Employee Promotion Prediction

Description

Background & Context

Employee Promotion means the ascension of an employee to higher ranks, this aspect of the job is what drives employees the most. The ultimate reward for dedication and loyalty towards an organization and HR team plays an important role in handling all these promotion tasks based on ratings and other attributes available.

The HR team in JMD company stored data of promotion cycle last year, which consists of details of all the employees in the company working last year and also if they got promoted or not, but every time this process gets delayed due to so many details available for each employee - it gets difficult to compare and decide.

So this time HR team wants to utilize the stored data to make a model, that will predict if a person is eligible for promotion or not.

You as a data scientist at JMD company, need to come up with a model that will help the HR team to predict if a person is eligible for promotion or not.

Objective

Explore and visualize the dataset. Build a classification model to predict if the employee has a higher probability of getting a promotion Optimize the model using appropriate techniques Generate a set of insights and recommendations that will help the company

Data Dictionary:

- employee_id: Unique ID for the employee
- department: Department of employee
- region: Region of employment (unordered)
- education: Education Level
- gender: Gender of Employee
- recruitment_channel: Channel of recruitment for employee
- no *of* trainings: no of other trainings completed in the previous year on soft skills, technical skills, etc.
- age: Age of Employee
- previous *year* rating: Employee Rating for the previous year
- length *of* service: Length of service in years
- awards_ won: if awards won during the previous year then 1 else 0
- avg *training* score: Average score in current training evaluations
- is_promoted: (Target) Recommended for promotion

Importing Libraries

In [1]:
```
# This will help in making the Python code more structured automatically (good coding practice)
%load_ext nb_black

# Libraries to help with reading and manipulating data
import pandas as pd
import numpy as np

# Libaries to help with data visualization
import matplotlib.pyplot as plt
import seaborn as sns

# To tune model, get different metric scores, and split data
from sklearn.metrics import (
    f1_score,
    accuracy_score,
    recall_score,
    precision_score,
    confusion_matrix,
    roc_auc_score,
    plot_confusion_matrix,
)
from sklearn.model_selection import train_test_split, StratifiedKFold, cross_val_score

# To be used for data scaling and one hot encoding
from sklearn.preprocessing import StandardScaler, MinMaxScaler, OneHotEncoder
```

```python
# To impute missing values
from sklearn.impute import SimpleImputer

# To oversample and undersample data
from imblearn.over_sampling import SMOTE
from imblearn.under_sampling import RandomUnderSampler

# To do hyperparameter tuning
from sklearn.model_selection import RandomizedSearchCV

# To be used for creating pipelines and personalizing them
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer

# To define maximum number of columns to be displayed in a dataframe
pd.set_option("display.max_columns", None)

# To supress scientific notations for a dataframe
pd.set_option("display.float_format", lambda x: "%.3f" % x)

# To help with model building
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import (
    AdaBoostClassifier,
    GradientBoostingClassifier,
    RandomForestClassifier,
    BaggingClassifier,
)
from xgboost import XGBClassifier

# To suppress scientific notations
pd.set_option("display.float_format", lambda x: "%.3f" % x)

# To supress warnings
import warnings

warnings.filterwarnings("ignore")
```

Loading Data

In [2]:
```python
prediction = pd.read_csv("employee_promotion.csv")
```

In [3]:
```python
# Checking the number of rows and columns in the data
prediction.shape
```

Out[3]: (54808, 13)

- The dataset has 54808 rows and 13 columns

Data Overview

In [4]:
```python
# let's create a copy of the data
data = prediction.copy()
```

In [5]:
```python
# let's view the first 5 rows of the data
data.head()
```

Out[5]:

	employee_id	department	region	education	gender	recruitment_channel	no_of_trainings	age	previous_year_rating	length_of_service	a
0	65438	Sales & Marketing	region_7	Master's & above	f	sourcing	1	35	5.000	8	
1	65141	Operations	region_22	Bachelor's	m	other	1	30	5.000	4	
2	7513	Sales & Marketing	region_19	Bachelor's	m	sourcing	1	34	3.000	7	
3	2542	Sales & Marketing	region_23	Bachelor's	m	other	2	39	1.000	10	
4	48945	Technology	region_26	Bachelor's	m	other	1	45	3.000	2	

In [6]:
```python
# let's view the last 5 rows of the data
data.tail()
```

Out[6]:

	employee_id	department	region	education	gender	recruitment_channel	no_of_trainings	age	previous_year_rating	length_of_servic
54803	3030	Technology	region_14	Bachelor's	m	sourcing	1	48	3.000	1
54804	74592	Operations	region_27	Master's & above	f	other	1	37	2.000	
54805	13918	Analytics	region_1	Bachelor's	m	other	1	27	5.000	
54806	13614	Sales & Marketing	region_9	NaN	m	sourcing	1	29	1.000	
54807	51526	HR	region_22	Bachelor's	m	other	1	27	1.000	

In [7]:
```python
# let's check the data types of the columns in the dataset
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 54808 entries, 0 to 54807
Data columns (total 13 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   employee_id           54808 non-null  int64  
 1   department            54808 non-null  object 
 2   region                54808 non-null  object 
 3   education             52399 non-null  object 
 4   gender                54808 non-null  object 
 5   recruitment_channel   54808 non-null  object 
 6   no_of_trainings       54808 non-null  int64  
 7   age                   54808 non-null  int64  
 8   previous_year_rating  50684 non-null  float64
 9   length_of_service     54808 non-null  int64  
 10  awards_won            54808 non-null  int64  
 11  avg_training_score    52248 non-null  float64
 12  is_promoted           54808 non-null  int64  
dtypes: float64(2), int64(6), object(5)
memory usage: 5.4+ MB
```

- 5 columns are of object type rest all are numerical.

In [8]:
```python
# let's check for duplicate values in the data
data.duplicated().sum()
```

Out[8]: 0

In [9]:
```python
# let's check for missing values in the data
round(data.isnull().sum() / data.isnull().count() * 100, 2)
```

Out[9]:
```
employee_id            0.000
department             0.000
region                 0.000
education              4.400
gender                 0.000
recruitment_channel    0.000
no_of_trainings        0.000
age                    0.000
previous_year_rating   7.520
length_of_service      0.000
awards_won             0.000
avg_training_score     4.670
is_promoted            0.000
dtype: float64
```

- Education_Level has 4.4% missing values
- previous_year_rating has 7.52% missing values
- average_training_score has 4.67% missing values

In [10]:

```
# let's view the statistical summary of the numerical columns in the data
data.describe().T
```

Out[10]:

	count	mean	std	min	25%	50%	75%	max
employee_id	54808.000	39195.831	22586.581	1.000	19669.750	39225.500	58730.500	78298.000
no_of_trainings	54808.000	1.253	0.609	1.000	1.000	1.000	1.000	10.000
age	54808.000	34.804	7.660	20.000	29.000	33.000	39.000	60.000
previous_year_rating	50684.000	3.329	1.260	1.000	3.000	3.000	4.000	5.000
length_of_service	54808.000	5.866	4.265	1.000	3.000	5.000	7.000	37.000
awards_won	54808.000	0.023	0.150	0.000	0.000	0.000	0.000	1.000
avg_training_score	52248.000	63.712	13.522	39.000	51.000	60.000	77.000	99.000
is_promoted	54808.000	0.085	0.279	0.000	0.000	0.000	0.000	1.000

Observations:

- employee_id: It is a unique identifier tht can be dropped for analysis
- no_of_rtrainings: Average trainings is 1.25, years, min is 1 and max is 10
- age: Average employee age is 34 years, min is 20 and max is 60
- previous_year_rating: The rating last year in average is 3.3 with a minimum of 1 and a maximum of 5
- length_of_service: On average the length of service is 5.8 years with a minimum of 1 year and a maximum of 37
- awards_won: On average JMD awards .02 awards with a minimum of 0 and a maximum of 1
- avg_training_score: THe average training score is 63 with a minimum score of 39 to 99
- is_promoted: This is our dependent variable

In [11]:

```
data.describe(include=["object"]).T
```

Out[11]:

	count	unique	top	freq
department	54808	9	Sales & Marketing	16840
region	54808	34	region_2	12343
education	52399	3	Bachelor's	36669
gender	54808	2	m	38496
recruitment_channel	54808	3	other	30446

In [12]:

```
for i in data.describe(include=["object"]).columns:
    print("Unique values in", i, "are :")
    print(data[i].value_counts())
    print("*" * 50)
```

```
Unique values in department are :
Sales & Marketing    16840
Operations           11348
Procurement           7138
Technology            7138
Analytics             5352
Finance               2536
HR                    2418
Legal                 1039
R&D                    999
Name: department, dtype: int64
**************************************************
Unique values in region are :
region_2     12343
region_22     6428
region_7      4843
region_15     2808
region_13     2648
region_26     2260
region_31     1935
region_4      1703
```

```
region_27     1659
region_16     1465
region_28     1318
region_11     1315
region_23     1175
region_29      994
region_32      945
region_19      874
region_20      850
region_14      827
region_25      819
region_17      796
region_5       766
region_6       690
region_30      657
region_8       655
region_10      648
region_1       610
region_24      508
region_12      500
region_9       420
region_21      411
region_3       346
region_34      292
region_33      269
region_18       31
Name: region, dtype: int64
**************************************************
Unique values in education are :
Bachelor's          36669
Master's & above    14925
Below Secondary       805
Name: education, dtype: int64
**************************************************
Unique values in gender are :
m    38496
f    16312
Name: gender, dtype: int64
**************************************************
Unique values in recruitment_channel are :
other       30446
sourcing    23220
referred     1142
Name: recruitment_channel, dtype: int64
**************************************************
```

Observations

- There are 9 distinct departments at JMD.
- Most of the employees are male at an approximate ration 2.5 to 1
- Most employees were recruited from other channels.
- Most employees have a bachelors degree.
- There are 34 different regions where employees work
- There are some missing values in previous_year_rating, education and average_training_score. Some of the missing values might be due to new hires

Data Pre-processing

In [13]:

```
# employee_id consists of uniques ID employees and hence will not add value to the modeling
data.drop(["employee_id"], axis=1, inplace=True)
```

