What causes employees to quit?

Agenda

1. Exploratory Data Analysis
2. Modelling and Evaluation
3. Discussion
4. Conclusion

Exploratory Data Analysis

EDA – data overview

```
> str(data)
'data.frame':   14999 obs. of  10 variables:
 $ satisfaction_level   : num  0.38 0.8 0.11 (
 $ last_evaluation      : num  0.53 0.86 0.88
 $ number_project       : int  2 5 7 5 2 2 6 5
 $ average_montly_hours : int  157 262 272 22
 $ time_spend_company   : int  3 6 4 5 3 3 4 5
 $ Work_accident        : int  0 0 0 0 0 0 0 (
 $ left                 : int  1 1 1 1 1 1 1 1
 $ promotion_last_5years: int  0 0 0 0 0 0 0 (
 $ sales                : Factor w/ 10 levels
 $ salary               : Factor w/ 3 levels '
```

```
> dim(data)
[1] 14999    10
```

```
> sum(is.na(data))
[1] 0
```

```
> attrition<-as.factor(data$left)
> summary(attrition)
    0     1
11428  3571
> perc_attrition_rate<-sum(data$left/length(data$left))*100
> print(perc_attrition_rate)
[1] 23.80825
```

- 15,000 employees
- 10 variables (features)
- No NaN values
- Turnover rate of 23.81%

EDA – transformation

Metrics for the employee population that left the company:

❑ Lower Satisfaction level, Higher # of Projects, and Higher # of Hours

```
> data.frame(table1)
  Category satisfaction_level last_evaluation number_project average_montly_hours time_spend_company Work_accident promotion_last_5years
1        0          0.6668096       0.7154734       3.786664             199.0602           3.380032    0.17500875           0.026251313
2        1          0.4400980       0.7181126       3.855503             207.4192           3.876505    0.04732568           0.005320638
```

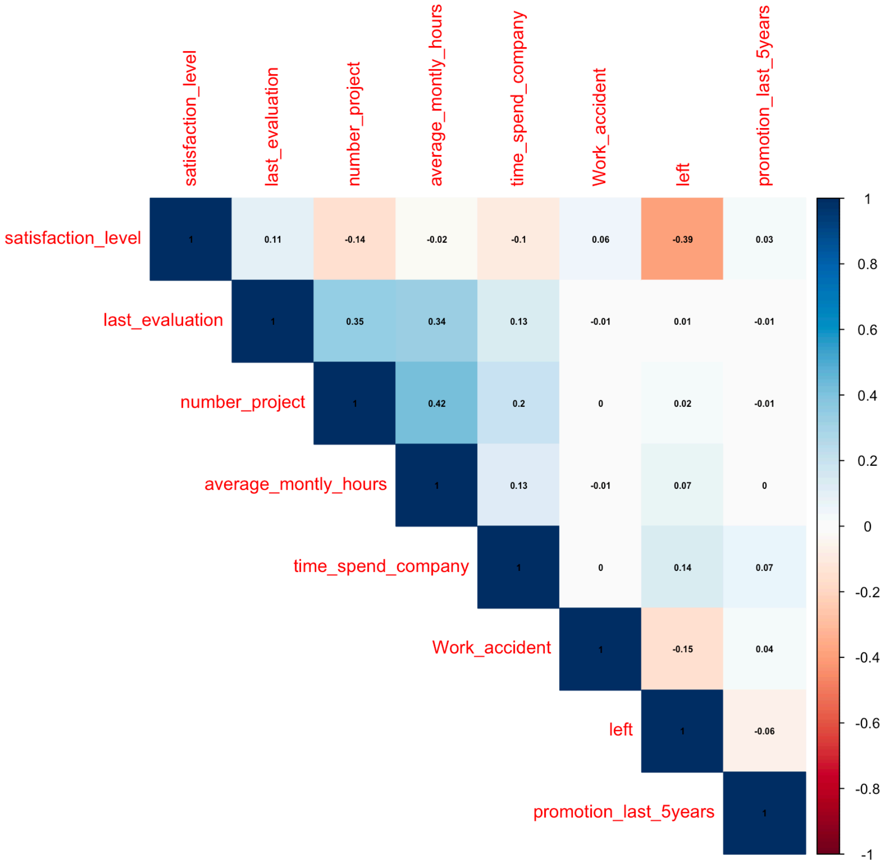
Created dummy variables for:

❑ Departments, and,

❑ Salary

```
> str(data2)
'data.frame':	14999 obs. of  19 variables:
 $ satisfaction_level   : num  0.38 0.8 0.11 0.72 0.37 0.
 $ last_evaluation      : num  0.53 0.86 0.88 0.87 0.52 0
 $ number_project       : num  2 5 7 5 2 2 6 5 5 2 ...
 $ average_montly_hours : num  157 262 272 223 159 153 24
 $ time_spend_company   : num  3 6 4 5 3 3 4 5 5 3 ...
 $ Work_accident        : num  0 0 0 0 0 0 0 0 0 0 ...
 $ left                 : num  1 1 1 1 1 1 1 1 1 1 ...
 $ promotion_last_5years: num  0 0 0 0 0 0 0 0 0 0 ...
 $ sales.hr             : num  0 0 0 0 0 0 0 0 0 0 ...
 $ sales.IT             : num  0 0 0 0 0 0 0 0 0 0 ...
 $ sales.management     : num  0 0 0 0 0 0 0 0 0 0 ...
 $ sales.marketing      : num  0 0 0 0 0 0 0 0 0 0 ...
 $ sales.product_mng    : num  0 0 0 0 0 0 0 0 0 0 ...
 $ sales.RandD          : num  0 0 0 0 0 0 0 0 0 0 ...
 $ sales.sales          : num  1 1 1 1 1 1 1 1 1 1 ...
 $ sales.support        : num  0 0 0 0 0 0 0 0 0 0 ...
 $ sales.technical      : num  0 0 0 0 0 0 0 0 0 0 ...
 $ salary.low           : num  1 0 0 1 1 1 1 1 1 1 ...
 $ salary.medium        : num  0 1 1 0 0 0 0 0 0 0 ...
```

EDA – correlation map



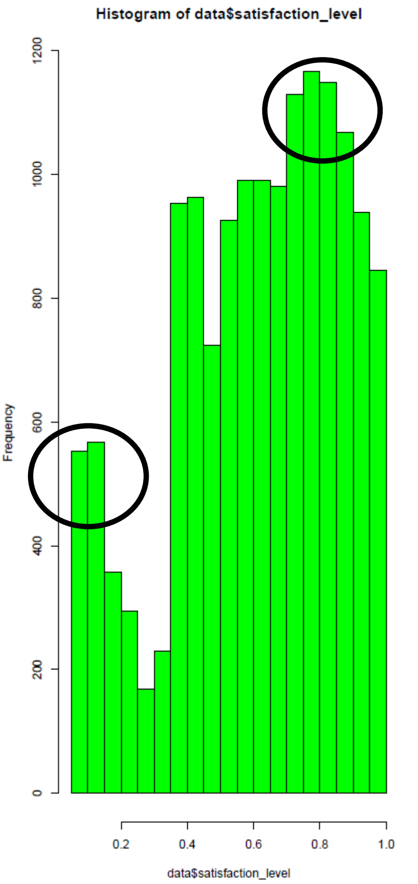
Positive correlation:

