Capstone: AI-Powered Attrition Classifier

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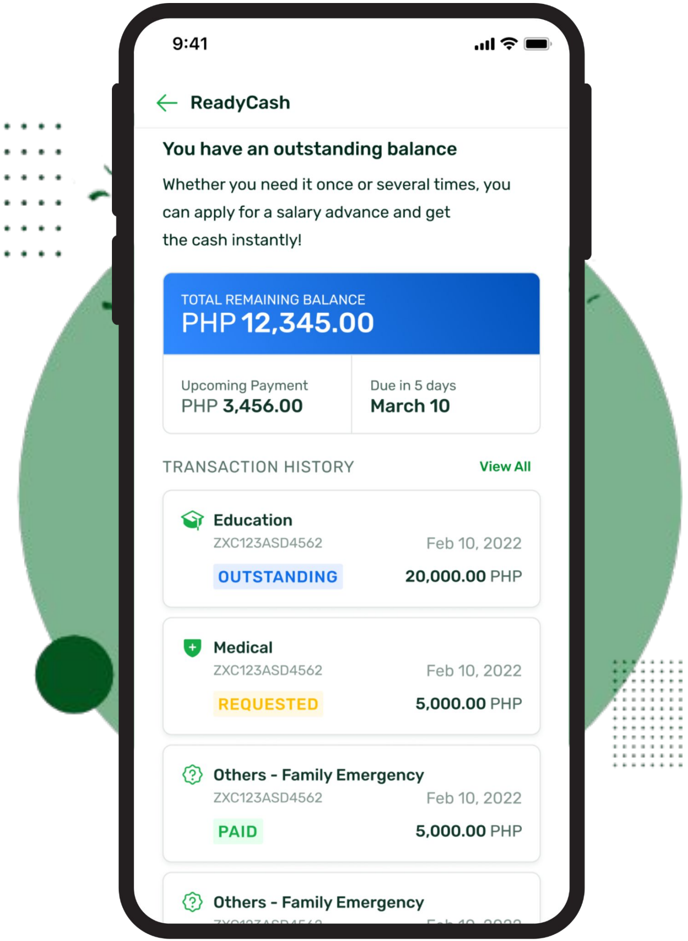
sprout SOLUTIONS

Overview

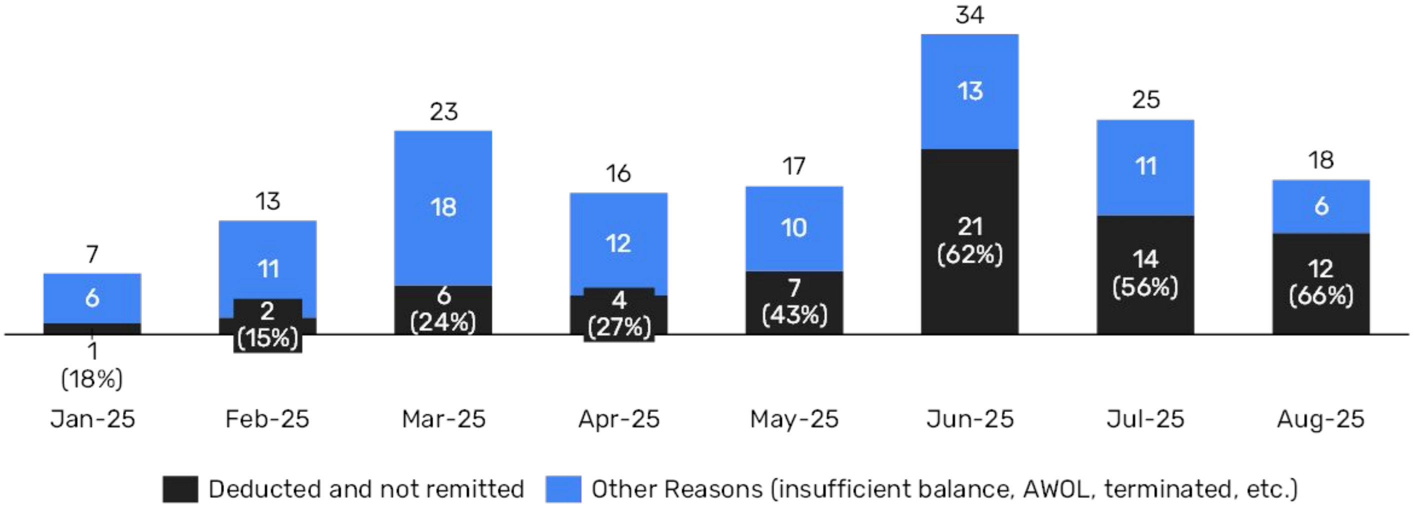
ReadyCash

Salary Advance solution providing your employees to **access emergency funds** when they need it most

1. **Immediate access to cash,** no delays or waiting periods between applications.
2. **Multiple applications** allowed within your existing credit limit, enabling flexibility
3. **Automatic payroll deductions** for sustainable and hassle-free repayments.



Problem: Non-Performing Loans have risen to >6% (goal is < 4%). 56% of NPLs are attrition-related while the rest are due to operational issues (which can still be collected)



How this happens

1) Employee uses ReadyCash

2) Employee resigns unexpectedly

3) Final pay is insufficient to cover loan payment

4) Loan becomes non-performing

Solution: AI-powered attrition classifier

MACHINE LEARNING MODEL

Predicts which employees are likely to resign **before** they apply for a loan

Model Accuracy

99.3%

Detection Rate

93%

Key Risk Indicators

- Job tenure and experience patterns
- Employee age and career stage
- Satisfaction survey responses
- Compensation competitiveness
- Promotion and growth trajectory

Solution: The classifier will be run during loan application. The available total loanable amount will then be adjusted based on the results.