In [14]:

```
## Encoding not promoted and promoted employees to 0 and 1 respectively, for analysis.
data["is_promoted"].replace("Employee", 0, inplace=True)
data["is_promoted"].replace("Promoted Employee", 1, inplace=True)
```

EDA

Univariate analysis

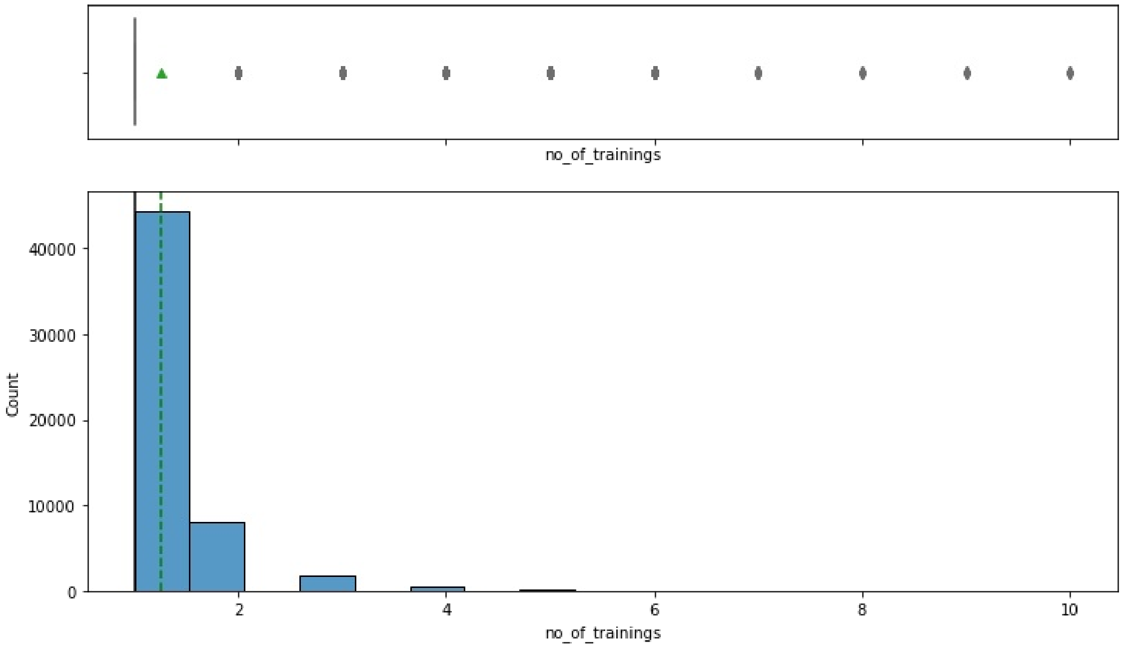
In [15]:

```
# function to plot a boxplot and a histogram along the same scale.


def histogram_boxplot(data, feature, figsize=(12, 7), kde=False, bins=None):
    """
    Boxplot and histogram combined

    data: dataframe
    feature: dataframe column
    figsize: size of figure (default (12,7))
    kde: whether to the show density curve (default False)
    bins: number of bins for histogram (default None)
    """
    f2, (ax_box2, ax_hist2) = plt.subplots(
        nrows=2,  # Number of rows of the subplot grid= 2
        sharex=True,  # x-axis will be shared among all subplots
        gridspec_kw={"height_ratios": (0.25, 0.75)},
        figsize=figsize,
    )  # creating the 2 subplots
    sns.boxplot(
        data=data, x=feature, ax=ax_box2, showmeans=True, color="violet"
    )  # boxplot will be created and a star will indicate the mean value of the column
    sns.histplot(
        data=data, x=feature, kde=kde, ax=ax_hist2, bins=bins, palette="winter"
    ) if bins else sns.histplot(
        data=data, x=feature, kde=kde, ax=ax_hist2
    )  # For histogram
    ax_hist2.axvline(
        data[feature].mean(), color="green", linestyle="--"
    )  # Add mean to the histogram
    ax_hist2.axvline(
        data[feature].median(), color="black", linestyle="-"
    )  # Add median to the histogram
```

Observations on no_of_trainings

In [16]:

```
histogram_boxplot(data, "no_of_trainings")
```

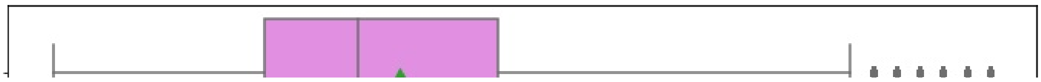


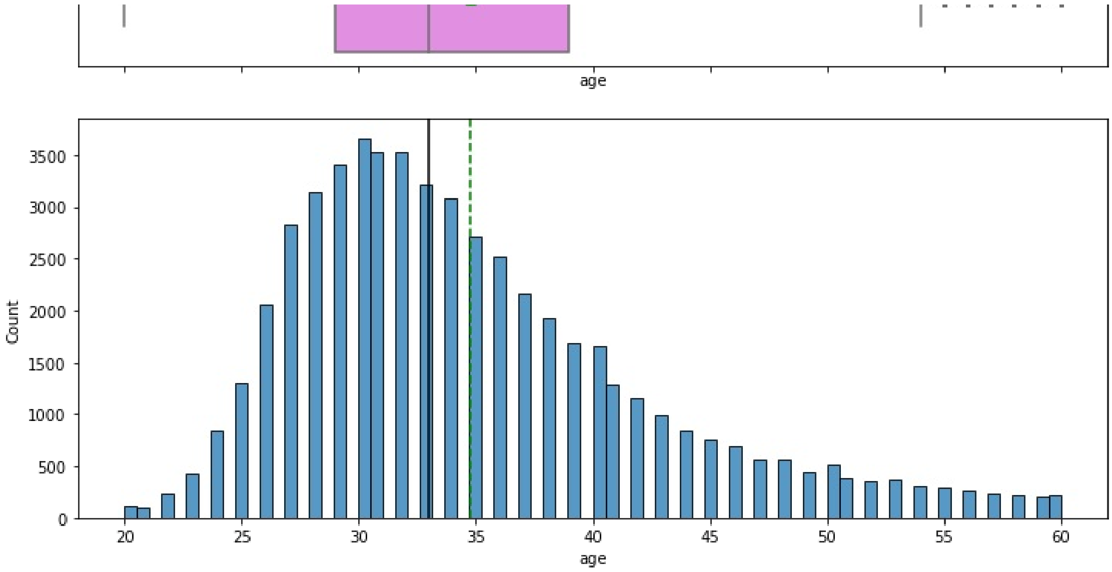
- The distribution of number of trainings is skewed to the right with most employees having less than 2 trainings
- From the boxplot, we can see that there are a several outliers.

Observations on age

In [17]:

```
histogram_boxplot(data, "age")
```

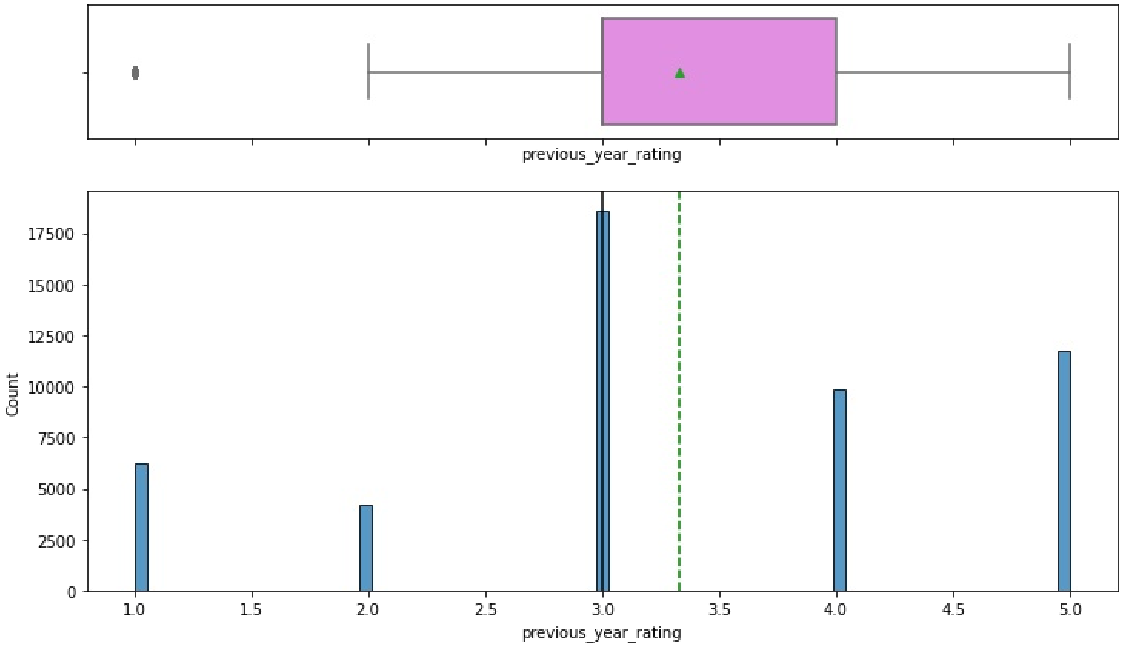




- The distribution of age is slightly skewed to the right with an average of 35 years old
- From the boxplot, we can see that there are outliers to the older side of age

Observations on previous_year_rating

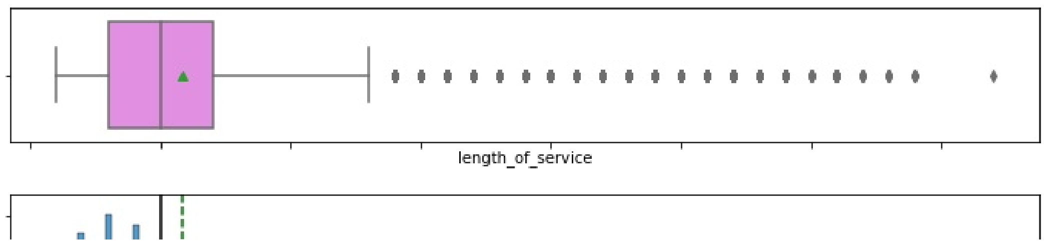
In [18]:
```
histogram_boxplot(data, "previous_year_rating")
```