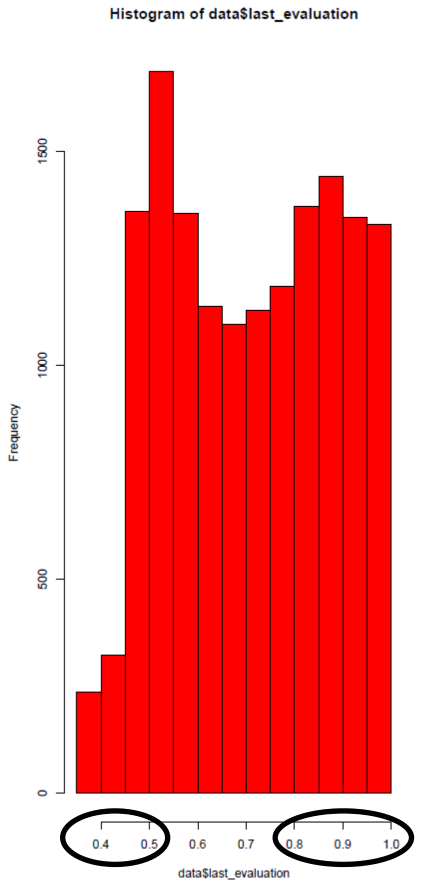
- Hours and Projects (0.42)
- Hours and Evaluation (0.34)
- Projects and Evaluation (0.35)

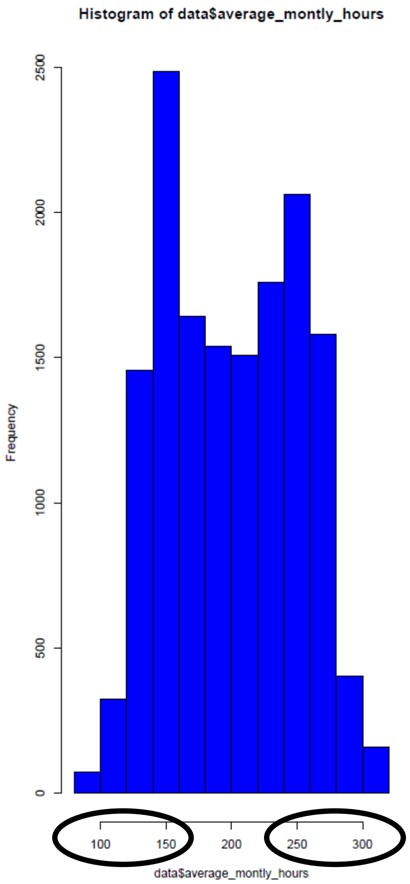
Negative correlation:

- Left and Satisfaction (-0.39)

EDA – Distribution







Satisfaction:

- ❑ Low spike
- ❑ High spike

Evaluation:

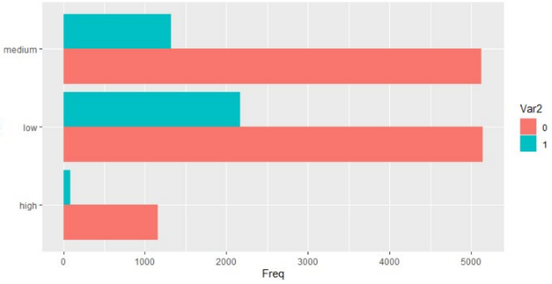
- ❑ Bimodal
  - <0.6
  - >0.8

Monthly hours:

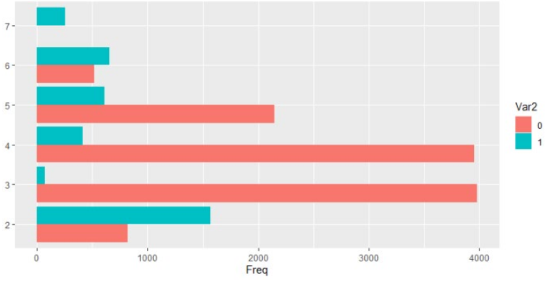
- ❑ Bimodal
  - <150
  - >250

EDA – variables and turnover

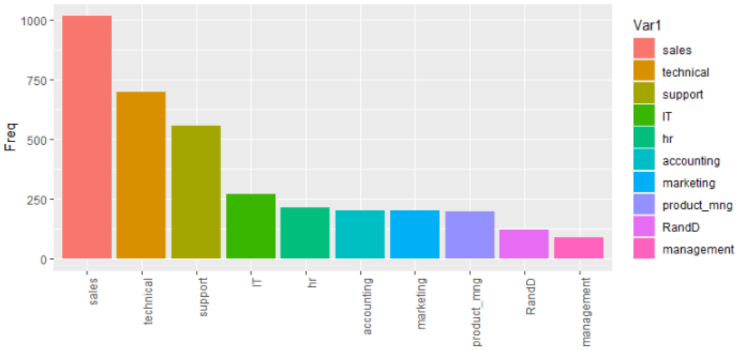
Salary vs. Turnover



Turnover vs. Project #



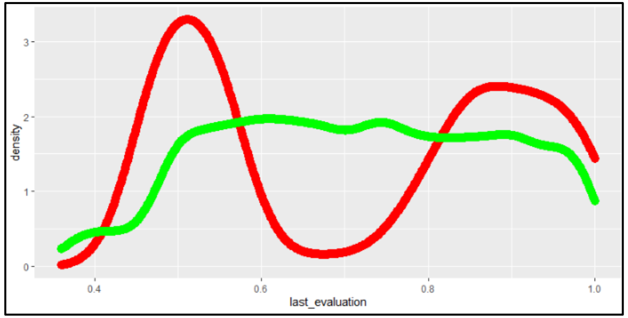
Turnover by Department



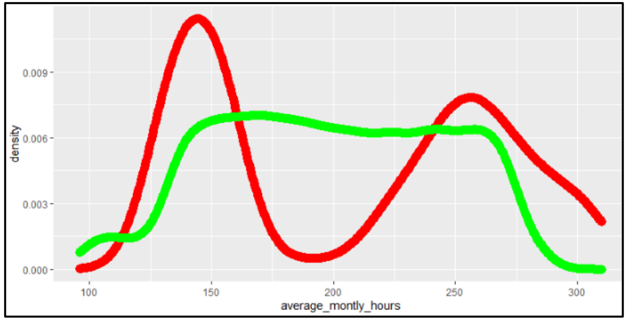
- ❑ Employees with low/avg salary leave
- ❑ Almost no one left with high salary
- ❑ All employees with 7 projects left
- ❑ Increase in turnover as project count increases
- ❑ Sales, technical, and support department have highest turnover
- ❑ Management has lowest turnover

