

# Employee Attrition Analysis at Salifort Motors

## Project Overview

This project analyzes the factors driving employee attrition at Salifort Motors and provides actionable insights for senior leadership and HR to improve satisfaction and retention. It also develops a logistic regression model to predict turnover and help identify employees most at risk of leaving.

## Key Insights

### GENERAL

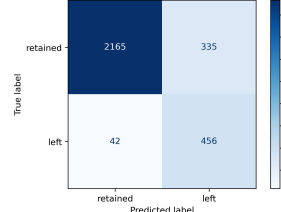
- The original dataset contained 14,999 employee records with 10 variables. After removing 3,008 were duplicates (20%), the analysis was performed on 11,991 unique employees.
- 16.6% of employees had left the company.
- Employees show **moderate satisfaction** on average (61%).
- **Workload is extremely high**, with an average of 200 hours per month.
- Only 2.1% of employees received a promotion in the last 5 years.
- Turnover appears **systematic across departments**, without any department-specific pattern.
- Some factors increase the odds of attrition:
  - ◆ Each **additional year of tenure** increases the odds of leaving by 67%.
  - ◆ Each **additional 50 hours worked per month** increases the odds by 84%.
- Several factors decrease the odds of attrition:
  - ◆ Moving to a **higher salary category** reduces the odds by 47%.
  - ◆ A **25% increase in satisfaction level** reduces the odds by 62%.
  - ◆ Having been **promoted in the last 5 years** appears to reduce the odds by around 75% (limited data).
- **Unequal system of promotion**: underperforming employees are as or more often recompensed than high performers.
- **Workload balance is critical**:
  - ◆ Employees with **3 projects** shows the lowest risk.
  - ◆ **2 projects or fewer**, as well as **6 projects or more**, strongly increase the risk of leaving.
- Distinct behavioral patterns appear in the data:
  - ◆ **3 patterns in satisfaction** among those who left.
  - ◆ **2 projects or fewer**, as well as **6 projects or more**, strongly increase the risk of leaving
  - ◆ Combined, these form **6 employees archetypes with different attrition risks** (shown on the right).

### MODELING

- Logistic regression was the model was chosen for its **interpretability, stability and overall good performance**
- The model was **optimized** (F2 score = 82%) to minimize the risk of losing an employee without seeing it coming, to a certain limit on the number of employees to make a follow-up.
  - ◆ This model **reduces by 73% the risk of an employee leaving without prevention**
  - ◆ **Implies a large involvement of HR** as the department will need to check on 26.38% of total employees considered at risk.
  - ◆ With this model, **only 8% will leave unnoticed**

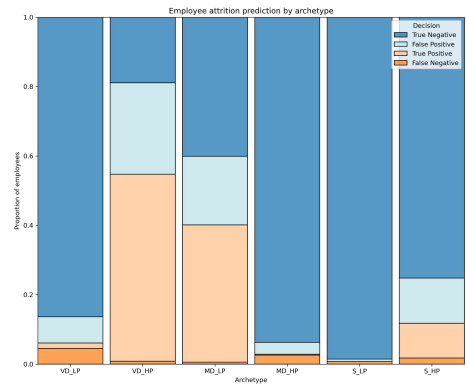
## Details

Confusion matrix of logistic regression model results on test data



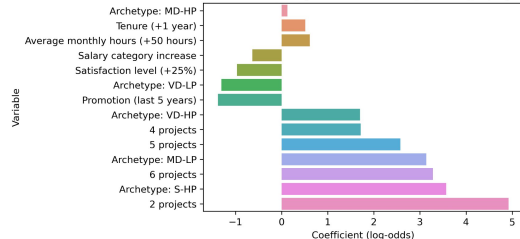
### ARCHETYPES

**VD\_LP** : Very dissatisfied and low performances  
**VD\_HP** : Very dissatisfied and high performances  
**MD\_LP** : Moderately dissatisfied and low performances  
**MD\_HP** : Moderately dissatisfied and high performances  
**S\_LP** : Satisfied to very satisfied and low performances  
**S\_HP** : Satisfied to very satisfied and high performances



- The graph above shows proportions within each archetype, not the actual size of each group in the workforce.
- The model successfully identifies the majority of VP\_HP and MD\_LP employees at risk of leaving. VP\_HP employees are particularly important for the company because they perform well and have the highest attrition rate. On the other hand, MD\_LP employees appear underutilized (fewer projects, fewer hours). Detecting them early then early gives HR a strong opportunity to retain them.
- S\_HP employees shows a surprisingly high departure rate. The model correctly flags most of them, but some still leave unnoticed. These are among the most experienced and valued employees, and understanding their reasons for leaving is essential.
- For the remaining archetypes (VD\_LP, MD\_HP and S\_LP) the model captures fewer clear patterns. In particular, VD\_LP employees appear already disengaged and may be less critical to retain compared to other groups.

Feature influences by coefficient value (excluding 7 projects)



## Next Steps

- **Address workload imbalance**  
Data shows that workload is a major driver of attrition. Employees with too few projects tend to disengage, while those with too many experience overload. Assigning **between 3 and 5 projects** appears optimal.
- **Improve performance-based rewards**  
Salary and promotion have a strong effect on retaining. The company should review its promotion policies and salary progression to ensure high-performing employees are consistently recognized and retained.
- **Investigate S\_HP departures more deeply**  
A significant portion of highly satisfied, high-performance employees still leave the company for reasons not fully captured by data. HR should conduct targeted interviews to understand what motivates these departures.
- **Integrate the predictive model into HR operations**  
If HR can handle follow-ups on a larger group of "at-risk" employees, this model reduces unnoticed departures substantially. We could determine the optimal intervention capacity of the HR team with a pilot phase
- **Explore other predictive models**  
While logistic regression offers interpretability, other models like Random Forest or XGBoost may improve prediction accuracy and would help to validate the robustness of the insights.