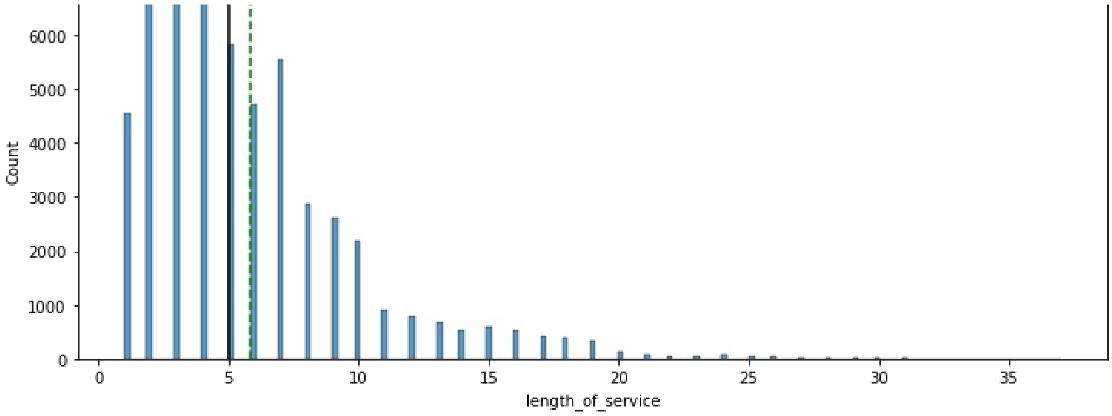


- This is a 5 odd distributed curve, most values are centered. However we can see that there is at least 10% of the population that is under-performing (score = 1) and about 20% is over-performing (score=5)

Observations on length_of_service

In [19]:
```
histogram_boxplot(data, "length_of_service")
```

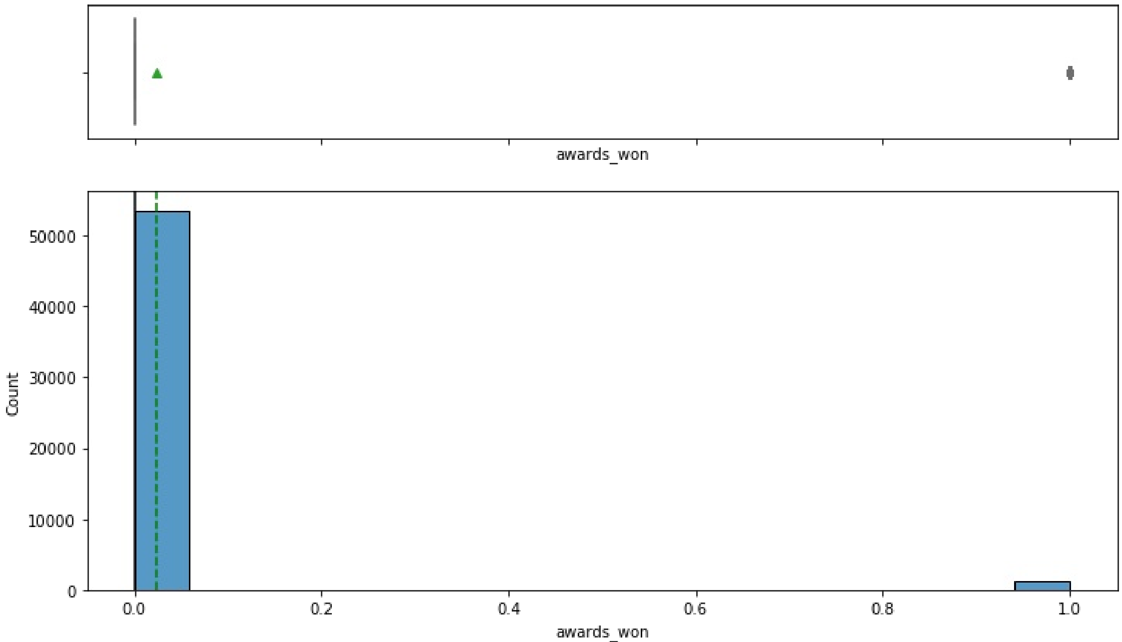




- The distribution of service is skewed to the right with several outlies passed 12 years of service
- Most of the employees have less than 7 years of service

Observations on awards_won

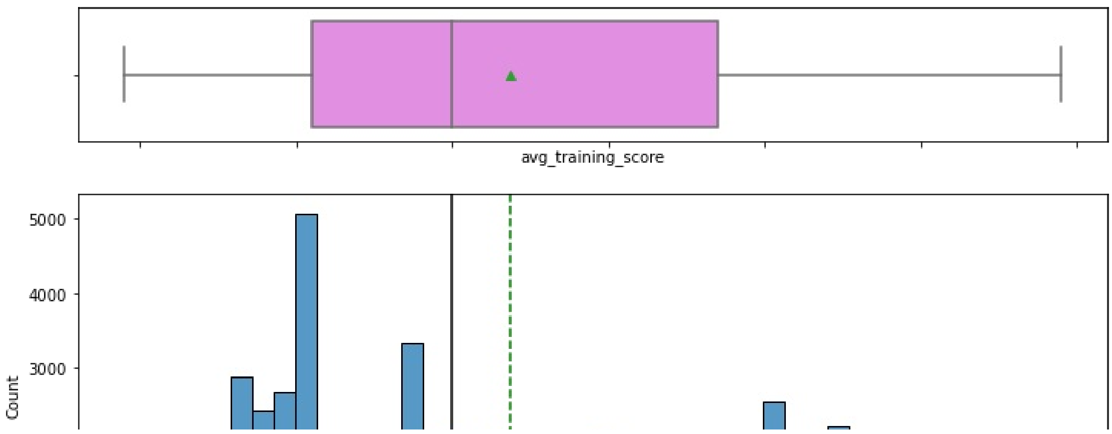
In [20]:
```
histogram_boxplot(data, "awards_won")
```

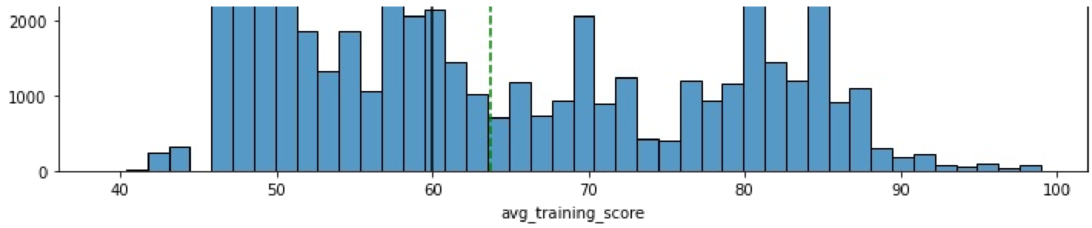


- Less than 1-2% have won an award

Observations on avg_training_score

In [21]:
```
histogram_boxplot(data, "avg_training_score")
```



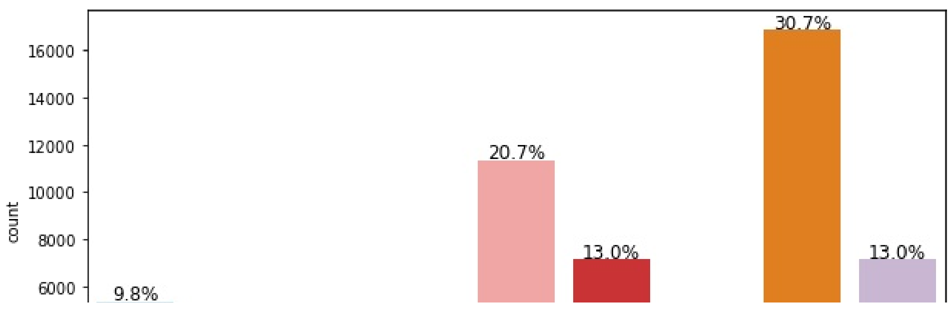


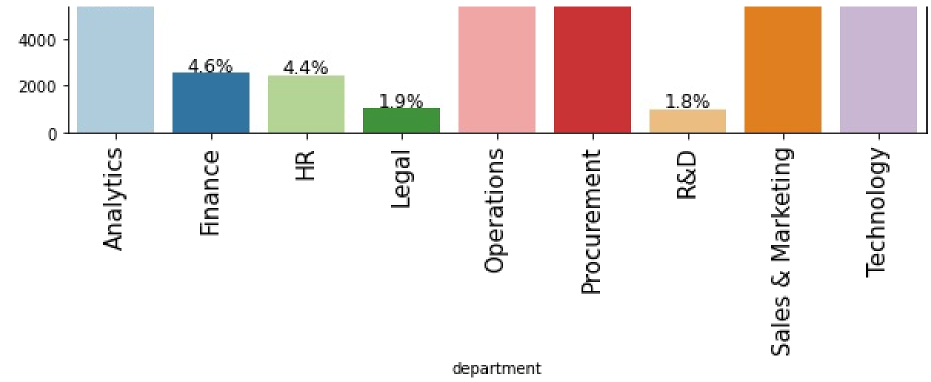
- The data is concentrated betwee 45 and 85 score

In [22]:
```
# function to create labeled barplots


def labeled_barplot(data, feature, perc=True, n=None):
    """
    Barplot with percentage at the top

    data: dataframe
    feature: dataframe column
    perc: whether to display percentages instead of count (default is False)
    n: displays the top n category levels (default is None, i.e., display all levels)
    """

    total = len(data[feature])  # length of the column
    count = data[feature].nunique()
    if n is None:
        plt.figure(figsize=(count + 1, 5))
    else:
        plt.figure(figsize=(n + 1, 5))

    plt.xticks(rotation=90, fontsize=15)
    ax = sns.countplot(
        data=data,
        x=feature,
        palette="Paired",
        order=data[feature].value_counts().index[:n].sort_values(),
    )

    for p in ax.patches:
        if perc == True:
            label = "{:.1f}%".format(
                100 * p.get_height() / total
            )  # percentage of each class of the category
        else:
            label = p.get_height()  # count of each level of the category

        x = p.get_x() + p.get_width() / 2  # width of the plot
        y = p.get_height()  # height of the plot

        ax.annotate(
            label,
            (x, y),
            ha="center",
            va="center",
            size=12,
            xytext=(0, 5),
            textcoords="offset points",
        )  # annotate the percentage

    plt.show()  # show the plot
```

