Planning cosmetics production with an AI predicting and analysing workload

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The Issue

- The planning problem:
  - My performances as responsible of automation heavily depended on **smooth planning.**
  - Impossible yet because >50% of urgent and custom orders, great variability of products (>1000), large quantities (10s of thousands), no visibility in the future and little communication.
- My idea:
  - Understood that accurately **estimating lead times and workloads** of orders was critical to:
    - Allocate the optimal resources on each order (manpower, space, time).
    - Forecast and plan the workload of the workshop.
    - Quantify the impact of each parameter on productivity.
- Constraints:
  - Data and planning spread between different branches.
  - Only tech-oriented engineer, solution had to be **simple** and **explainable** to catch on.
  - Largest hurdle: accompany innovations department to support new 4.0 technologies (data, Python) → motivation for my current internship in data and strategy consulting.

Impact

- Direct results:
  - Optimize resource allocation to complete orders (7% productivity increase, no late deliveries).
  - Smooth globally production workload (from 70% variability to 10%).
  - **Increase machine utilisation** by 50%.
- Indirect results:
  - First clean and complete dataset for other logistics analysts.
  - Switch from push to just-in-time strategies.
  - Plan staffing weeks instead of days in advance.
  - Explain productivity of the workshop, anticipate crises and quantify pricing → Analyses/tracking.
  - Scientifically organize the workshop (**lean 6 sigma**).

My Model

Objective

LVMH Order data vector → lead time value

Regression algorithm (supervised)

The dataset

40k cleaned datapoints consolidated from the **workshop's 6-month history and LVMH.**

16 features about product, client & process

Categorical: Machine, country, actions required (labels, leaflet, cello)

Numerical: Product & label size, weight, quantity, number of tables and worker, seniority

The CatBoost algorithm

Why? Fast, suited for categorical and uneven data, widely used and well documented, handled missing and new data, **explanability** through shapley values

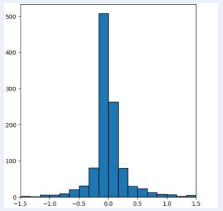
AI KPIs

$R^2 = 0.93$

RMSE = 12 min

<15% error 90% of the time

$\sigma \approx 0.18$ manhours



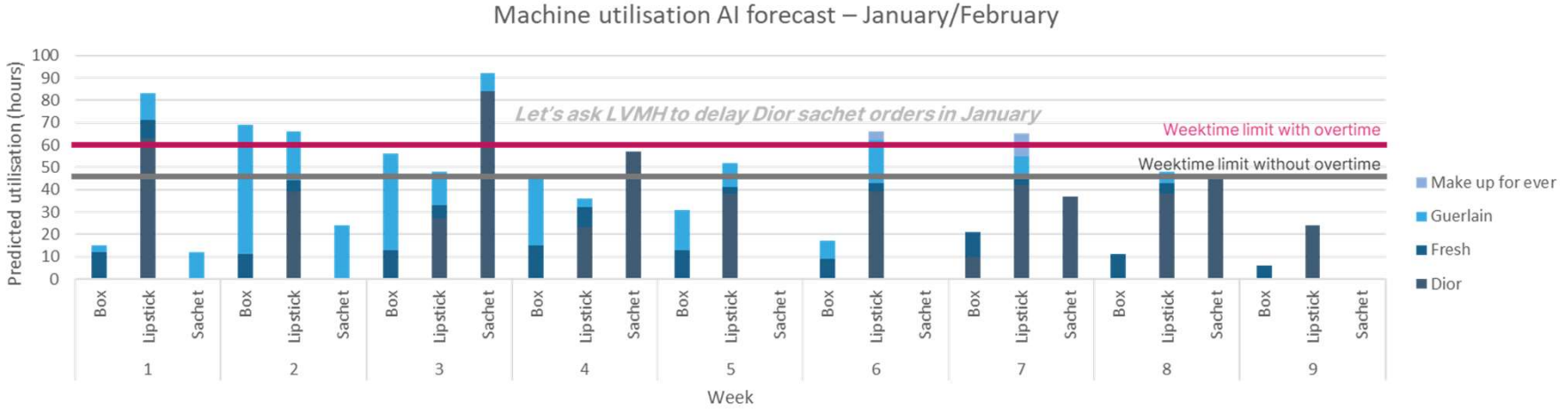
Lead time (hour) error frequency distribution

Adapted from November's monthly meeting

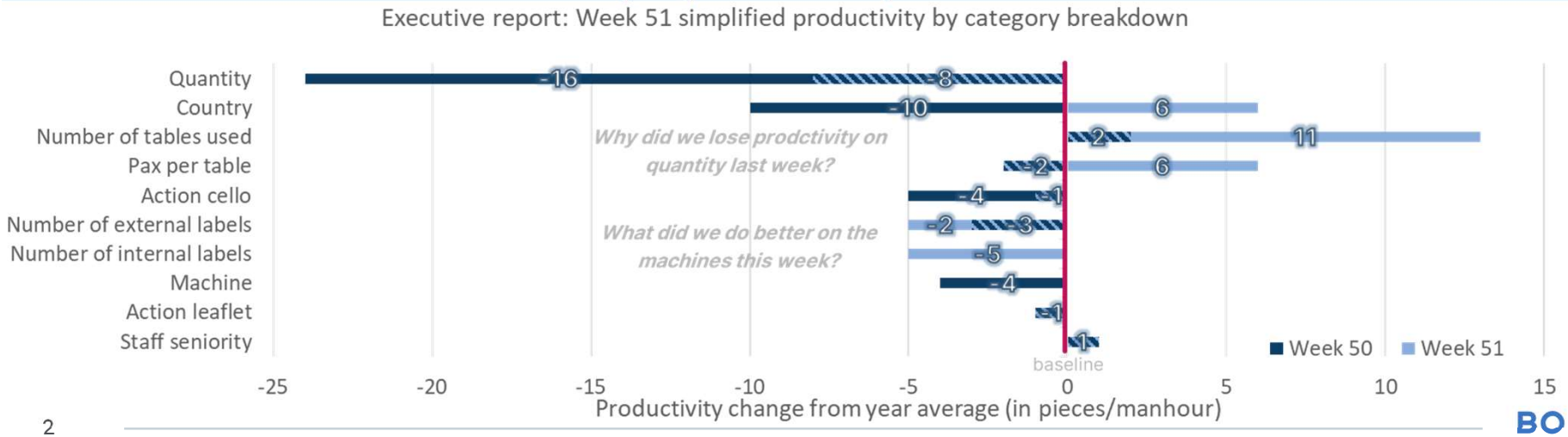
BOLLORÉ LOGISTICS

VAS AI Prediction

Machine planning for operations



Weekly insights for the management team



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