LOW RISK

82% of employees

50%

of net pay

Up to: P50,000

MEDIUM RISK

4% of employees

35%

of net pay

Up to: P35,000

HIGH RISK

14% of employees

0%

of net pay

*****employee classification percentages are based on the open-source dataset used to train the model. We will have to repeat and slightly modify the training of the model using our actual data before we can test.**

Dataset Used: IBM HR Analytics Data from Kaggle

IBM HR Analytics - Cleaned & Merged Master

Data Card   Code (1)   Discussion (0)   Suggestions (0)

Content The dataset is comprised of 3 separate CSV files that covers 4,410 employees and includes demographic details, w

https://www.kaggle.com/datasets/aryanpatel212/ibm-hr-analytics-cleaned-and-merged-master

Dataset Details:

General: 4,410 rows × 24 cols Employee

Data: 4,410 rows × 4 cols

Manager Data: 4,410 rows × 3 cols

Merged Dataset: 4,410 rows × 29 cols

Total Employees: 4,410

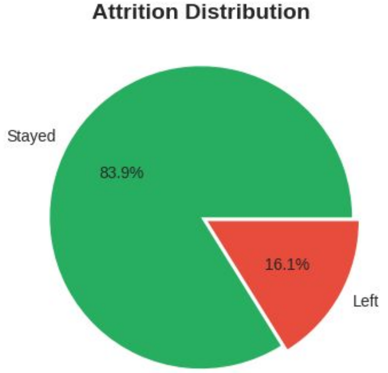
	Age	Attrition	BusinessTravel	Department	DistanceFromHome	Education	EducationField	EmployeeCount	EmployeeID	Gender	JobLevel
0	51	No	Travel_Rarely	Sales	6	2	Life Sciences	1	1	Female	1
1	31	Yes	Travel_Frequently	Research & Development	10	1	Life Sciences	1	2	Female	1
2	32	No	Travel_Frequently	Research & Development	17	4	Other	1	3	Male	4
3	38	No	Non-Travel	Research & Development	2	5	Life Sciences	1	4	Male	3
4	32	No	Travel_Rarely	Research & Development	10	1	Medical	1	5	Male	1

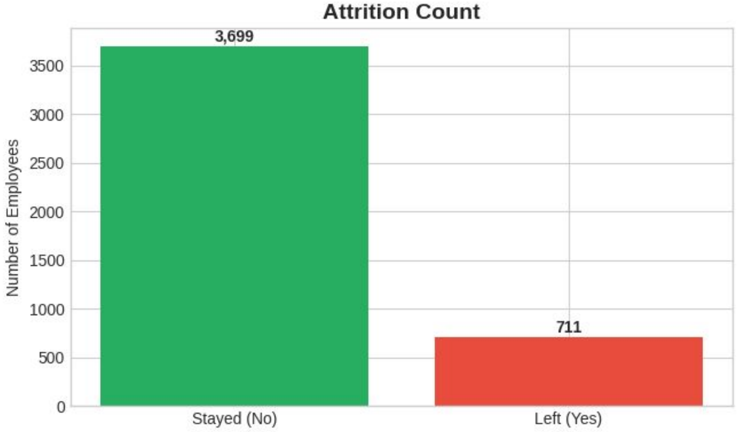
Understanding the goal - What are we trying to predict?

Key Question:

Did the employee leave the company? Based on the dataset

- YES - Attrited employee (potential source of NPL)
- NO - Employee stayed (loan can potentially be repaid





Key Insight:

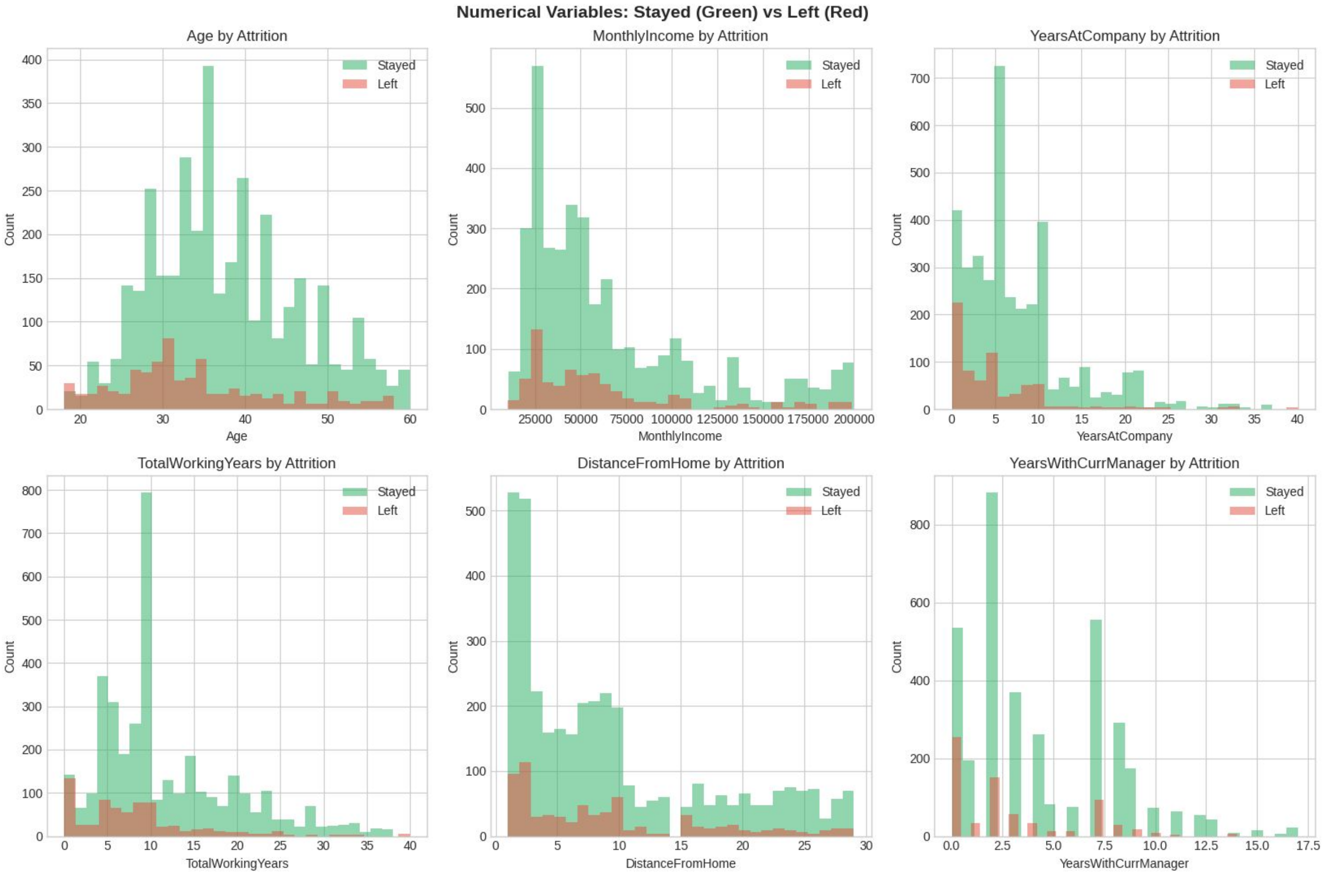
- Based on the data, only 16% of employees left. This is an imbalanced dataset. Furthermore:
  - A model predicting 'No' always would be 84% accurate.
  - I'll use 'class_weight=balanced' in the models to mitigate the imbalance.