Observations on Department

In [23]:
```
labeled_barplot(data, "department")
```

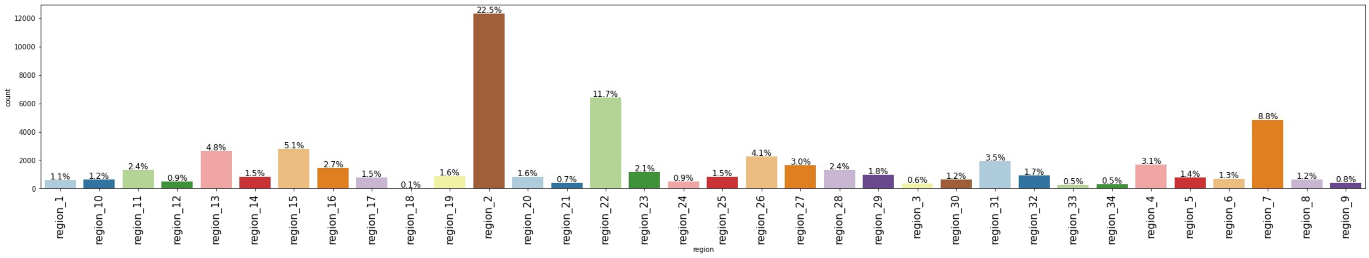




- The majority of employees belong to Sales & Marketing, Operations, Procurement and Technology.

Observations on region

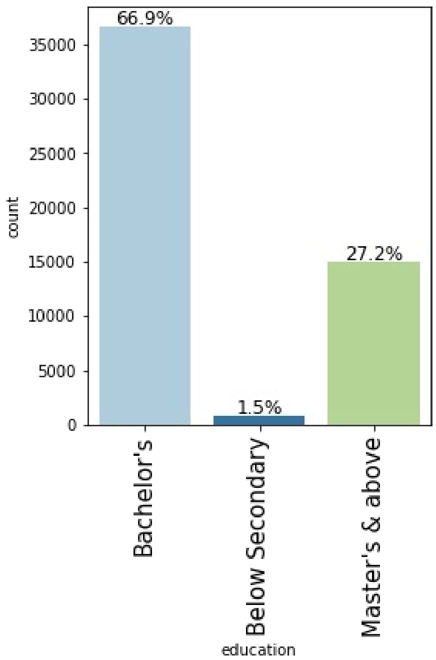
In [24]:
```
labeled_barplot(data, "region")
```



- Region 2, 7 and 22 are highly populated

Observations on Education

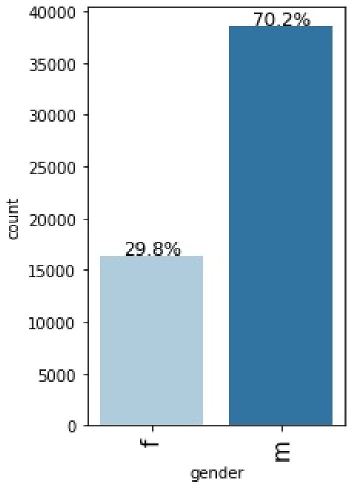
In [25]:
```
labeled_barplot(data, "education")
```



- Most employees have a bachelors degree with 66%

Observations on Gender

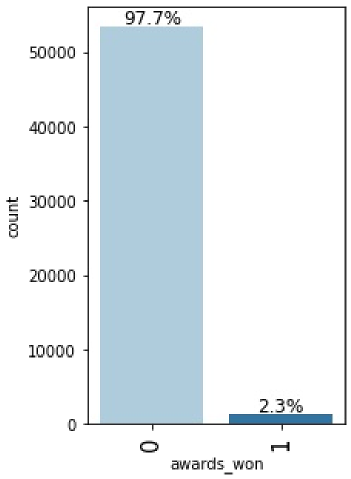
In [26]:
```
labeled_barplot(data, "gender")
```



- There are 70% male employees in JMD

Observations on Awards won

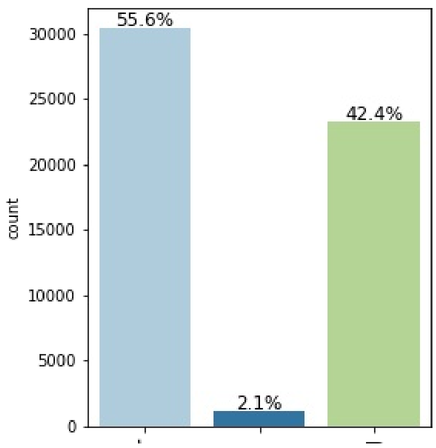
In [27]:
```
labeled_barplot(data, "awards_won")
```



- The vast majority of employees have not won an award

Observations on Recruitment channel

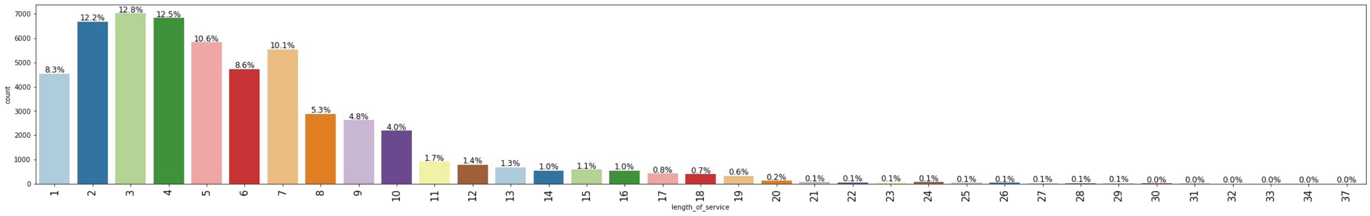
In [28]:
```
labeled_barplot(data, "recruitment_channel")
```



- 55% of employees were recruited through "other" channels and 42% through sourcing

Observations on Length of service

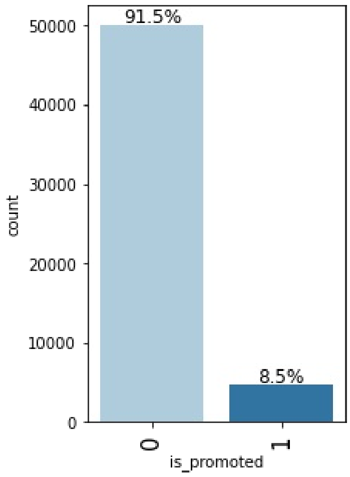
In [29]:
```
labeled_barplot(data, "length_of_service")
```



- As mentioned high percent of the population has less than 7 years of service

In [30]:
```
### Observations on promotion
```

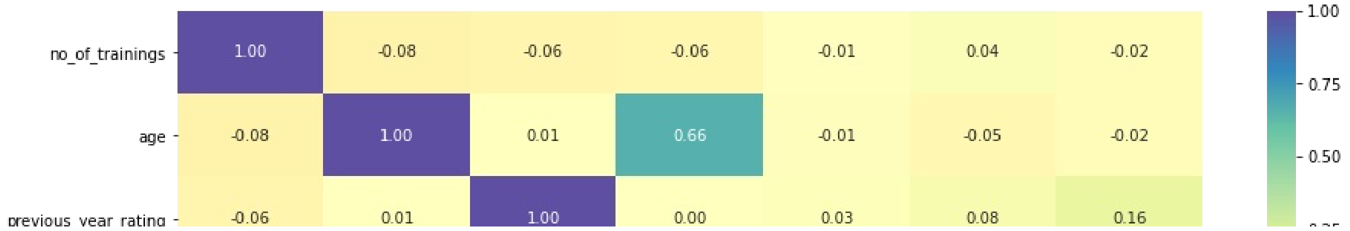
In [31]:
```
labeled_barplot(data, "is_promoted")
```

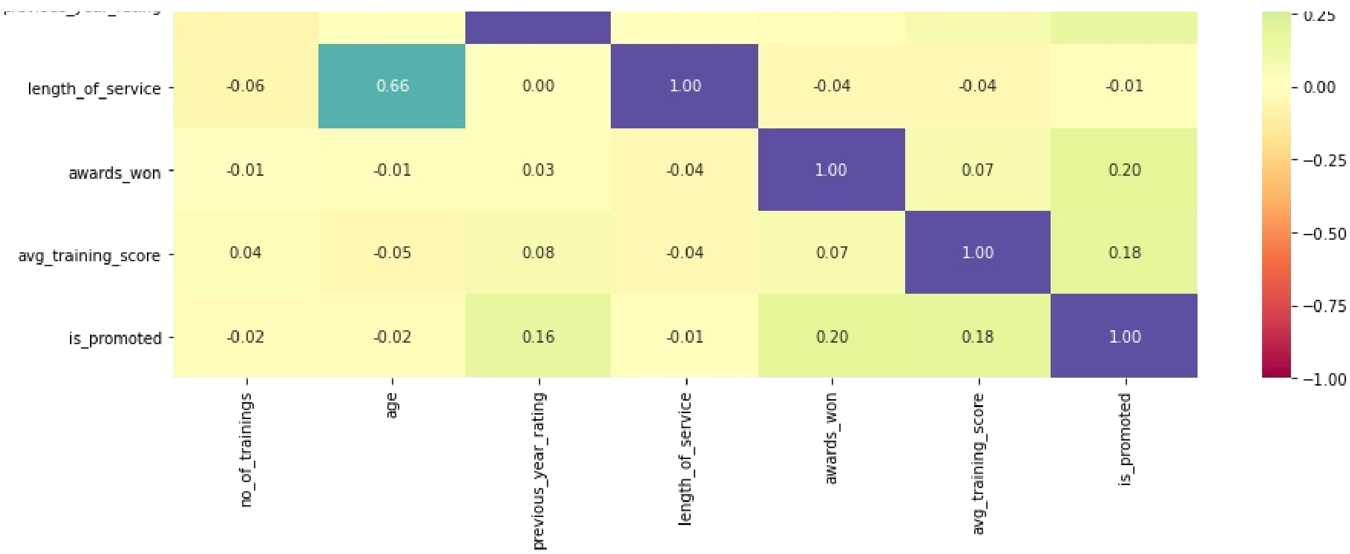


- Only 8% of the employees have received a promotion
- This indicates an imbalance in the data.