EDA – Turnover Density

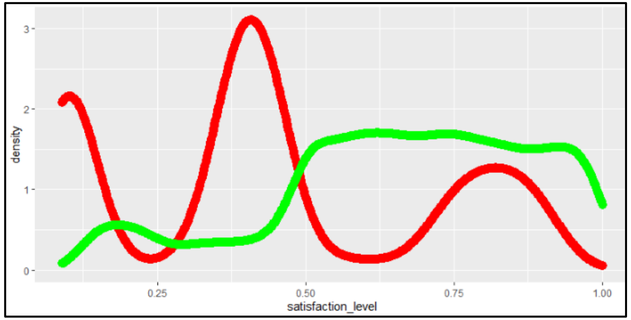
Turnover & Evaluation



Turnover & Hours



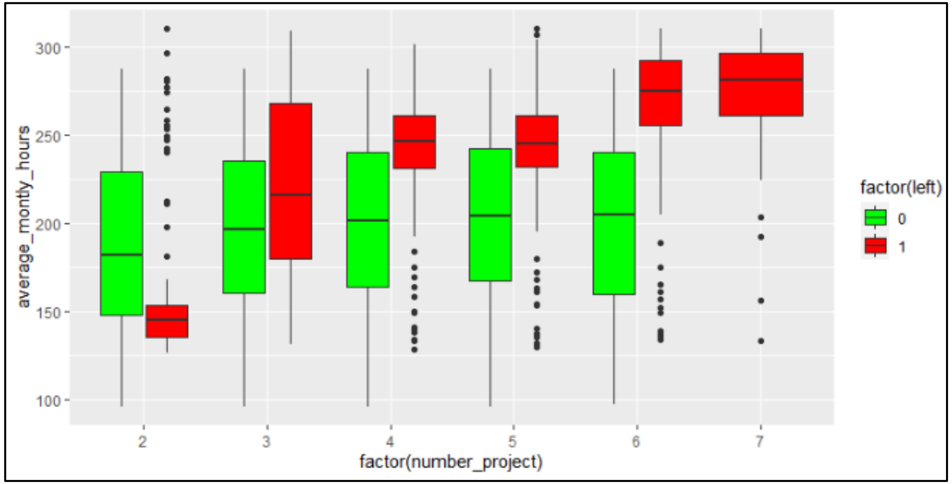
Turnover & Satisfaction



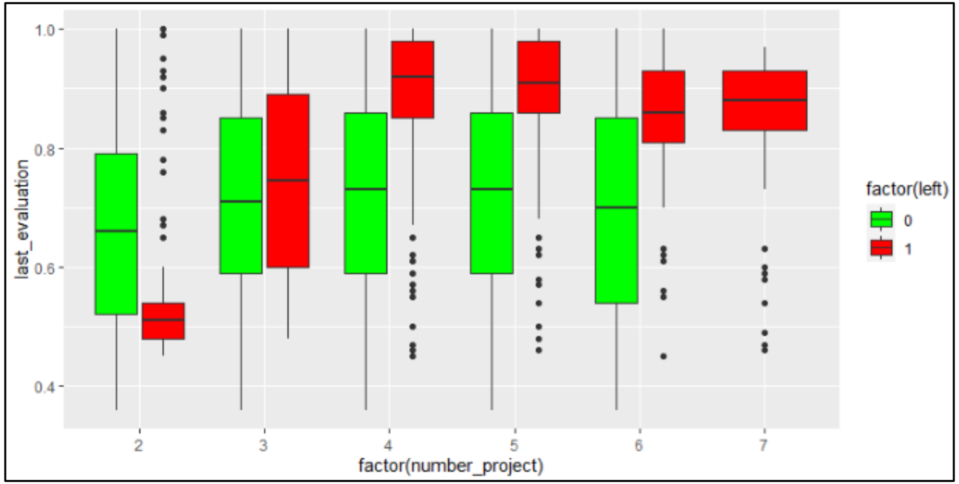
- ❑ Employees with low and high evaluation leave
- ❑ Employees with 0.6-0.8 stay
- ❑ Employees with hours<150 (underworked) and hours>250 (overworked) leave
- ❑ Employees who had 150-250 hours stay
- ❑ Employees with low satisfaction <0.2 and 0.3-0.5 leave
- ❑ Employees with high satisfaction (over 0.75) leave more than stay

EDA – Number of Projects

Projects & Hours



Projects & Evaluation

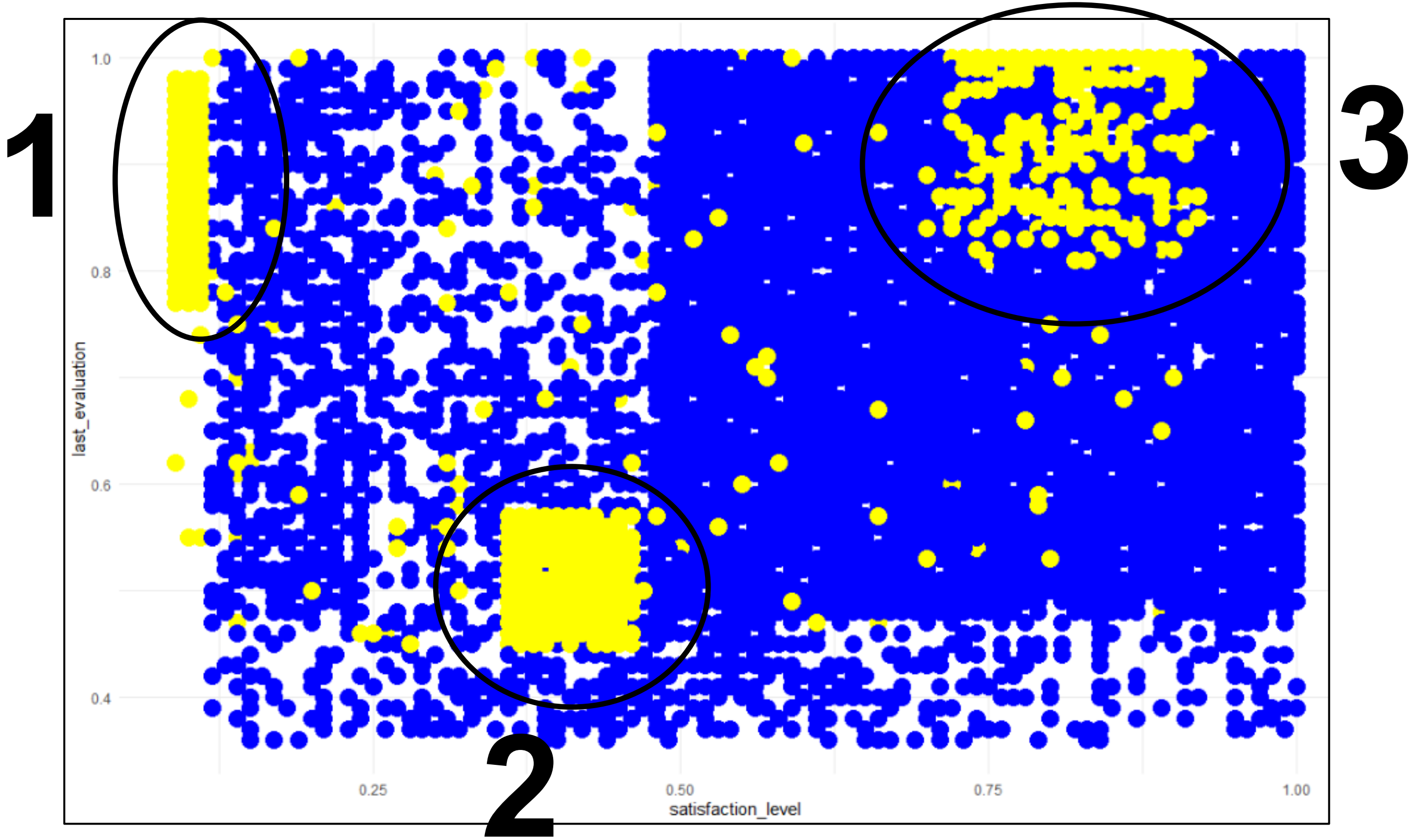


- ❑ Employees that stayed had 200 average hours, regardless of projects number
- ❑ Employees that left had increased hours as projects increased in count