EDA: Numerical Variable Distribution

Key Insights:

- YOUNGER employees tend to leave more
- LOWER income employees leave more often
- SHORT tenure employees leave more

Good insights but we need investigate more to determine how much of these influence attrition.

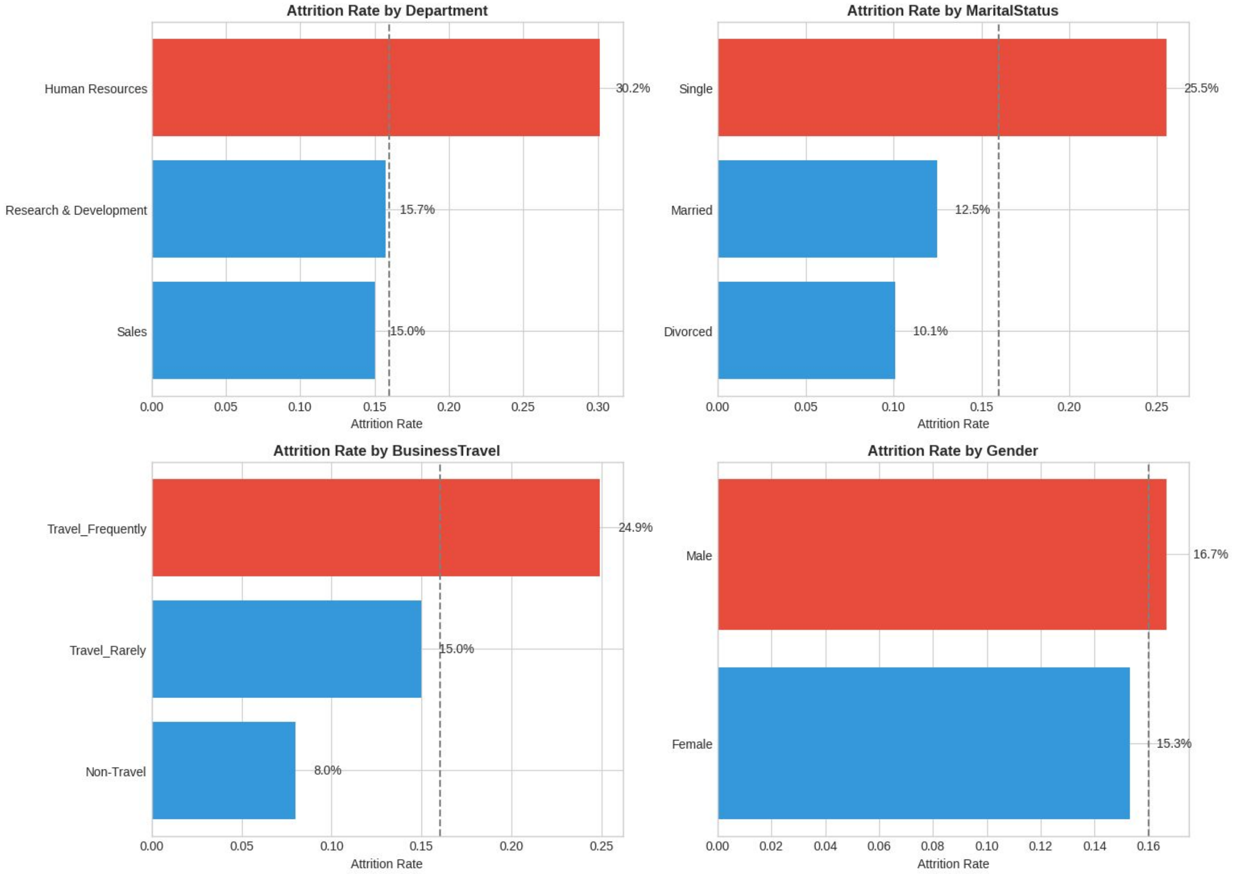


EDA: Categorical Variable Analysis

Key Insights:

- Human resources has highest attrition (30%!)
- Single employees leave at 26% vs 10-12% for married/divorced
- Frequent travellers leave more

Good insights but we need investigate more to determine how much of these influence attrition.