Bivariate Analysis

In [32]:
```
plt.figure(figsize=(15, 7))
sns.heatmap(data.corr(), annot=True, vmin=-1, vmax=1, fmt=".2f", cmap="Spectral")
plt.show()
```





- Length of service and age show a bit of correlation.
- All other features seem to be independent

In [33]:

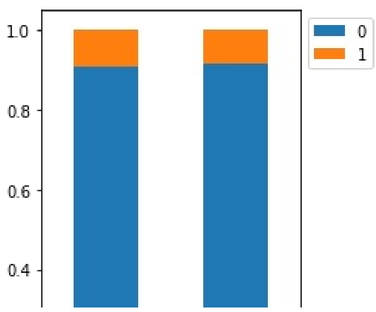
```
# function to plot stacked bar chart


def stacked_barplot(data, predictor, target):
    """
    Print the category counts and plot a stacked bar chart

    data: dataframe
    predictor: independent variable
    target: target variable
    """
    count = data[predictor].nunique()
    sorter = data[target].value_counts().index[-1]
    tab1 = pd.crosstab(data[predictor], data[target], margins=True).sort_values(
        by=sorter, ascending=False
    )
    print(tab1)
    print("-" * 120)
    tab = pd.crosstab(data[predictor], data[target], normalize="index").sort_values(
        by=sorter, ascending=False
    )
    tab.plot(kind="bar", stacked=True, figsize=(count + 1, 5))
    plt.legend(
        loc="lower left", frameon=False,
    )
    plt.legend(loc="upper left", bbox_to_anchor=(1, 1))
    plt.show()
```

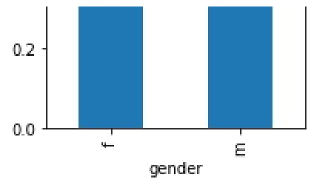
Promoted vs Gender

In [34]:

```
stacked_barplot(data, "gender", "is_promoted")
```

```
is_promoted      0     1    All
gender
All          50140  4668  54808
m            35295  3201  38496
f            14845  1467  16312
------------------------------------------------------------------------------------------------------------------------
```





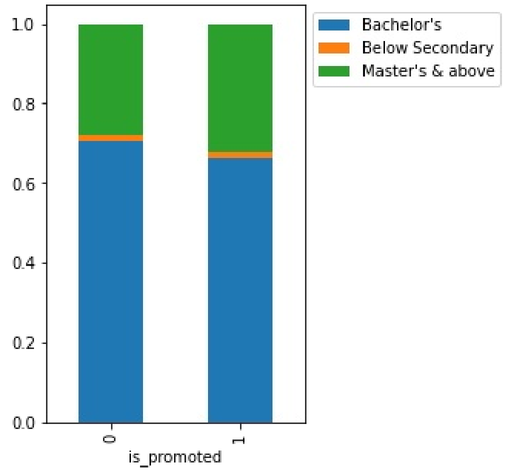
- There's no difference when female/male(s) are being promoted

Promoted vs Education

In [35]:

```
stacked_barplot(data, "is_promoted", "education")
```

```
education     Bachelor's  Below Secondary  Master's & above    All
is_promoted
All                36669              805             14925  52399
0                  33661              738             13454  47853
1                   3008               67              1471   4546
------------------------------------------------------------------------------------------------------------------------
-------
```



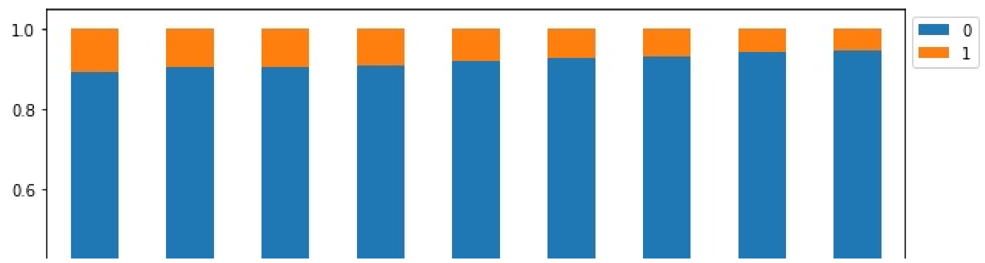
- Employees with a masters degree or above seem to have a higher edge when it comes to promotion.

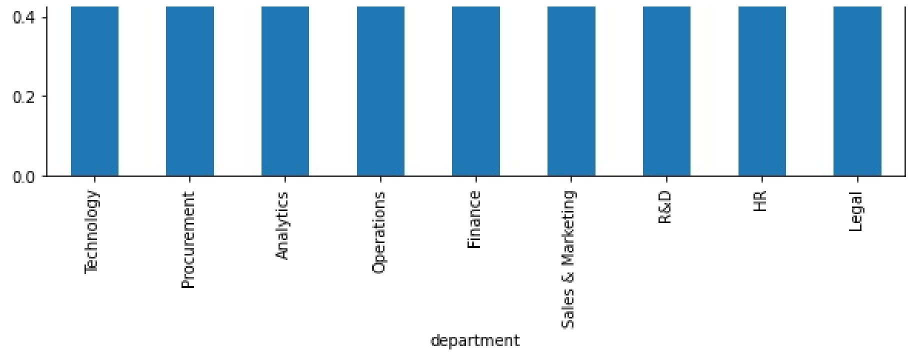
Promoted vs Department

In [36]:

```
stacked_barplot(data, "department", "is_promoted")
```

```
is_promoted            0     1    All
department
All                50140  4668  54808
Sales & Marketing  15627  1213  16840
Operations         10325  1023  11348
Technology          6370   768   7138
Procurement         6450   688   7138
Analytics           4840   512   5352
Finance             2330   206   2536
HR                  2282   136   2418
R&D                  930    69    999
Legal                986    53   1039
------------------------------------------------------------------------------------------------------------------------
-------
```





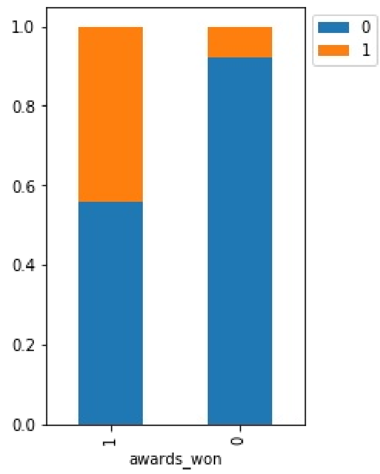
- Technology, Procurement, Analytics and Operations employees seem to be promoted more than employees in other departments

Promoted vs awards won

In [37]:

```python
stacked_barplot(data, "awards_won", "is_promoted")
```

```
is_promoted      0     1    All
awards_won
All          50140  4668  54808
0            49429  4109  53538
1              711   559   1270
------------------------------------------------------------------------------------------------------------------------
```



- It is evient that if you have won an award at JMD there is a high likelihood of promotion

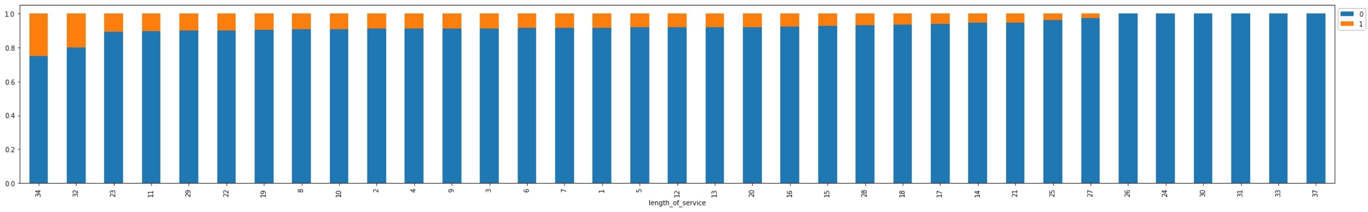
Promoted vs Length of service

In [38]:

```python
stacked_barplot(data, "length_of_service", "is_promoted")
```

```
is_promoted            0     1    All
length_of_service
All                50140  4668  54808
3                   6424   609   7033
4                   6238   598   6836
2                   6089   595   6684
5                   5357   475   5832
7                   5087   464   5551
6                   4333   401   4734
1                   4170   377   4547
8                   2614   269   2883
9                   2400   229   2629
10                  1989   204   2193
11                   820    96    916
12                   731    63    794
13                   633    54    687
```

15	550	43	593
16	507	41	548
19	297	32	329
14	520	29	549
17	406	26	432
18	367	25	392
20	118	10	128
23	58	7	65
22	55	6	61
21	74	4	78
29	27	3	30
25	49	2	51
28	28	2	30
32	8	2	10
34	3	1	4
27	35	1	36
24	70	0	70
26	41	0	41
30	12	0	12
31	20	0	20
33	9	0	9
37	1	0	1



- The higher the years of service the more likely that the employee will be promoted

