ReAL

Use Cases

ORS GROUP
APPLIED A.I.

Case study #1
The impact of ORS ReAL for our customers

FASHION COMPANY USE CASE

Context

- Fashion company – 1 billion € revenues
- Network KPIs
  - 297 Stores (retail, outlet, web)
  - 2 Distribution Centers

Problem Complexity

3.5 millions of SKU/store combinations

The starting Point

- Global fashion company with increasing lost sales

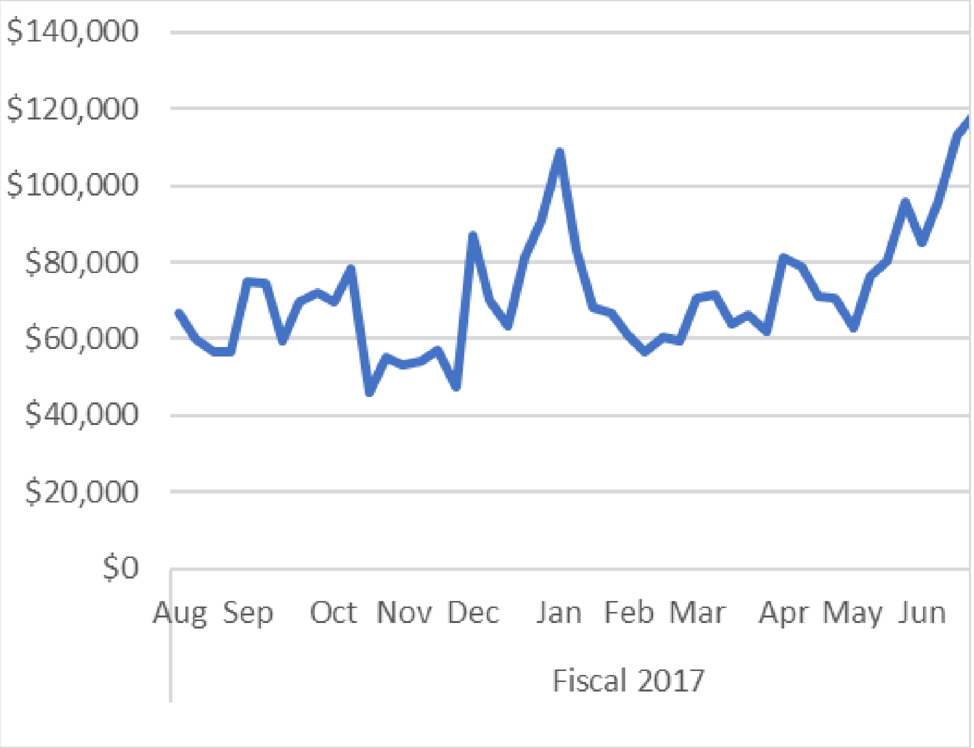
Main Results

- **-87% Lost Sales**
- **-7% Average STOCK**

THE IMPACT OF ORS ReAL – *Situation Before*

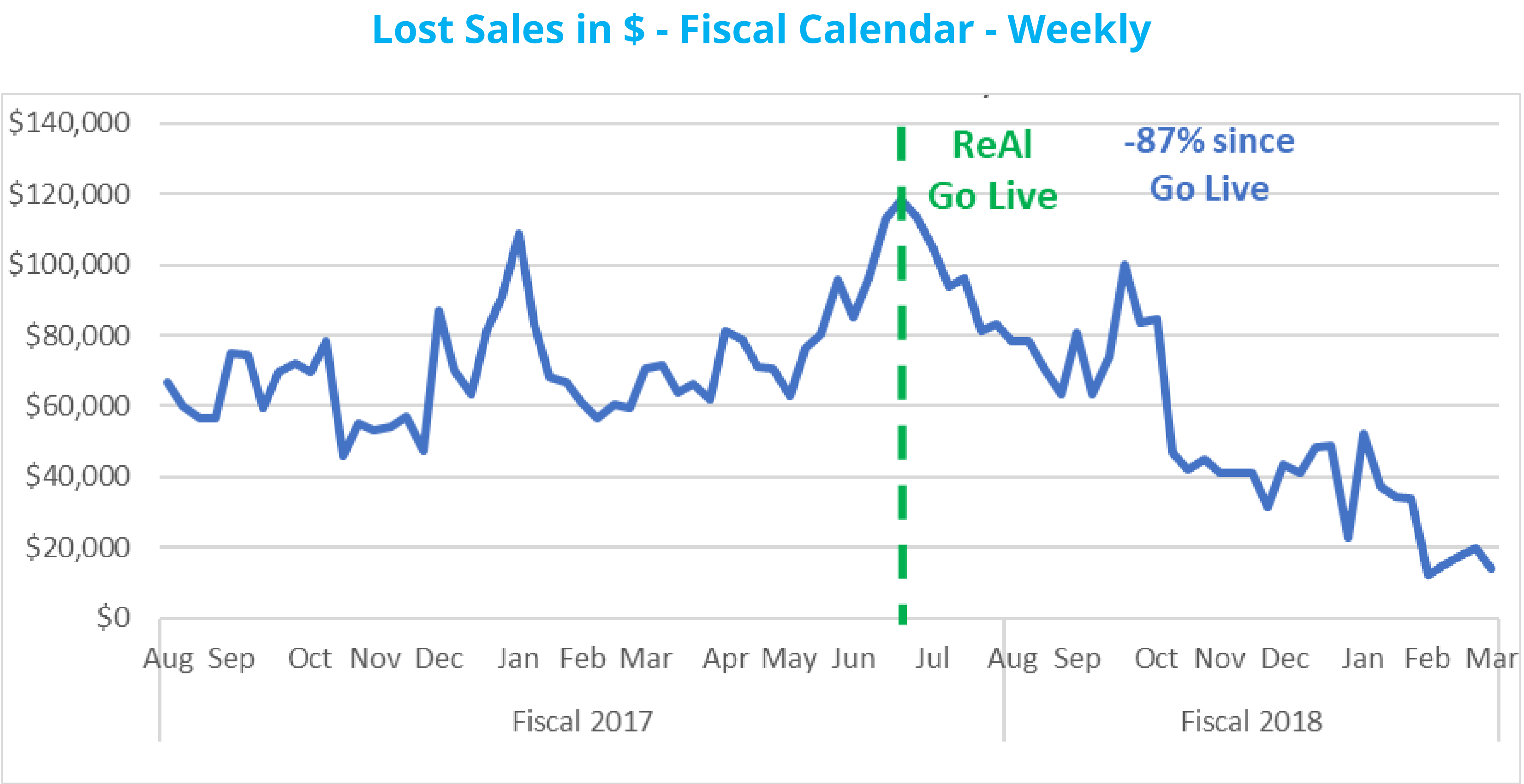
Situation Before ReAL Implementation: Fashion retail company with an increasing trend of lost sales