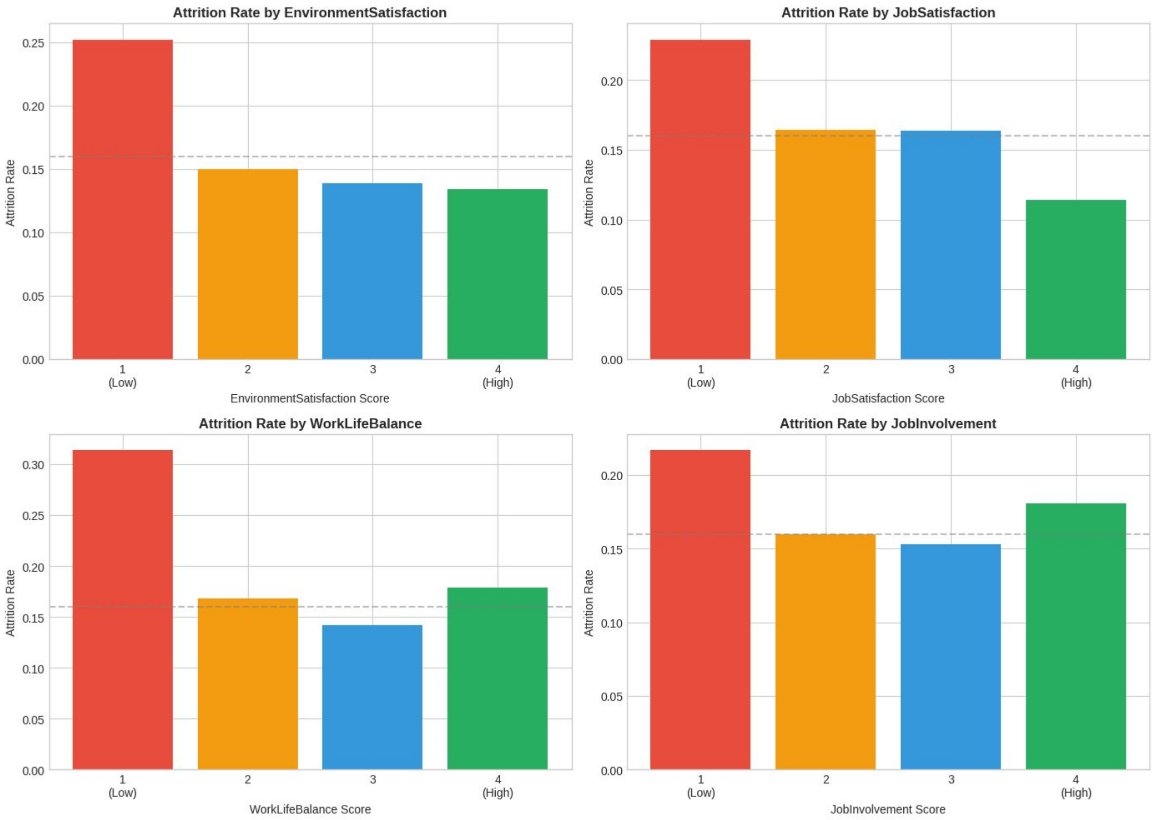


EDA: Analyzing survey scores

Key Insights:

- A discernible pattern emerged -> Lower satisfaction = higher attrition
- Score 1 → ~25% attrition | Score 4 → ~13% attrition

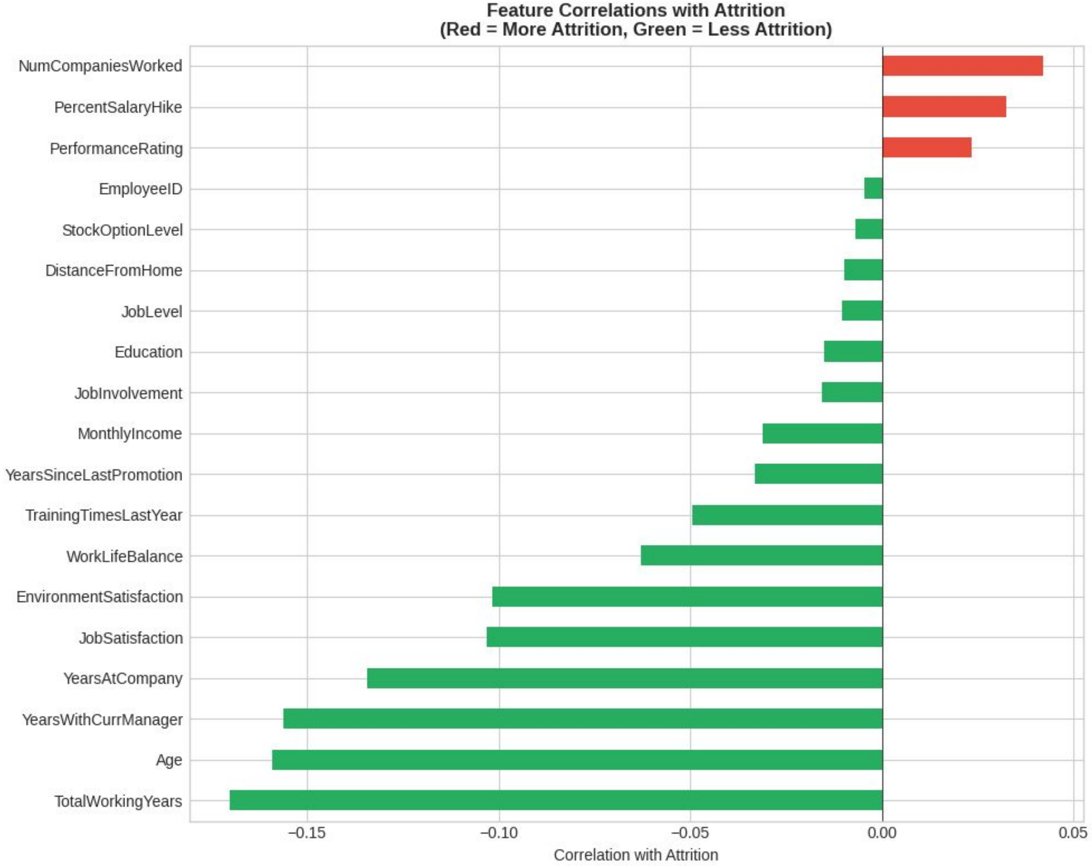
It looks like that the survey scores can be predictive of attrition. Again, we need to check how much do the scores influence attrition.