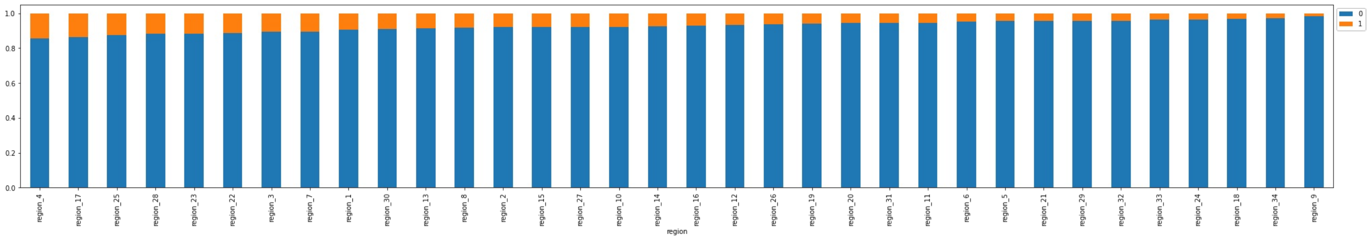
Promoted vs Region

In [39]:

```
stacked_barplot(data, "region", "is_promoted")
```

is_promoted	0	1	All
region			
All	50140	4668	54808
region_2	11354	989	12343
region_22	5694	734	6428
region_7	4327	516	4843
region_4	1457	246	1703
region_13	2418	230	2648
region_15	2586	222	2808
region_28	1164	154	1318
region_26	2117	143	2260
region_23	1038	137	1175
region_27	1528	131	1659
region_31	1825	110	1935
region_17	687	109	796
region_25	716	103	819
region_16	1363	102	1465
region_11	1241	74	1315
region_14	765	62	827
region_30	598	59	657
region_1	552	58	610
region_19	821	53	874
region_8	602	53	655
region_10	597	51	648
region_20	801	49	850
region_29	951	43	994
region_32	905	40	945
region_3	309	37	346
region_5	731	35	766
region_12	467	33	500
region_6	658	32	690
region_24	490	18	508
region_21	393	18	411
region_33	259	10	269
region_34	284	8	292
region_9	412	8	420
region_18	30	1	31

```
------------------------------------------------------------------------------------------------------------------------
-------
```



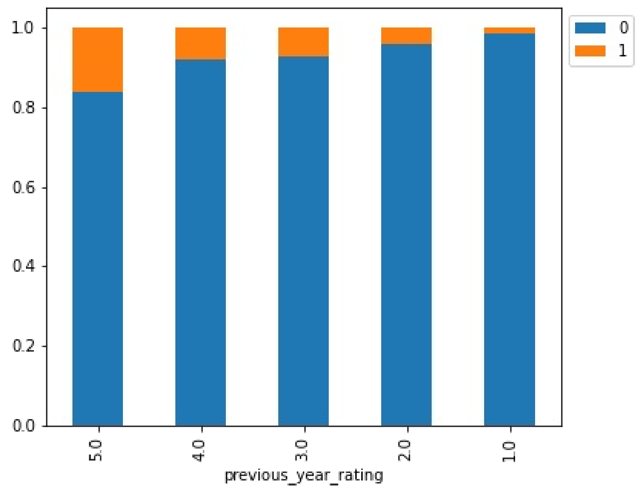
- There are several regions where promotion is higher

Promoted vs Previous year rating

In [40]:

```python
stacked_barplot(data, "previous_year_rating", "is_promoted")
```

```
is_promoted               0     1    All
previous_year_rating                    
All                   46355  4329  50684
5.0                    9820  1921  11741
3.0                   17263  1355  18618
4.0                    9093   784   9877
2.0                    4044   181   4225
1.0                    6135    88   6223
------------------------------------------------------------------------------------------------------------------------
-------
```



- As expected the higher the rating from last year the better opportunites for promotion

In [41]:

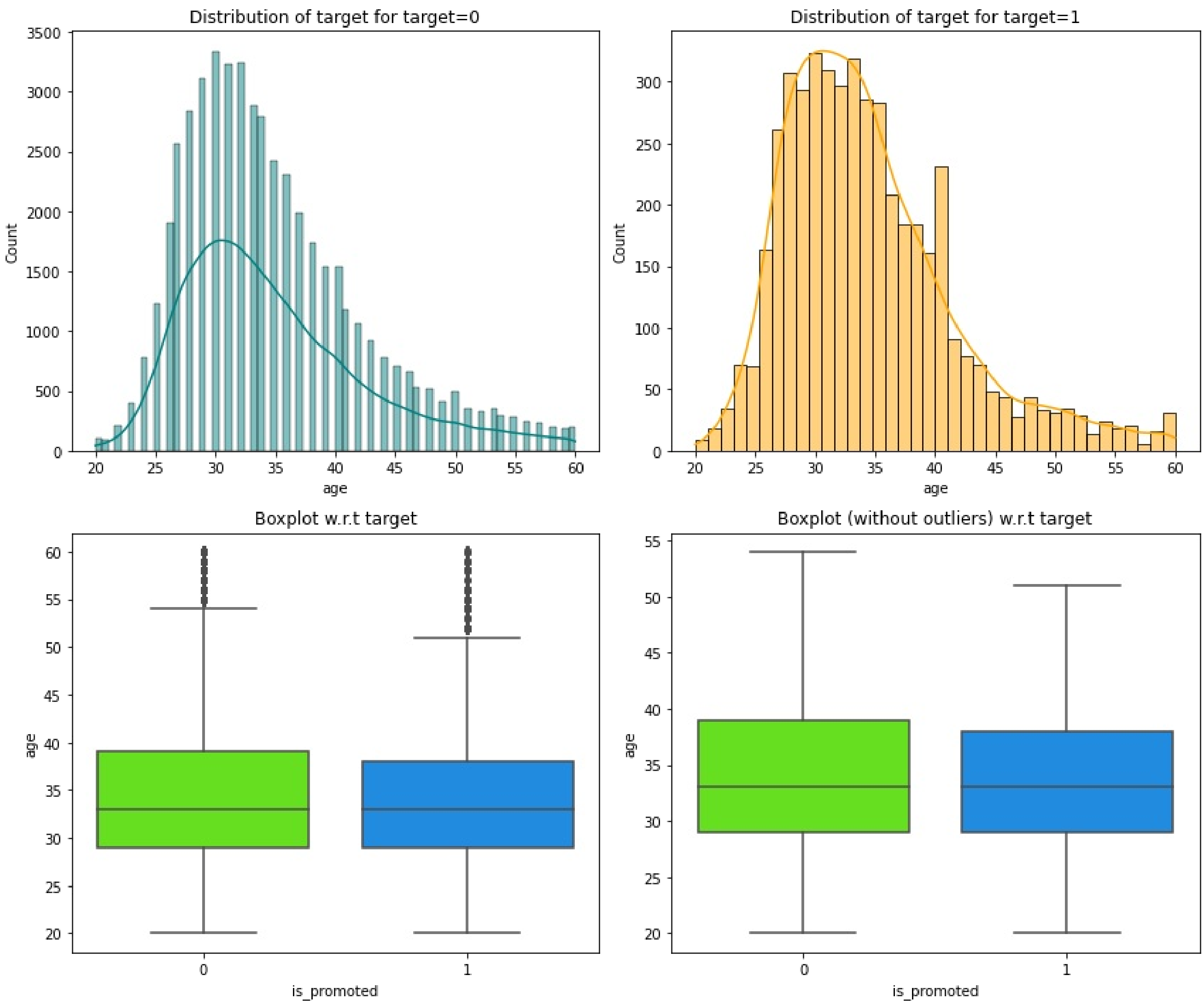
```python
### Function to plot distributions


def distribution_plot_wrt_target(data, predictor, target):

    fig, axs = plt.subplots(2, 2, figsize=(12, 10))

    target_uniq = data[target].unique()

    axs[0, 0].set_title("Distribution of target for target=" + str(target_uniq[0]))
    sns.histplot(
        data=data[data[target] == target_uniq[0]],
        x=predictor,
        kde=True,
        ax=axs[0, 0],
        color="teal",
    )

    axs[0, 1].set_title("Distribution of target for target=" + str(target_uniq[1]))
    sns.histplot(
        data=data[data[target] == target_uniq[1]],
```

```
        x=predictor,
        kde=True,
        ax=axs[0, 1],
        color="orange",
    )

    axs[1, 0].set_title("Boxplot w.r.t target")
    sns.boxplot(data=data, x=target, y=predictor, ax=axs[1, 0], palette="gist_rainbow")

    axs[1, 1].set_title("Boxplot (without outliers) w.r.t target")
    sns.boxplot(
        data=data,
        x=target,
        y=predictor,
        ax=axs[1, 1],
        showfliers=False,
        palette="gist_rainbow",
    )

    plt.tight_layout()
    plt.show()
```