Lost Sales in $ - Fiscal Calendar - Weekly

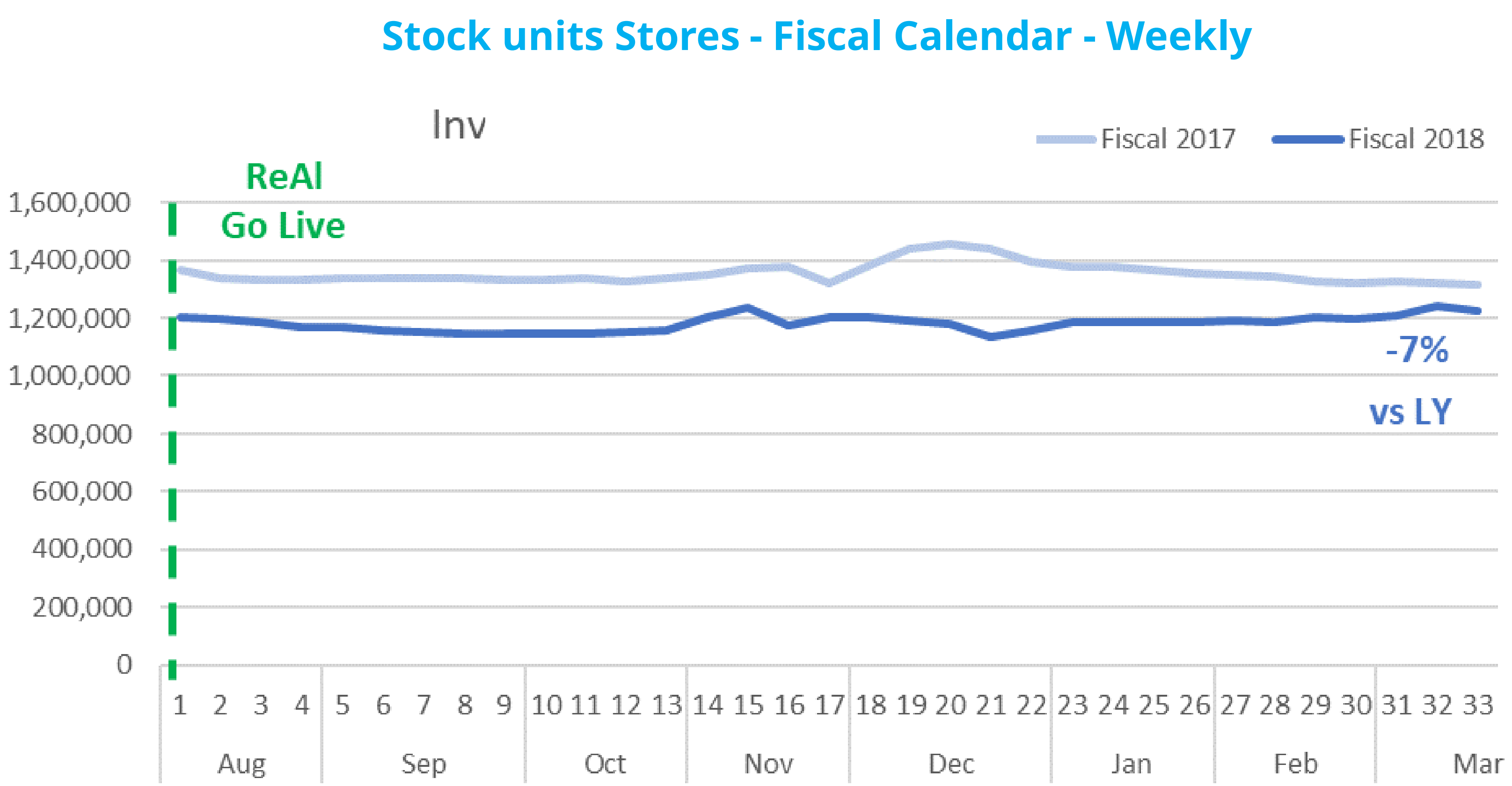


THE IMPACT OF ORS ReAL – *Situation After*

Applying ORS ReAL



THE IMPACT OF ORS ReAL – *Situation After*



Case study #2
The impact of ORS ReAL shown in a PoC

LUXURY COMPANY USE CASE

Context

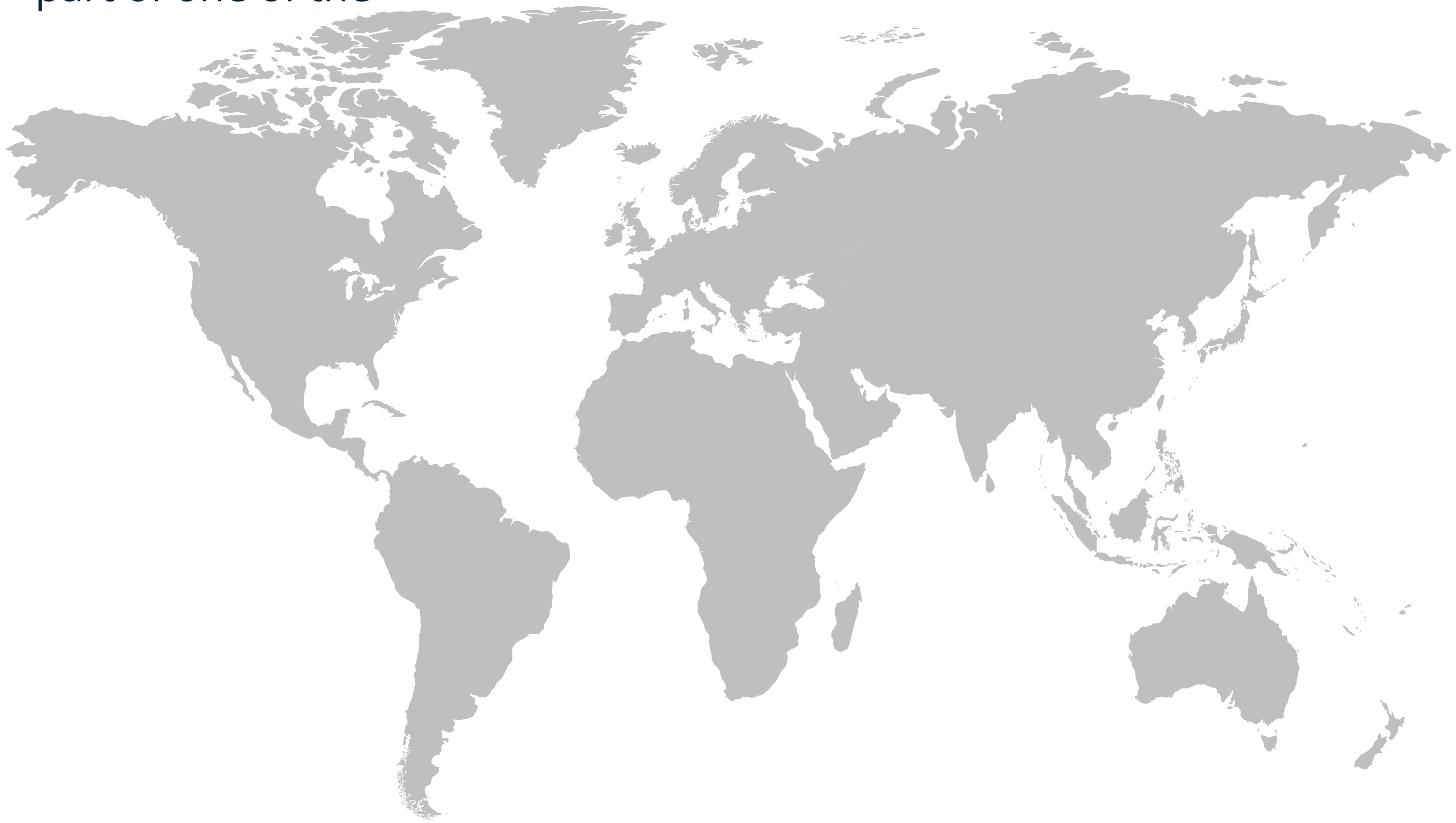
- Italian luxury brand (1 billion € revenues) - part of one of the leading global fashion group
- Network KPIs:
  - 208 Stores globally
  - 163 items
  - 1 Central Warehouse

Problem Complexity

7,605 Store-SKUs combinations

Results

-30% Average STOCK
-20% Out of Stock



THE DATASET

Dataset Description

- Inventory and sales history (weekly data) of 163 products in 208 stores from 2016 used before the simulation time window.
- Inventory warehouses history (weekly data) from 2016.
- In transit quantity (weekly data) from DC to stores from 2016.
- Products sales history used before the experiment.
- Simulation horizon = validation period = last 6 months (from Oct 2018 to March 2019)
- Allocation map: 7605 store-SKU combinations.

Missing Data

Products hierarchy or classification.