EDA: Feature correlation with attrition

Key Insights:

- I'd like to focus on the factors that reduce attrition (keep employees) rather than those that increase attrition (push employees out) as those have a larger correlation.
- The top 5 factors that reduce attrition:
  - Total working years
  - Age
  - Years with current manager
  - Tenure
  - Job satisfaction



Feature Engineering: Created new variables using the existing ones to better predict attrition.

New Ratio Features Created:

- Years Per Company - job-hopping indicator
- Promotion Rate - career growth
- Tenure Ratio - proxy for company loyalty
- Income Per Year Experience - pay competitiveness
- Overall Satisfaction - average of all satisfaction scores
- Job Engagement - Average of involvement and performance

New Groupings Created:

- Age Group - 18-25, 26-35, 36-45, 46-55, 56-65

New Binary Features Created:

- High Commute - distance > 15km)
- Low Satisfaction - any satisfaction ≤ 2
- Has Stock Option - has stock options
- Frequent Traveler - 1 for frequent travel, 0 for all else

One-Hot Encoding:

- 'BusinessTravel', 'Department', 'EducationField', 'Gender', 'JobRole', 'MaritalStatus', 'AgeGroup'

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Total Features

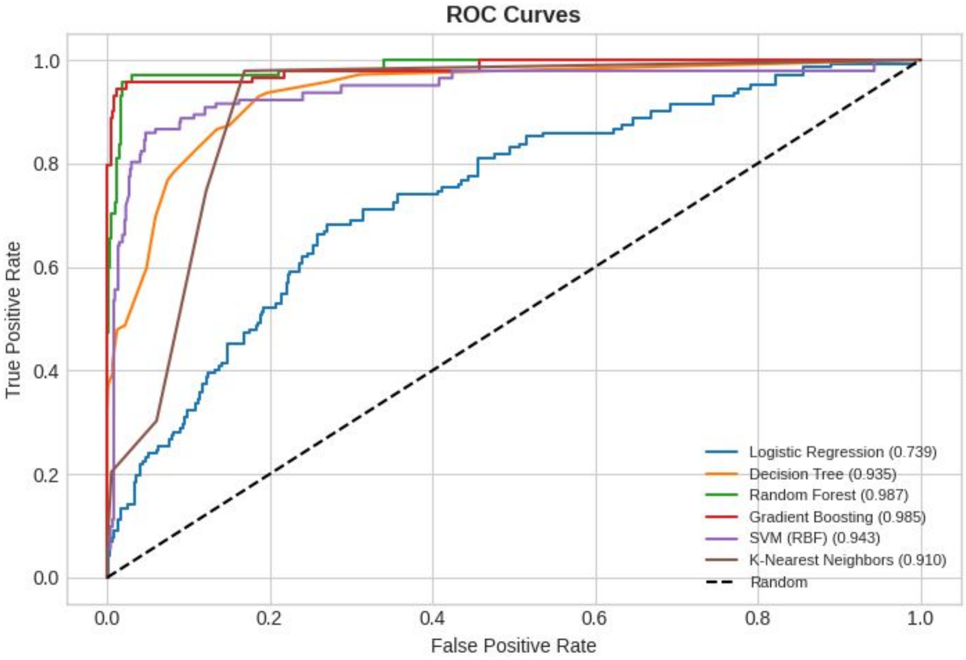
Model Creation and Comparison - 5 potential models were trained and performance compared.

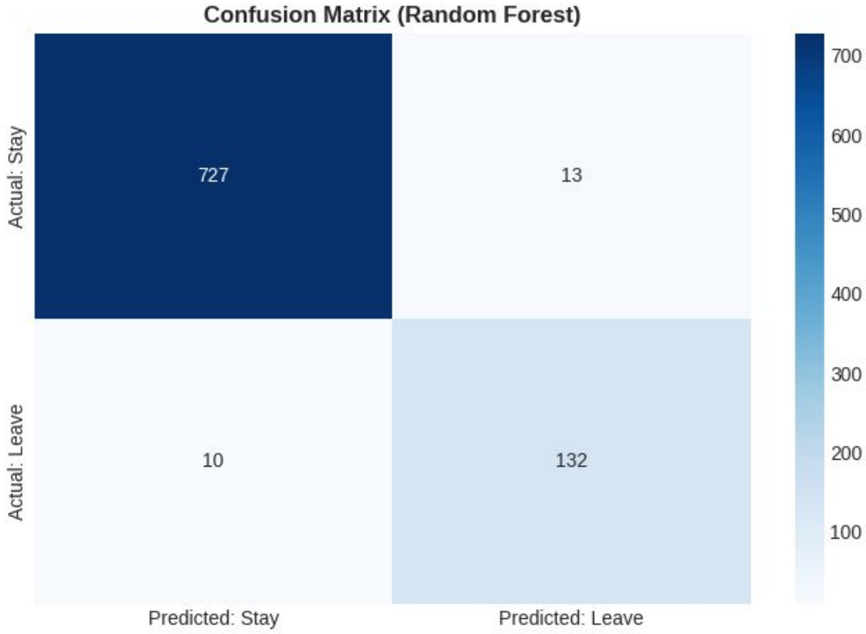
6 models:

- Logistic Regression: Baseline
- Trees: Given that there several features with potentially high correlation to attrition that can processed via if-then relationships, trees can be used.
  - Decision Tree
  - Random Forest
  - Gradient Boosting
- K-Nearest Neighbor - We can find clusters of similar employees and those can be used to determine attrition risk.