Promoted vs Age

In [42]:

```
distribution_plot_wrt_target(data, "age", "is_promoted")
```

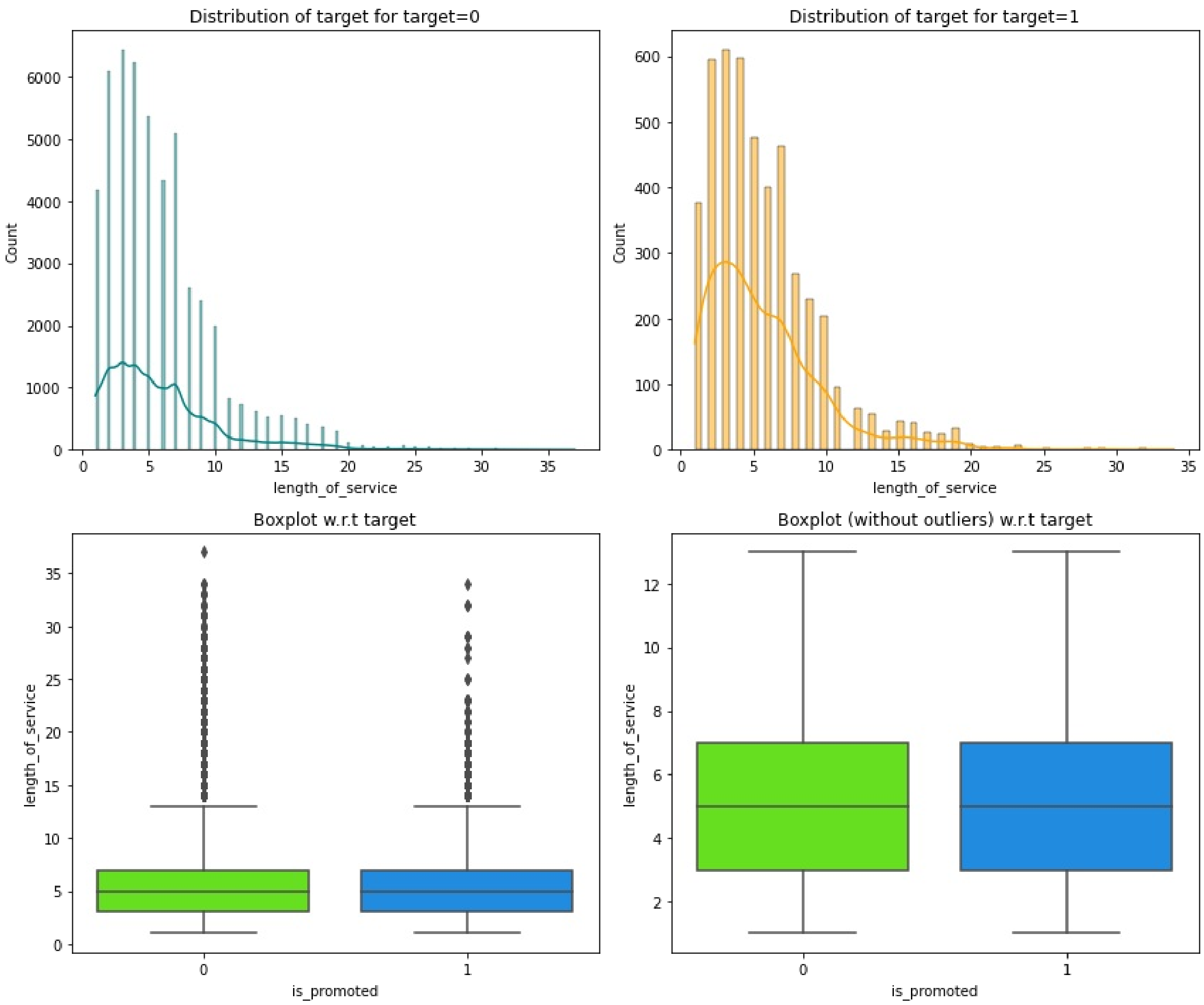


- There's a slight difference in age for employees not promoted vs promoted.

Promoted vs Length of service

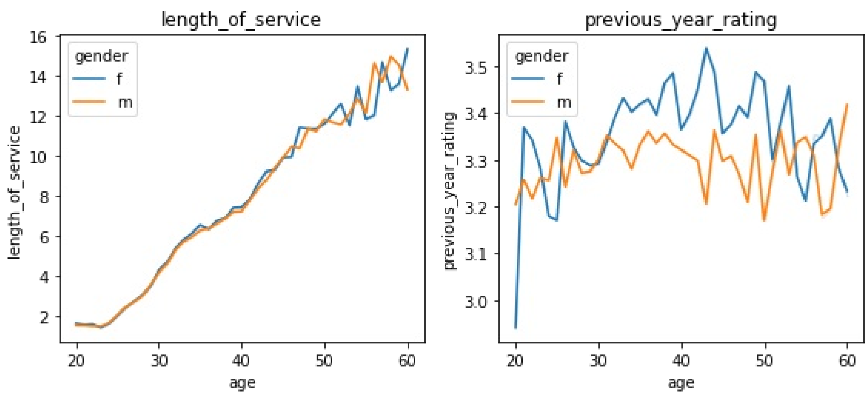
In [43]:

```
distribution_plot_wrt_target(data, "length_of_service", "is_promoted")
```



- Tenure has little impact on promotion.

In [44]:
```python
cols = data[["length_of_service", "previous_year_rating",]].columns.tolist()
plt.figure(figsize=(12, 10))
for i, variable in enumerate(cols):
    plt.subplot(3, 3, i + 1)
    sns.lineplot(data["age"], data[variable], hue=data["gender"], ci=0)
    plt.tight_layout()
    plt.title(variable)
plt.show()
```



- It seems that age and gender follow very closely when it comes to years of service.
- From age 30-50 females seem to do better during previous year rating

Percentage of outliers, in each column of the data, using IQR.

In [45]:
```
Q1 = data.quantile(0.25)  # To find the 25th percentile and 75th percentile.
Q3 = data.quantile(0.75)

IQR = Q3 - Q1  # Inter Quantile Range (75th perentile - 25th percentile)

lower = (
    Q1 - 1.5 * IQR
)  # Finding lower and upper bounds for all values. All values outside these bounds are outliers
upper = Q3 + 1.5 * IQR
```

In [46]:
```
(
    (data.select_dtypes(include=["float64", "int64"]) < lower)
    | (data.select_dtypes(include=["float64", "int64"]) > upper)
).sum() / len(data) * 100
```

Out[46]:
```
no_of_trainings        19.030
age                     2.618
previous_year_rating   11.354
length_of_service       6.366
awards_won              2.317
avg_training_score      0.000
is_promoted             8.517
dtype: float64
```

- There are some high percentage of outliers when it comes to no_of_trainings and previous_year_rating. The outliers are typical and will not be treated for this example

Missing value imputation

- We will impute missing values in all 3 columns (education, previous_year_rating and avg_training_score using mode)

In [47]:
```
data1 = data.copy()
```

In [48]:
```
data1.isna().sum()
```

Out[48]:
```
department                 0
region                     0
education               2409
gender                     0
recruitment_channel        0
no_of_trainings            0
age                        0
previous_year_rating    4124
length_of_service          0
awards_won                 0
avg_training_score      2560
is_promoted                0
dtype: int64
```

In [49]:
```
imputer = SimpleImputer(strategy="most_frequent")
```

In [50]:
```
X = data1.drop(["is_promoted"], axis=1)
y = data1["is_promoted"]
```

In [51]:
```
# Splitting data into training, validation and test set:
# first we split data into 2 parts, say temporary and test

X_temp, X_test, y_temp, y_test = train_test_split(
    X, y, test_size=0.2, random_state=1, stratify=y
)
```

```
# then we split the temporary set into train and validation

X_train, X_val, y_train, y_val = train_test_split(
    X_temp, y_temp, test_size=0.25, random_state=1, stratify=y_temp
)
print(X_train.shape, X_val.shape, X_test.shape)
```

```
(32884, 11) (10962, 11) (10962, 11)
```

In [52]:

```
reqd_col_for_impute = ["education", "previous_year_rating", "avg_training_score"]
```

In [53]:

```
# Fit and transform the train data
X_train[reqd_col_for_impute] = imputer.fit_transform(X_train[reqd_col_for_impute])

# Transform the validation data
X_val[reqd_col_for_impute] = imputer.transform(X_val[reqd_col_for_impute])

# Transform the test data
X_test[reqd_col_for_impute] = imputer.transform(X_test[reqd_col_for_impute])
```

In [54]:

```
# Checking that no column has missing values in train or test sets
print(X_train.isna().sum())
print("-" * 30)
print(X_val.isna().sum())
print("-" * 30)
print(X_test.isna().sum())
```

```
department              0
region                  0
education               0
gender                  0
recruitment_channel     0
no_of_trainings         0
age                     0
previous_year_rating    0
length_of_service       0
awards_won              0
avg_training_score      0
dtype: int64
------------------------------
department              0
region                  0
education               0
gender                  0
recruitment_channel     0
no_of_trainings         0
age                     0
previous_year_rating    0
length_of_service       0
awards_won              0
avg_training_score      0
dtype: int64
------------------------------
department              0
region                  0
education               0
gender                  0
recruitment_channel     0
no_of_trainings         0
age                     0
previous_year_rating    0
length_of_service       0
awards_won              0
avg_training_score      0
dtype: int64
```

- All missing values have been treated.

In [55]:

```
cols = X_train.select_dtypes(include=["object", "category"])
for i in cols.columns:
```

```
    print(X_train[i].value_counts())
    print("*" * 30)
```

```
Sales & Marketing    9989
Operations           6746
Technology           4383
Procurement          4330
Analytics            3173
Finance              1570
HR                   1482
R&D                   613
Legal                 598
Name: department, dtype: int64
******************************
region_2     7351
region_22    3867
region_7     2973
region_15    1706
region_13    1584
region_26    1344
region_31    1132
region_4      987
region_27     983
region_16     893
region_11     799
region_28     780
region_23     688
region_29     601
region_32     577
region_19     533
region_20     525
region_14     510
region_17     498
region_25     480
region_5      442
region_8      411
region_6      408
region_10     407
region_30     396
region_1      368
region_12     312
region_24     306
region_9      242
region_21     230
region_3      212
region_34     167
region_33     155
region_18      17
Name: region, dtype: int64
******************************
Bachelor's          23562
Master's & above     8840
Below Secondary       482
Name: education, dtype: int64
******************************
m    22989
f     9895
Name: gender, dtype: int64
******************************
other       18260
sourcing    13942
referred      682
Name: recruitment_channel, dtype: int64
******************************
```

In [56]:

```
cols = X_val.select_dtypes(include=["object", "category"])
for i in cols.columns:
    print(X_val[i].value_counts())
    print("*" * 30)
```

```
Sales & Marketing    3454
Operations           2315
Procurement          1392
Technology           1364
Analytics            1072
Finance               485
HR                    456
Legal                 227
R&D                   197
Name: department, dtype: int64
```

```
******************************
region_2     2478
region_22    1262
region_7      915
region_15     557
region_13     533
region_26     466
region_31     431
region_27     358
region_4      351
region_16     288
region_11     262
region_28     252
region_23     248
region_32     201
region_29     201
region_19     176
region_20     171
region_14     167
region_25     156
region_5      154
region_17     149
region_6      138
region_1      133
region_30     132
region_8      126
region_10     119
region_24     106
region_21      93
region_12      86
region_9       83
region_3       62
region_33      60
region_34      44
region_18       4
Name: region, dtype: int64
******************************
Bachelor's          7744
Master's & above    3053
Below Secondary      165
Name: education, dtype: int64
******************************
m    7809
f    3153
Name: gender, dtype: int64
******************************
other       6073
sourcing    4666
referred     223
Name: recruitment_channel, dtype: int64
******************************
```