- ❑ Employees that left with high project count had better evaluation (0.9)
- ❑ Employes that stayed had consistent evaluation (0.7) even when project count increased

EDA – Clusters

1. **Overworked:** Good workers (0.8-1), not satisfied (<0.2)
2. **Low Performers**: Poor workers(<0.6), not satisfied (0.3-0.5)
3. **Found new jobs**: Good workers (0.8-1), satisfied (0.7-1)



Modelling and Evaluation

Handle skewed data

Use random sampling
to reduce problem of skewed data

Data transformation

logistic regression & decision tree
based on 4 datasets

1 **Unbalanced**
target variable: **stay 76%** / **left 24%**
prediction maybe biased

2 **Upscaling**
repetitive sampling minority
no loss of information
possible overfitting because of repetition

3 **Downscaling**
decrease observations of majority
loss of information because of deletion

4 **Combine upscaling and downscaling**
upscaling minority
downscaling majority

Data structure and transformation

dataset	∆ left	∆ stay
both scaling	+4042	-3592
downscaling	0	-7857
upscaling	+7857	0
unbalanced	0	0

Logistic regression

```
Call:
glm(formula = left ~ ., family = binomial(link = "logit"), data = train2)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-3.1155  -0.8023  -0.1286   0.8532   2.6986

Coefficients:
                      Estimate Std. Error z value Pr(>|z|)
(Intercept)         -0.8354700  0.1417253  -5.895 3.75e-09 ***
satisfaction_level  -4.4710581  0.0831603 -53.764  < 2e-16 ***
last_evaluation      1.2074695  0.1339403   9.015  < 2e-16 ***
number_project      -0.4112927  0.0188218 -21.852  < 2e-16 ***
average_montly_hours 0.0043704  0.0004637   9.424  < 2e-16 ***
time_spend_company   0.4720184  0.0157744  29.923  < 2e-16 ***
Work_accident       -1.5171569  0.0660595 -22.967  < 2e-16 ***
promotion_last_5years -1.6378044 0.1929152  -8.490  < 2e-16 ***
saleshr              0.1829799  0.1080691   1.693   0.0904 .
salesIT             -0.1976384  0.0992580  -1.991   0.0465 *
salesmanagement     -0.6045804  0.1257290  -4.809 1.52e-06 ***
salesmarketing      -0.0262874  0.1061853  -0.248   0.8045
salesproduct_mng    -0.1625303  0.1047838  -1.551   0.1209
salesRandD          -0.4999757  0.1126530  -4.438 9.07e-06 ***
salessales          -0.1324757  0.0836440  -1.584   0.1132
salessupport         0.0095572  0.0893444   0.107   0.9148
salestechnical       0.0488175  0.0868779   0.562   0.5742
salarylow            1.9356937  0.0929182  20.832  < 2e-16 ***
salarymedium         1.4620357  0.0935297  15.632  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 25346  on 18283  degrees of freedom
Residual deviance: 18907  on 18265  degrees of freedom
AIC: 18945

Number of Fisher Scoring iterations: 5
```

Upscaling Example

Data Structure
total: 22856
left: 11428 (50%)
stay: 11428 (50%)
train/test = 4:1

Package & Function
ROSE package
ovun.sample()

Classification threshold
probability: 0.5

Coefficients by descending order
satisfaction level
low salary
promotion in last 5 years
work accident
medium salary
last evaluation

Decision Tree

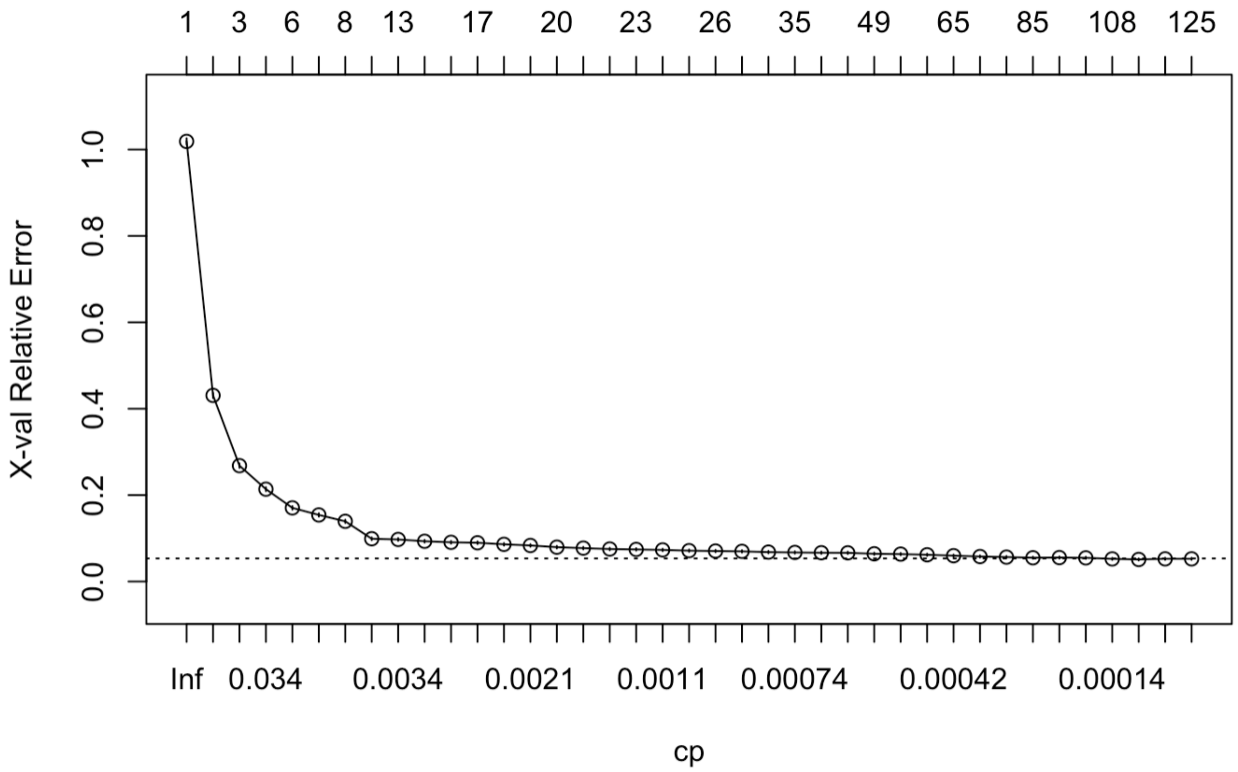
3 X 3 Trees

We build 9 decision trees in total, for each of the sampling method, we build the tree in 3 ways, then select the most satisfied one.