Model	Accuracy	Precision	Recall	F1-Score	AUC-ROC
Random Forest	0.973923	0.910345	0.929577	0.919861	0.986506
Gradient Boosting	0.959184	1.000000	0.746479	0.854839	0.984812
Decision Tree	0.865079	0.551570	0.866197	0.673973	0.935473
K-Nearest Neighbors	0.836735	0.488636	0.302817	0.373913	0.909759
Logistic Regression	0.717687	0.322259	0.683099	0.437923	0.738942

Model Creation and Comparison: Based on the highest AUC score and recall (need to make sure to catch high-risk employees), I chose Random Forest as the best model.





Sample model predictions - full predictions can be seen in the data_with_predictions.csv file in the results folder

Cells in orange are the actual attrition data from the dataset while the cells in teal are the predictions from the model.

Attrition	EmployeeID	MonthlyIncome	YearsPerCompany	JobEngagement	HighCommute	LowSatisfaction	FrequentTraveler	AgeGroup	Attrition_Probability	Risk_Category
No	1	131160	0.50	3.0	0	0	0	46-55	0.0731	Low
Yes	2	41890	6.00	3.0	0	1	1	26-35	0.7611	High
No	3	193280	2.50	3.0	1	1	1	26-35	0.1610	Low
No	4	83210	3.25	2.5	0	0	0	36-45	0.0941	Low
No	5	23420	1.80	3.0	0	1	0	26-35	0.1443	Low
No	6	40710	7.00	3.0	0	1	0	46-55	0.0933	Low
Yes	7	58130	1.67	3.5	0	1	0	26-35	0.9067	High
No	8	31430	3.33	3.5	1	1	0	26-35	0.2114	Low
No	9	20440	10.00	3.5	0	1	0	26-35	0.1172	Low
No	10	134640	3.00	3.0	0	1	0	18-25	0.1502	Low
No	11	79910	21.00	2.5	1	0	0	36-45	0.0313	Low

Bias and Fairness: The model treats different groups (age, gender, status) fairly.

Gender

Gender	Count	Actual Attrition	Predicted Attrition
Female	1764	0.1531	0.1627
Male	2646	0.1667	0.1674

Predictions for both groups are similar and if we compute for demographic party (min(m,f) / max(m,f), the result is 0.97. Using the 4/5 rule, we can say that the predictions are generally fair.

Age Group

Age	Count	Actual Attrition	Predicted Attrition
18-25	369	0.3577	0.3821
26-35	1818	0.1914	0.2008
36-45	1404	0.0919	0.0912
46-55	678	0.1150	0.1062
56-65	141	0.1702	0.1531

Predicted attrition is higher in younger employees. This reflects reality.

Marital Status

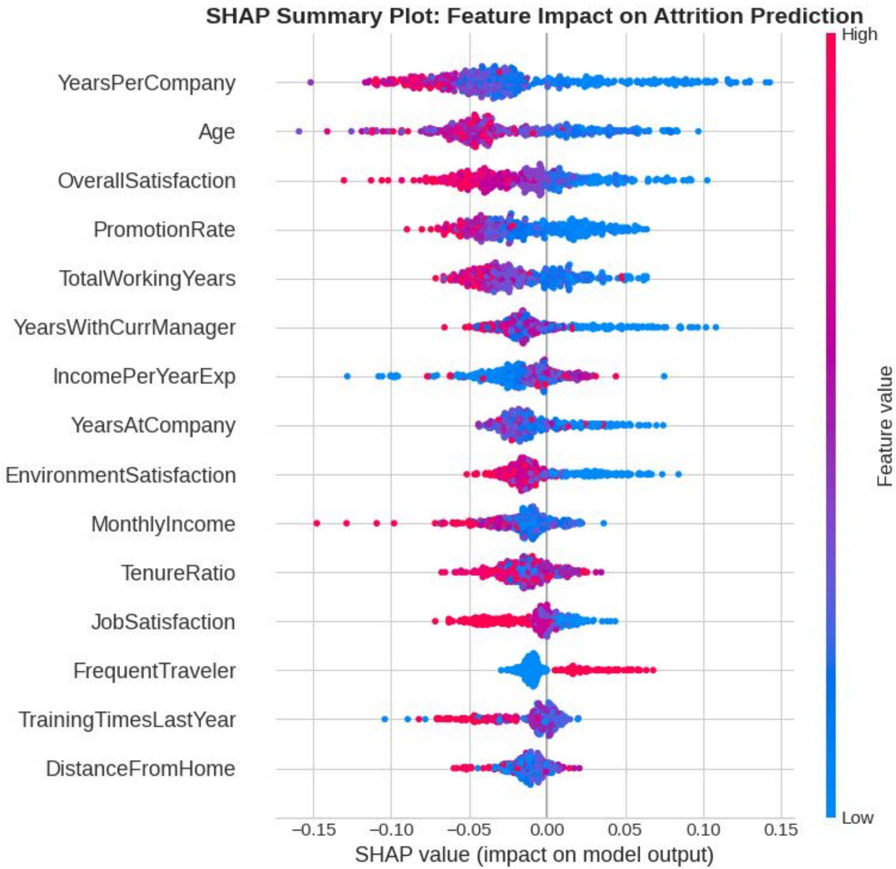
Status	Count	Actual Attrition	Predicted Attrition
Single	1410	0.2553	0.2596
Divorced	981	0.1009	0.1152
Married	2019	0.1248	0.1243

Predicted attrition is higher in younger employees. This reflects attrition patterns.