THE APPROACH

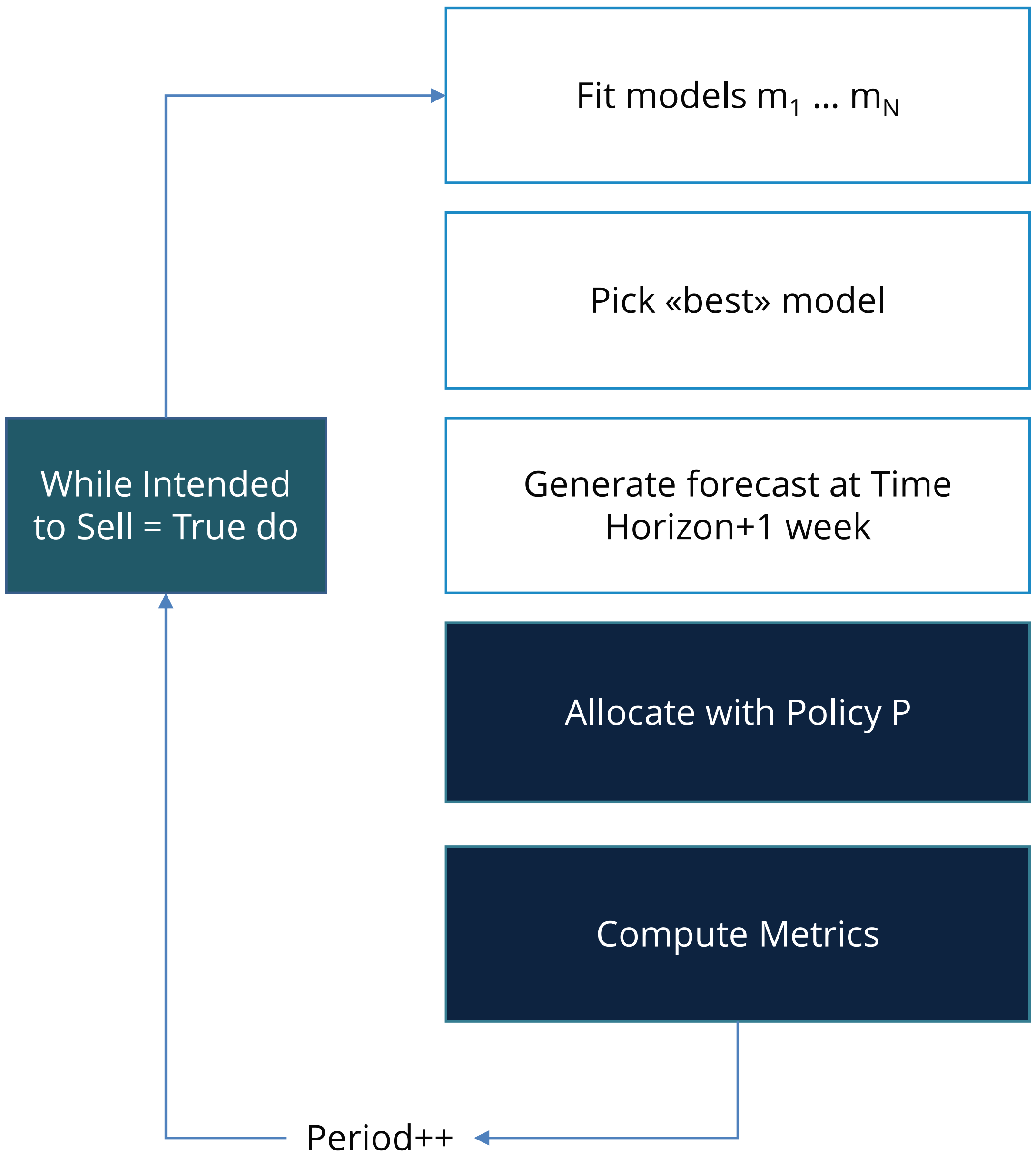
1. **Learning Phase** - The forecast algorithm is trained over a period in the past.

2. **Benchmark Phase -** The allocation and replenishment algorithm ran in a *production mode* over a benchmark period (year, season, etc...).

3. **Results** - ORS results are then compared with customer's real past data.

The tool helps:

- To understand the results and the goodness of the allocation model.
- To test the stability and robustness of the allocation model.
- To calibrate the set of parameters.



THE RESULTS

For all the SKU@Store combinations with low sales volume in the last six months:

	O.R.S. Simulation	Actual Stock	Absolute Difference	Percentage Difference
Average Stock (Units)	[illegible]	[illegible]	[illegible]	-30.50%
Out Of Stock (NWeeks)	[illegible]	[illegible]	[illegible]	-7.50%

For all the SKU@Store combinations with high sales volume in the last six months:

	O.R.S. Simulation	Actual Stock	Absolute Difference	Percentage Difference
Average Stock (Units)	[illegible]	[illegible]	[illegible]	-30.00%
Out Of Stock (Nweeks)	[illegible]	[illegible]	[illegible]	-34.00%

Based on these figures, and on ORS demand forecast a **reduction in lost sales of 50%** was estimated