Under-Sampling | **Combined** | **Over-Sampling**

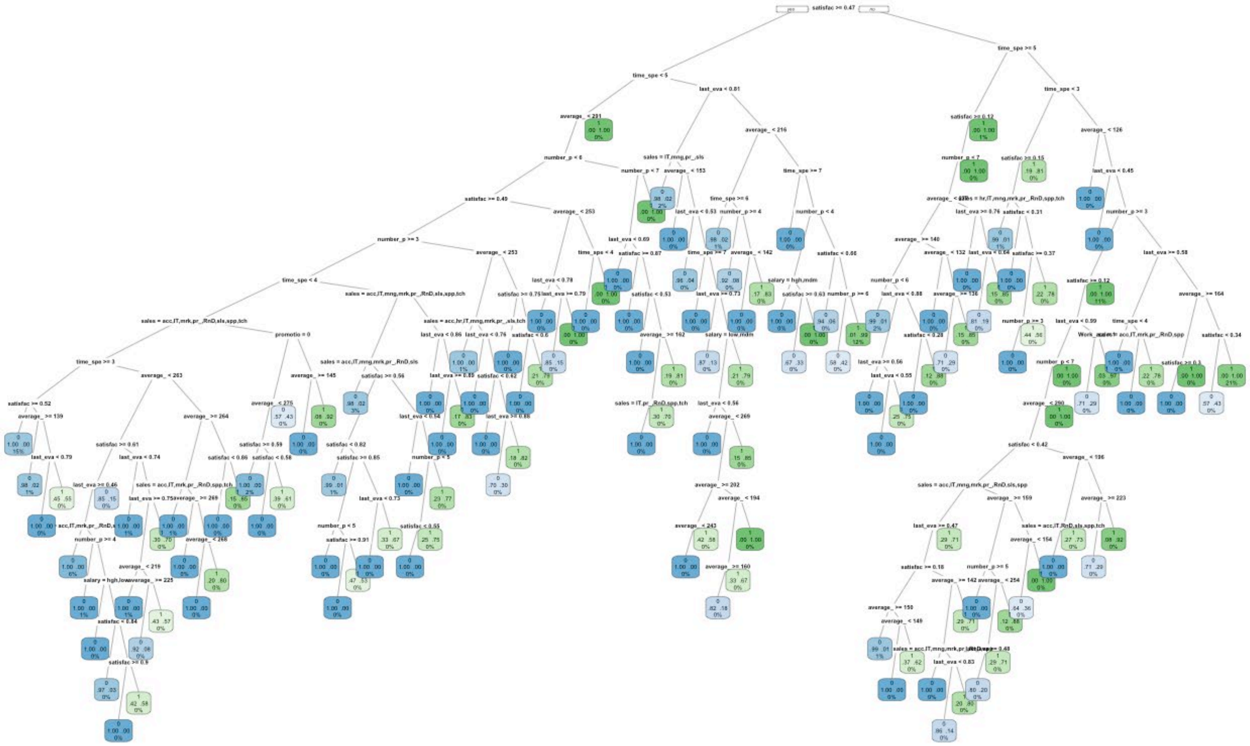
Pre-Pruning | **Base** | **Post-Pruning**

CP Plot



1 3 6 8 13 17 20 23 26 35 49 65 85 108 125
X-val Relative Error
0.0 0.2 0.4 0.6 0.8 1.0
Inf 0.034 0.0034 0.0021 0.0011 0.00074 0.00042 0.00014
cp

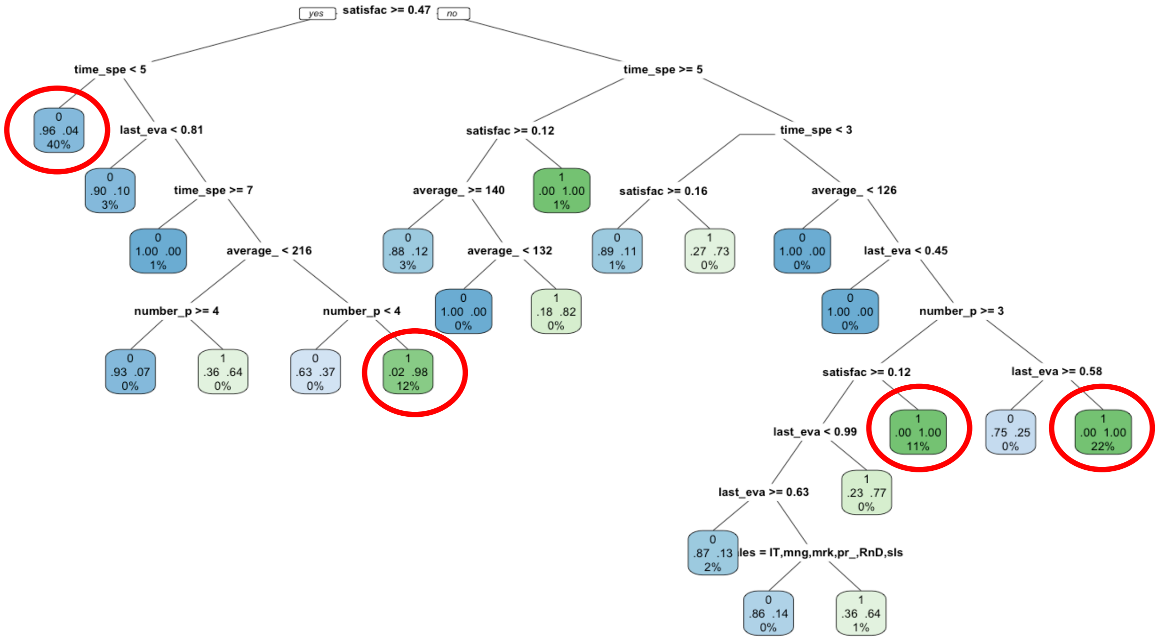
Tree Without Pruning



Why we need pruning?