Model Explainability - SHapely Additive exPLanations (SHAP)

Key Insights:

- Years per company shows a “-” SHAP, meaning it decreases attrition probability. Furthermore, the red color shows a high feature value. Putting these together tells us that the model considers higher tenured employees to have lower attrition risk and vice versa.
- The Age SHAP plot shows a “+” SHAP, meaning it increases attrition probability. Furthermore, the blue color shows a low feature value. Putting these together tells us that the model considers younger employees to have higher attrition risk.
- You can look at the SHAP plots of the other features to see how the model predicts attrition using those features.



Model Explainability - Local Interpretable Model-agnostic Explanations (LIME)

Key Insights:

- Using LIME we can see that for individual employees, the factors that helped the model predict attrition is generally similar to those in SHAP plots.
- This consistency again, explains how the random forest model determines the prediction.

High-Risk: Employee ID 3483

Predicted probability:	96.8%
Top factors pushing toward attrition:	
↑ YearsPerCompany	+0.089
↑ TotalWorkingYears	+0.053
↑ YearsWithCurrManager	+0.052
↑ Age	+0.050
↑ YearsAtCompany	+0.048

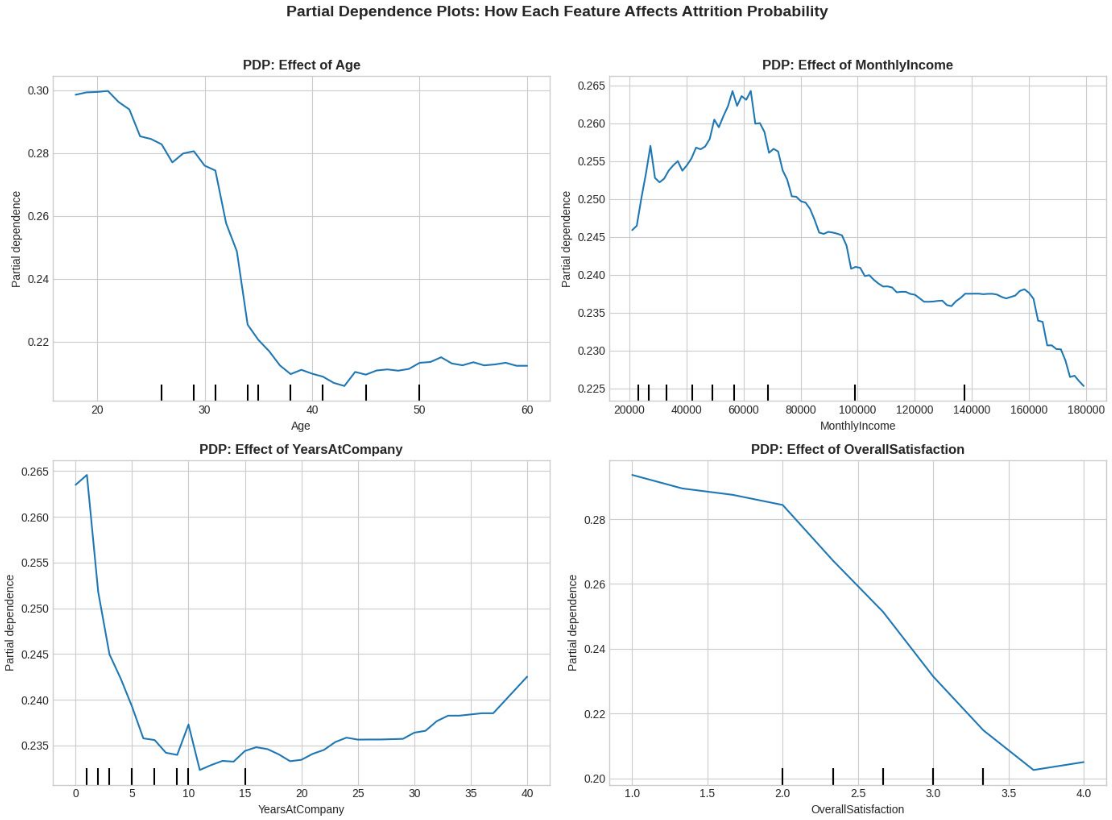
Low-Risk: Employee ID 494

Predicted probability:	1.3%
Top factors keeping the employee:	
↓ YearsPerCompany	-0.074
↓ PromotionRate	-0.053
↓ Age	-0.046
↓ TotalWorkingYears	-0.042
↓ OverallSatisfaction	-0.040

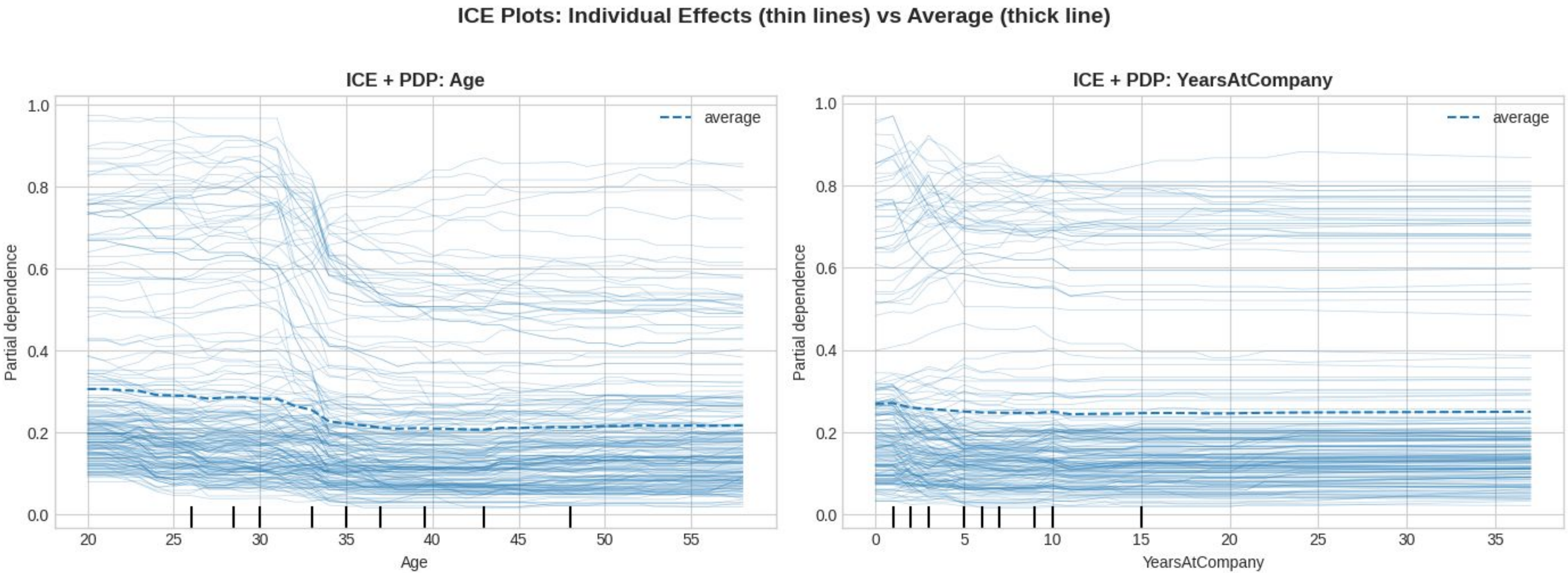
Model Explainability - Partial Dependence Plots (PDP)

