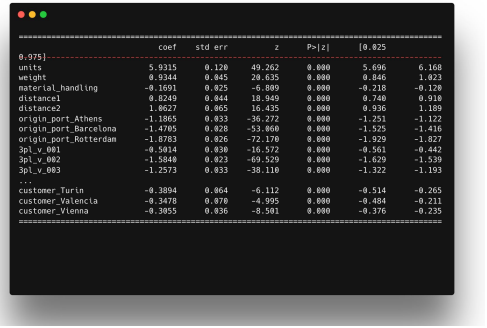
	coef	std err	z	P>|z|	[0.025	0.975]
units	5.9315	0.120	49.262	0.000	5.696	6.168
weight	0.9344	0.045	20.635	0.000	0.846	1.023
material_handling	-0.1691	0.025	-6.809	0.000	-0.218	-0.120
distance1	0.8249	0.044	18.949	0.000	0.740	0.910
distance2	1.0627	0.065	16.435	0.000	0.936	1.189
origin_port_Athens	-1.1865	0.033	-36.272	0.000	-1.251	-1.122
origin_port_Barcelona	-1.4705	0.028	-53.060	0.000	-1.525	-1.416
origin_port_Rotterdam	-1.8783	0.026	-72.170	0.000	-1.929	-1.827
3pl_v_001	-0.5014	0.030	-16.572	0.000	-0.561	-0.442
3pl_v_002	-1.5840	0.023	-69.529	0.000	-1.629	-1.539
3pl_v_003	-1.2573	0.033	-38.110	0.000	-1.322	-1.193
...						
customer_Turin	-0.3894	0.064	-6.112	0.000	-0.514	-0.265
customer_Valencia	-0.3478	0.070	-4.995	0.000	-0.484	-0.211
customer_Vienna	-0.3055	0.036	-8.501	0.000	-0.376	-0.235



Use cases

Model Explainability





	coef	std err	z	P>|z|	[0.025
0.975]					
units	5.9315	0.120	49.262	0.000	5.696
6.168					
weight	0.9344	0.045	20.635	0.000	0.846
1.023					
material_handling	-0.1691	0.025	-6.809	0.000	-0.218
-0.120					
distance1	0.8249	0.044	18.949	0.000	0.740
0.910					
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3pl_v_003	-1.2573	0.033	-38.110	0.000	-1.322
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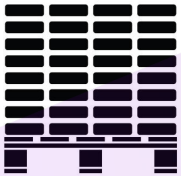
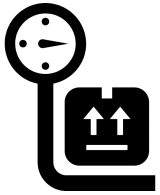


Units is the ***root cause*** that most affect to **delays**

Distance **Logistical hub - customer destination** is **more critical** than Distance from origin - Logistical hub



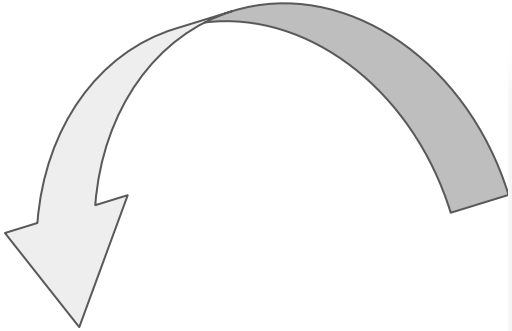
Package **weight** is the **3rd cause** of delays

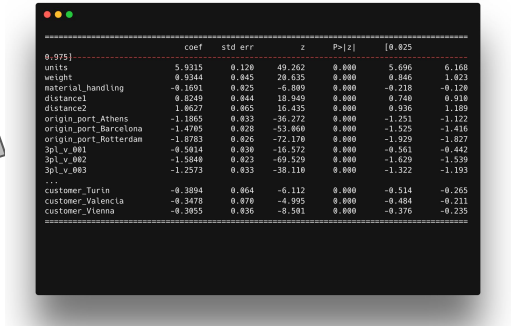
Rotterdam is the **most confident** logistic hub and Athenes the worst

👍 **Rotterdam** 😓 **Rotterdam**

Use cases

Model Explainability





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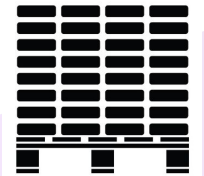
Third party logistic company	RANKING
V_002	1
V_003	2
V_001	3

TOP 3 - 3rd party logistic companies that provide better solutions against delays

Conclusions

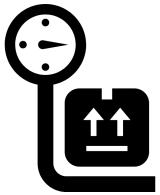
How those insights can be translated to business actions and value proposition?

Dealing with root causes …



Try to optimize of units deliveries and control packages where amount of units is elevated

Try to optimize* and track units deliveries in logic hub and between final destination



Try to optimize weight in packages by offering customers better solutions

Try to perform Athenes logic hub KPI or try to move location or reorganize it

Conclusions

How those insights can be translated to business actions and value proposition?

*** We would propose to place new logistic hubs on locations based on top destinations, in order to optimize CO2 emissions and shipment distance.**

Thank you 4 your attention !

Repository is available to check it out (⭐ are welcomed ! :))

https://github.com/bcatala/Datathon