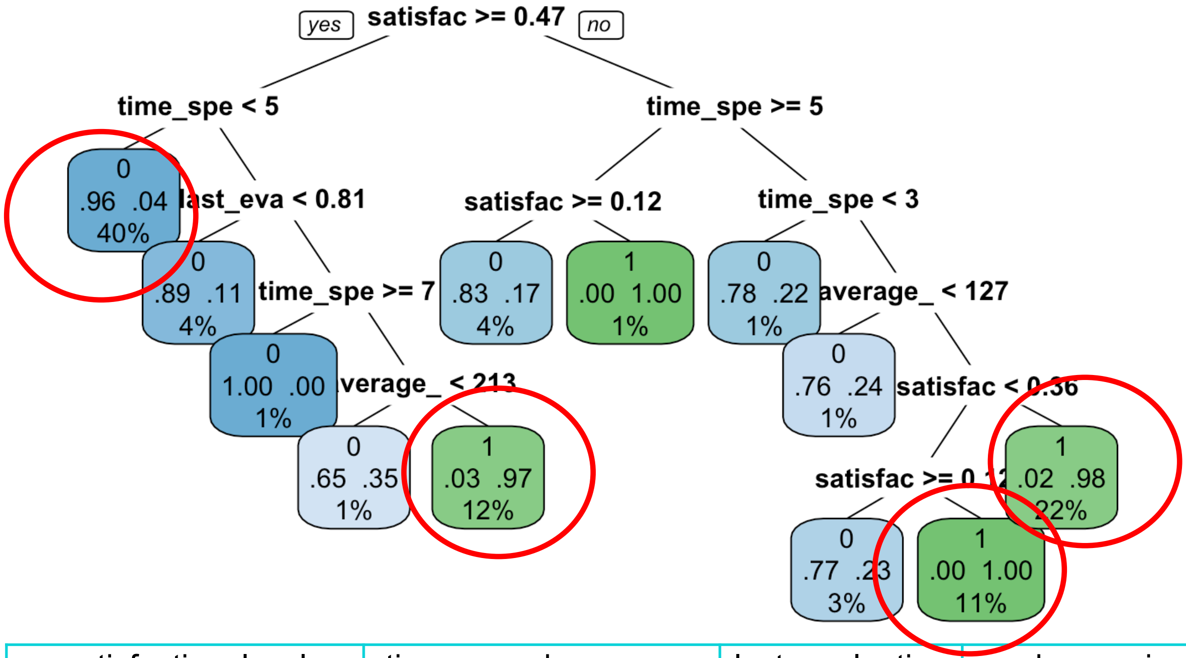
Over fitting

Over-Sampling Post-Pruning



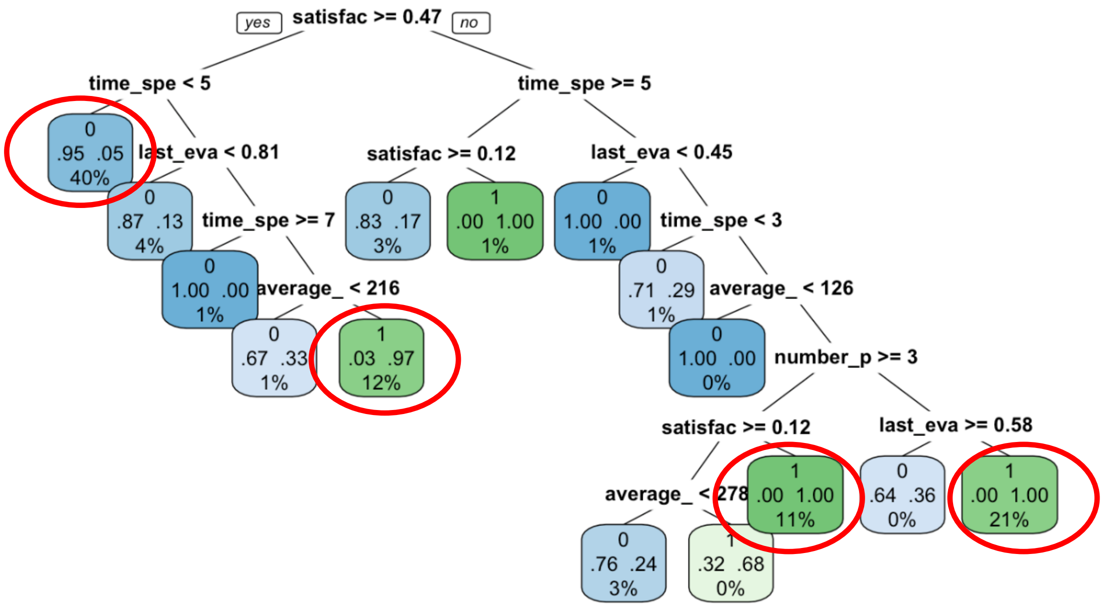
satisfaction_level	time_spend_company	last_evaluation	number_project
3918.83508	3342.14371	2483.91322	2046.43165
average_montly_hours	salary	sales	promotion_last_5years
1950.82373	70.21370	44.21282	13.39175

Under-Sampling Pre-Pruning



satisfaction_level	time_spend_company	last_evaluation	number_project
1277.054544	1019.755047	713.394546	656.744017
average_montly_hours	promotion_last_5years	sales	Work_acciden
625.559809	20.798779	8.946267	6.652014

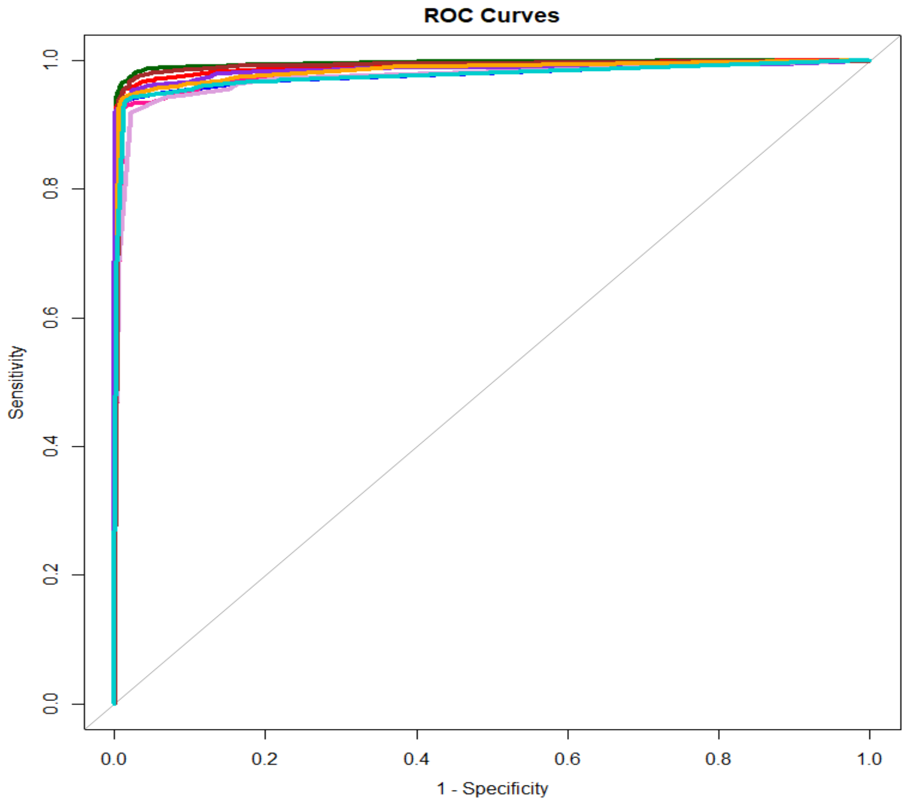
Both-Sampling Post-Pruning



satisfaction_level	time_spend_company	last_evaluation	number_project
2491.88129	2138.28538	1587.84219	1273.81460
average_montly_hours	salary	promotion_last_5years	sales
1187.82363	34.76908	34.60430	10.02167