Key Insights:

- Looking at the PDP's, we can see how the feature affect attrition probability.
- For Age and Tenure, we can see a sharp downward trend as the employee gets older or stays longer in the company. This means that attrition risk goes down as the values of both features increase.
- We can see the same trend in satisfaction. As satisfaction increases, attrition risk decreases - same as what we see in reality.
- While there is a sharp upward trend as in the Monthly Income PDP indicating higher attrition risk for a range of salaries, the line drops sharply past a certain point.
- Just like SHAP or LIME, PDP shows how the model uses the key features to come up with predictions.



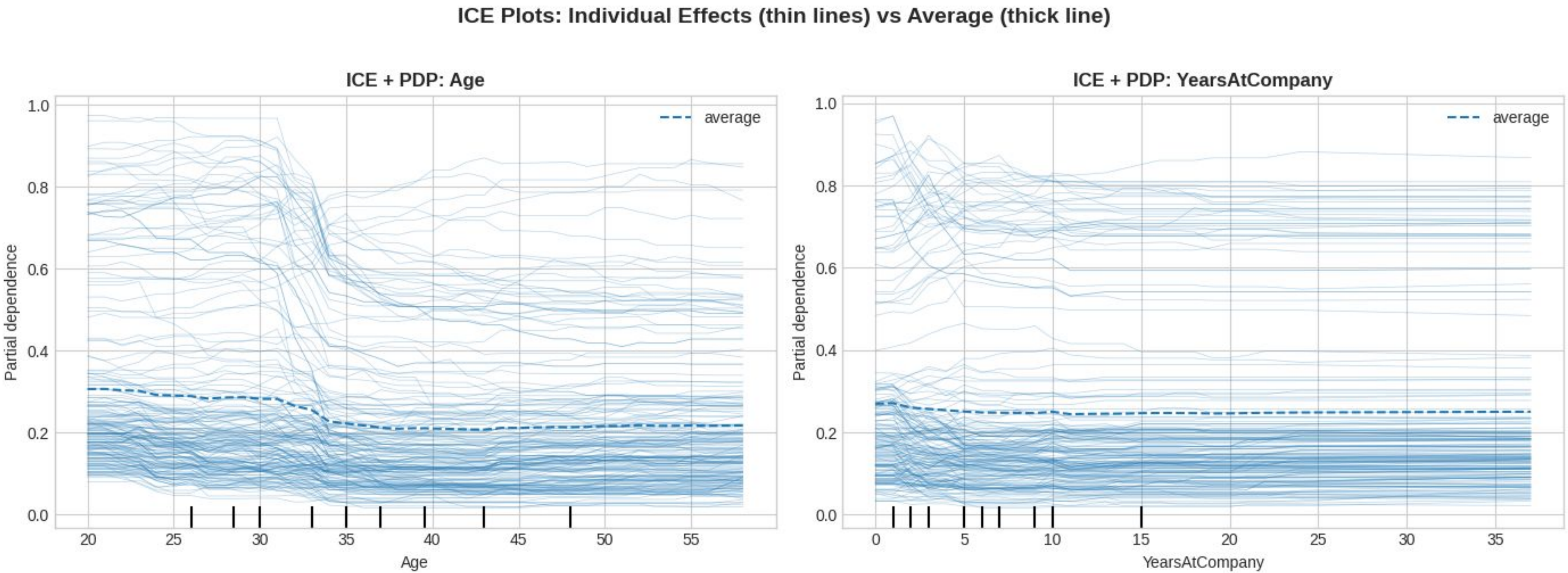
Model Explainability - Individual Conditional Expectation (ICE)



Key Insights:

- Despite some criss-crossing between 30-35 years (telling us that impact of age on attrition is not the same for everyone), the ICE lines are still generally parallel, meaning similar impact of attrition.
- For tenure, the ICE lines become extremely parallel past 5 years, indicating that impact of tenure on attrition is the same for all.

Model Explainability - Individual Conditional Expectation (ICE)



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Summary

AI model predicts employee attrition with 99% AUC-ROC

Based on the dataset - 636 high-risk, 184 medium-risk and, 3,590 low-risk employees were classified.

For now, we can use the risk classification to adjust the total loanable balance of an individual (100% for high, 50% for medium and 0% for low)

We would need to modify and rerun the training, evaluation pipeline using actual ReadyCash and Sprout data before we can run any POC