Model Evaluation: Decision Tree

◆ **ROC and AUC for Decision Tree Models**



Highest AUC

ROC	AUC
Over Base	0.995
Over Pre	0.991
Over Post	0.977
Under Base	0.986
Under Pre	0.976
Under Post	0.974
Both Base	0.991
Both Pre	0.985
Both Post	0.976

We choose
Decision Tree Over Sampling Post

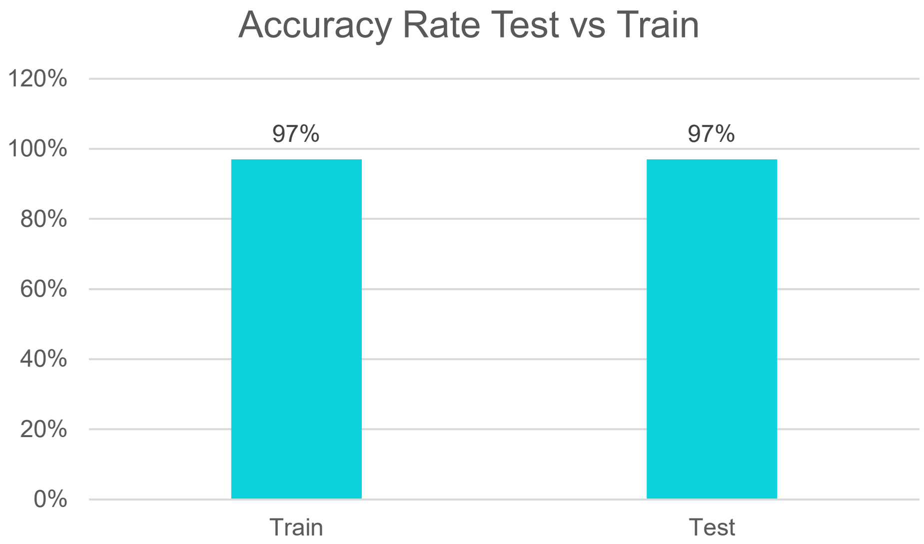
Decision Tree Over Sampling Post: Confusion Matrix Test vs Train

train data

actual / predict	left	stay
left	8851	215
stay	330	8888

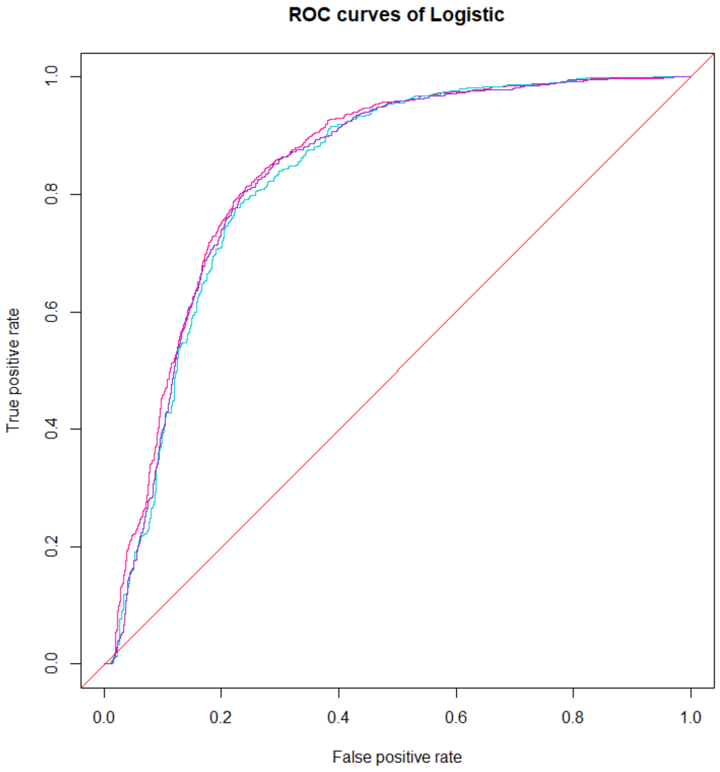
test data

actual / predict	left	stay
left	2154	39
stay	93	2286

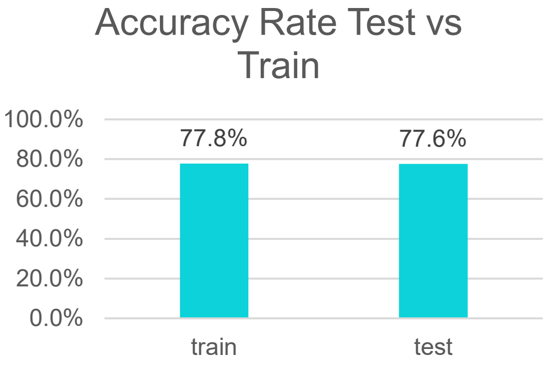


Model Evaluation: Logistic

◆ **ROC and AUC for Logistic Models**



We choose
Logistic Over Sampling



test data

actual / predict	Left	Stay
Left	**1509**	**793**
Stay	**363**	**1907**

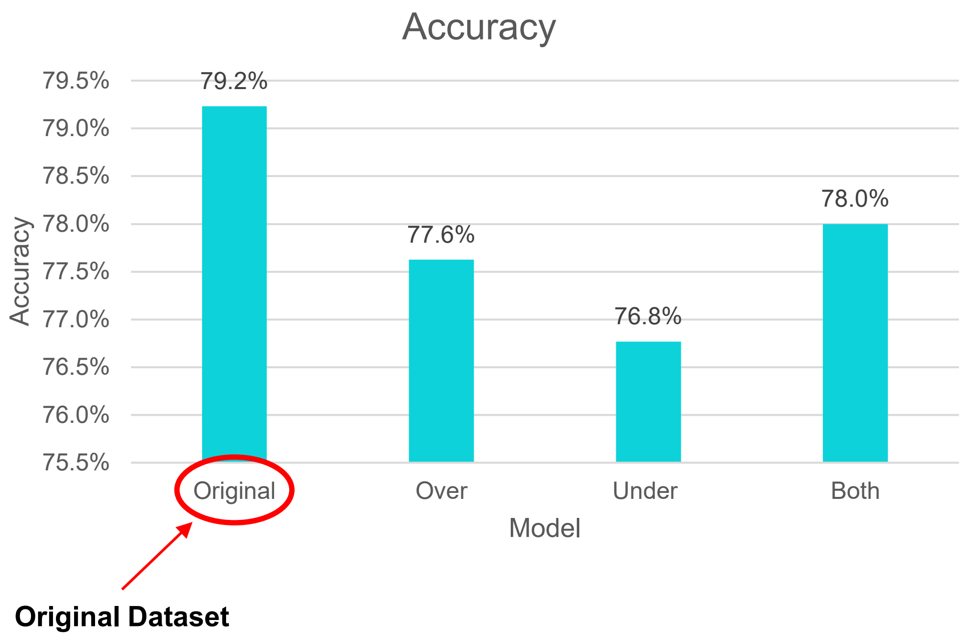
train data

actual / predict	left	stay
left	**6121**	**1468**
stay	**3021**	**7674**

ROC	AUC
Over	0.840
Under	0.827
Both	0.832

Highest AUC

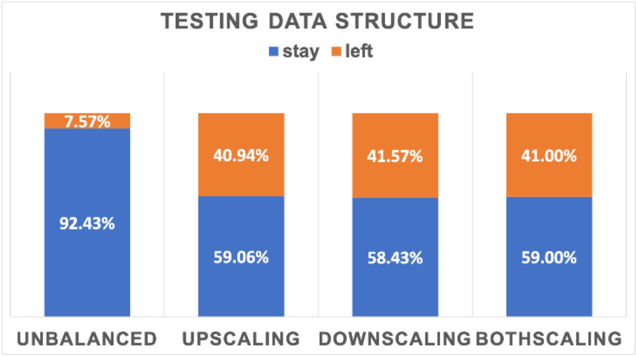
Problem of plain accuracy



Why unbalanced dataset has highest accuracy rate?

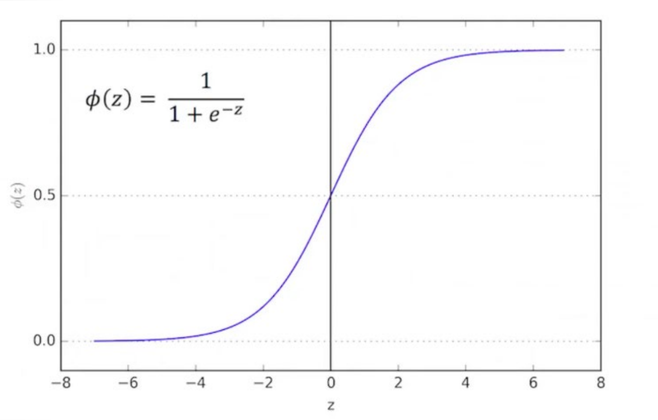
when dataset is imbalanced,
plain accuracy as metrics is unreliable

In this scenario,
majority of target variable are "stay"

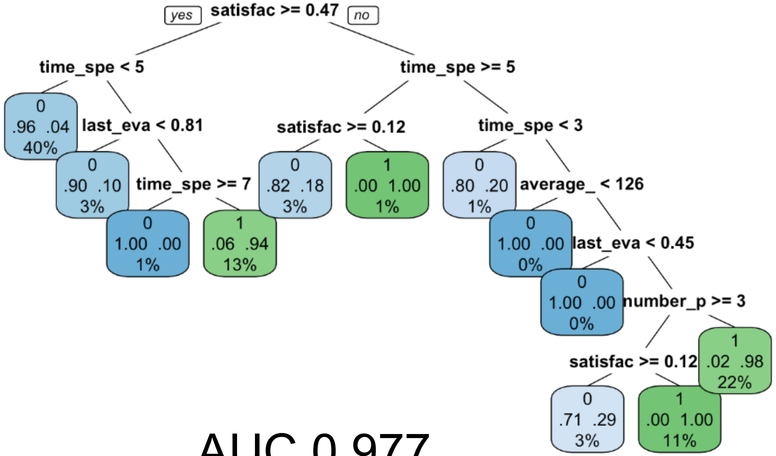


Best Model Selection

Logistic Over Sampling ***vs*** ***Decision Tree Over Sampling Post***



AUC 0.84



AUC 0.977

Discussion

Significance and Variable Importance

```
Coefficients:
                      Estimate Std. Error z value Pr(>|z|)    
(Intercept)         -1.0790735  0.1807179  -5.971 2.36e-09 ***
satisfaction_level  -4.3548582  0.1023754 -42.538  < 2e-16 ***
last_evaluation      1.0391039  0.1640957   6.332 2.42e-10 ***
number_project      -0.4036782  0.0229564 -17.585  < 2e-16 ***
average_montly_hours  0.0048783  0.0005744   8.493  < 2e-16 ***
time_spend_company   0.5158183  0.0199218  25.892  < 2e-16 ***
Work_accident       -1.5741703  0.0850502 -18.509  < 2e-16 ***
promotion_last_5years -1.2608875  0.2289697  -5.507 3.65e-08 ***
saleshr              0.2103128  0.1356101   1.551 0.120934    
salesIT             -0.1129359  0.1236374  -0.913 0.361009    
salesmanagement     -0.7738073  0.1632937  -4.739 2.15e-06 ***
salesmarketing      -0.2040456  0.1347283  -1.514 0.129900    
salesproduct_mng    -0.0880587  0.1297237  -0.679 0.497253    
salesRandD          -0.5161202  0.1421686  -3.630 0.000283 ***
salessales          -0.0198721  0.1038984  -0.191 0.848318    
salessupport        -0.0073203  0.1107439  -0.066 0.947298    
salestechnical       0.0504218  0.1078021   0.468 0.639980    
salarylow            1.8938792  0.1202924  15.744  < 2e-16 ***
salarymedium         1.4235010  0.1211372  11.751  < 2e-16 ***
```

	Satisfaction_level	Last_evaluation	Time_spend_company
Over_Post	3873	3311	2410

Satisfaction Level

- Berties, etc.(2019):
  - People with higher autonomy in working condition
    - Have better critical-thinking skills and low psychological outlook to leave
  - Therefore, having lower autonomy for people decisions might lead to low job satisfaction that contributes to their desire to stay in their organization

Recommendations

- Prioritise employee well-being
  - Motivating employees towards achieving a fitness milestone
  - Encouraging them to disconnect when they are feeling the early signs of burnout

Time_Spend_Company (Tenure)

- Human capital theorists associated increased length of tenure with employee's value in the labour market (Ng & Feldman, 2013)

Retention Strategies

Remain employed

Rewarded attainment

Increase length of tenure

Long-tenured employees are **reluctant to leave** because of the accumulation of organ izational investment

Recommendations

- Celebrate Milestones
  - E.g. Organizations should reward/recognize employees who have stayed in the company for certain years like 5 years or 10 years
- Celebrate positive experiences
  - Organizations need to have a way for each manager to analyse i f their teams have been made to feel special

Last Evaluation (Job Performance)

- Performance directly affects the motivation of employees to search other jobs (Jackofsky,1986)
  - High-performance employees leave the job more easily than low-performance employees do
  - High performance will enhance
    - Employee's expectation regarding organizational rewards

Recommendations

- Match Task to Skills and Give Decent Salary
  - Knowing employee's skills and behavioral styles
  - For example, an extrooverted, creative thinker is probably a great person to pitch ideas to clients.
  - However, they might struggle if they are given a more rule-intensive, detail-oriendted task
  - Meantime, give reasonable salary base on their performance

Reference

- Lévy-Garboua, L. et al., 2007. Job satisfaction and quits. Labour Economics Volume 14, Issue 2, April 2007, Pages 251-268.

- D'Ambrosio, Conchita. et al., 2018. Unfairness at work: Well-being and quits. Labour Economics Volume 51, April 2018, Pages 307-316.

- Freeman, R.B., 1978. Job Satisfaction as an Economic Variable. American economic association 68, 135 – 141. Available at: https://www.nber.org/system/files/working_papers/w0225/w0225.pdf

- Martin, T., Price, J. , Mueller, C.(1981). Job performance and turnover. [J]. Journal of Applied Psychology, 66, 116-119