In [57]:

```
cols = X_test.select_dtypes(include=["object", "category"])
for i in cols.columns:
    print(X_train[i].value_counts())
    print("*" * 30)
```

```
Sales & Marketing    9989
Operations           6746
Technology           4383
Procurement          4330
Analytics            3173
Finance              1570
HR                   1482
R&D                   613
Legal                 598
Name: department, dtype: int64
******************************
region_2     7351
region_22    3867
region_7     2973
region_15    1706
region_13    1584
region_26    1344
region_31    1132
region_4      987
region_27     983
region_16     893
region_11     799
region_28     780
```

```
region_23     688
region_29     601
region_32     577
region_19     533
region_20     525
region_14     510
region_17     498
region_25     480
region_5      442
region_8      411
region_6      408
region_10     407
region_30     396
region_1      368
region_12     312
region_24     306
region_9      242
region_21     230
region_3      212
region_34     167
region_33     155
region_18      17
Name: region, dtype: int64
******************************
Bachelor's          23562
Master's & above     8840
Below Secondary       482
Name: education, dtype: int64
******************************
m    22989
f     9895
Name: gender, dtype: int64
******************************
other       18260
sourcing    13942
referred      682
Name: recruitment_channel, dtype: int64
******************************
```

Encoding categorical variables

In [58]:

```
X_train = pd.get_dummies(X_train, drop_first=True)
X_val = pd.get_dummies(X_val, drop_first=True)
X_test = pd.get_dummies(X_test, drop_first=True)
print(X_train.shape, X_val.shape, X_test.shape)
```

```
(32884, 52) (10962, 52) (10962, 52)
```

- After encoding there are 52 columns.

In [59]:

```
X_train.head()
```

Out[59]:

	no_of_trainings	age	previous_year_rating	length_of_service	awards_won	avg_training_score	department_Finance	department_HR	dep
24986	2	34	3.000	4	0	85.000	0	0	
42259	1	35	3.000	10	0	65.000	0	0	
51748	2	28	4.000	3	0	50.000	0	0	
48031	1	38	1.000	9	0	51.000	0	0	
36827	1	39	5.000	12	0	88.000	0	0	

Building the model

Model evaluation criterion

Model can make wrong predictions as:

1. Predicting an employee will be promoted and the employee is not promoted
2. Predicting an employee will not be promoted and the employee is promoted

Which case is more important?

- In my opinion both are valuable pieces of information but it would be interesting to understand the Recall of the problem when the employee is not expected to be promoted but it is promoted

How to reduce this loss i.e need to reduce False Negatives?

- Use `Recall` to be maximized, greater the Recall higher the chances of minimizing false negatives. Hence, the focus should be on increasing Recall or minimizing the false negatives or in other words identifying the true positives(i.e. Class 1).

Functions to calculate different metrics and confusion matrix

In [60]:

```
# defining a function to compute different metrics to check performance of a classification model built using ski
def model_performance_classification_sklearn(model, predictors, target):
    """
    Function to compute different metrics to check classification model performance

    model: classifier
    predictors: independent variables
    target: dependent variable
    """

    # predicting using the independent variables
    pred = model.predict(predictors)

    acc = accuracy_score(target, pred)  # to compute Accuracy
    recall = recall_score(target, pred)  # to compute Recall
    precision = precision_score(target, pred)  # to compute Precision
    f1 = f1_score(target, pred)  # to compute F1-score

    # creating a dataframe of metrics
    df_perf = pd.DataFrame(
        {"Accuracy": acc, "Recall": recall, "Precision": precision, "F1": f1,},
        index=[0],
    )

    return df_perf
```

In [61]:

```
def confusion_matrix_sklearn(model, predictors, target):
    """
    To plot the confusion_matrix with percentages

    model: classifier
    predictors: independent variables
    target: dependent variable
    """
    y_pred = model.predict(predictors)
    cm = confusion_matrix(target, y_pred)
    labels = np.asarray(
        [
            ["{0:0.0f}".format(item) + "\n{0:.2%}".format(item / cm.flatten().sum())]
            for item in cm.flatten()
        ]
    ).reshape(2, 2)

    plt.figure(figsize=(6, 4))
    sns.heatmap(cm, annot=labels, fmt="")
    plt.ylabel("True label")
    plt.xlabel("Predicted label")
```

Model with original data

In [62]:

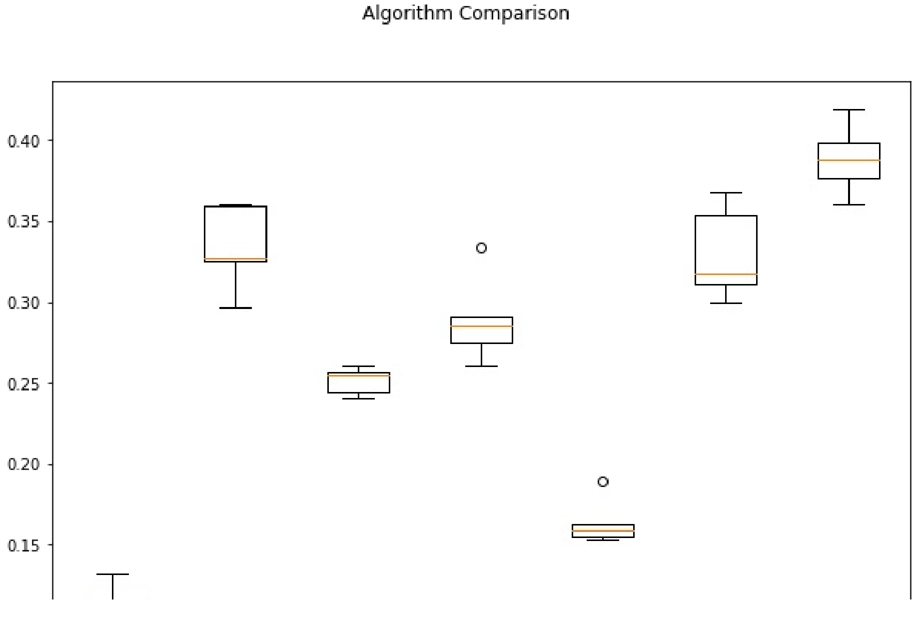
```
models = []  # Empty list to store all the models

# Appending models into the list
models.append(("Logistic regression", LogisticRegression(random_state=1)))
models.append(("Bagging", BaggingClassifier(random_state=1)))
models.append(("Random forest", RandomForestClassifier(random_state=1)))
models.append(("GBM", GradientBoostingClassifier(random_state=1)))
models.append(("Adaboost", AdaBoostClassifier(random_state=1)))
models.append(("Xgboost", XGBClassifier(random_state=1, eval_metric="logloss")))
```

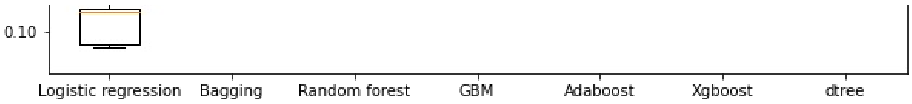
```
models.append(("dtree", DecisionTreeClassifier(random_state=1)))

results1 = []  # Empty list to store all model's CV scores
names = []  # Empty list to store name of the models


# loop through all models to get the mean cross validated score
print("\n" "Cross-Validation Performance:" "\n")

for name, model in models:
    scoring = "recall"
    kfold = StratifiedKFold(
        n_splits=5, shuffle=True, random_state=1
    )  # Setting number of splits equal to 5
    cv_result = cross_val_score(
        estimator=model, X=X_train, y=y_train, scoring=scoring, cv=kfold
    )
    results1.append(cv_result)
    names.append(name)
    print("{}: {}".format(name, cv_result.mean() * 100))

print("\n" "Validation Performance:" "\n")

for name, model in models:
    model.fit(X_train, y_train)
    scores = recall_score(y_val, model.predict(X_val))
    print("{}: {}".format(name, scores))
```

```
Cross-Validation Performance:

Logistic regression: 10.857142857142858
Bagging: 33.357142857142854
Random forest: 25.178571428571427
GBM: 28.92857142857143
Adaboost: 16.392857142857142
Xgboost: 33.0
dtree: 38.857142857142854

Validation Performance:

Logistic regression: 0.12098501070663811
Bagging: 0.33190578158458245
Random forest: 0.25910064239828695
GBM: 0.2826552462526767
Adaboost: 0.16059957173447537
Xgboost: 0.33190578158458245
dtree: 0.3854389721627409
```

In [63]:

```
# Plotting boxplots for CV scores of all models defined above
fig = plt.figure(figsize=(10, 7))

fig.suptitle("Algorithm Comparison")
ax = fig.add_subplot(111)

plt.boxplot(results1)
ax.set_xticklabels(names)

plt.show()
```





Performance comparison

- dtree has the best performance followed by bagging

Models with Oversampled data

In [64]:

```
print("Before Oversampling, counts of label 'Yes': {}".format(sum(y_train == 1)))
print("Before Oversampling, counts of label 'No': {} \n".format(sum(y_train == 0)))

sm = SMOTE(
    sampling_strategy=1, k_neighbors=5, random_state=1
)  # Synthetic Minority Over Sampling Technique
X_train_over, y_train_over = sm.fit_resample(X_train, y_train)


print("After Oversampling, counts of label 'Yes': {}".format(sum(y_train_over == 1)))
print("After Oversampling, counts of label 'No': {} \n".format(sum(y_train_over == 0)))


print("After Oversampling, the shape of train_X: {}".format(X_train_over.shape))
print("After Oversampling, the shape of train_y: {} \n".format(y_train_over.shape))
```

```
Before Oversampling, counts of label 'Yes': 2800
Before Oversampling, counts of label 'No': 30084

After Oversampling, counts of label 'Yes': 30084
After Oversampling, counts of label 'No': 30084

After Oversampling, the shape of train_X: (60168, 52)
After Oversampling, the shape of train_y: (60168,)
```

In [65]:

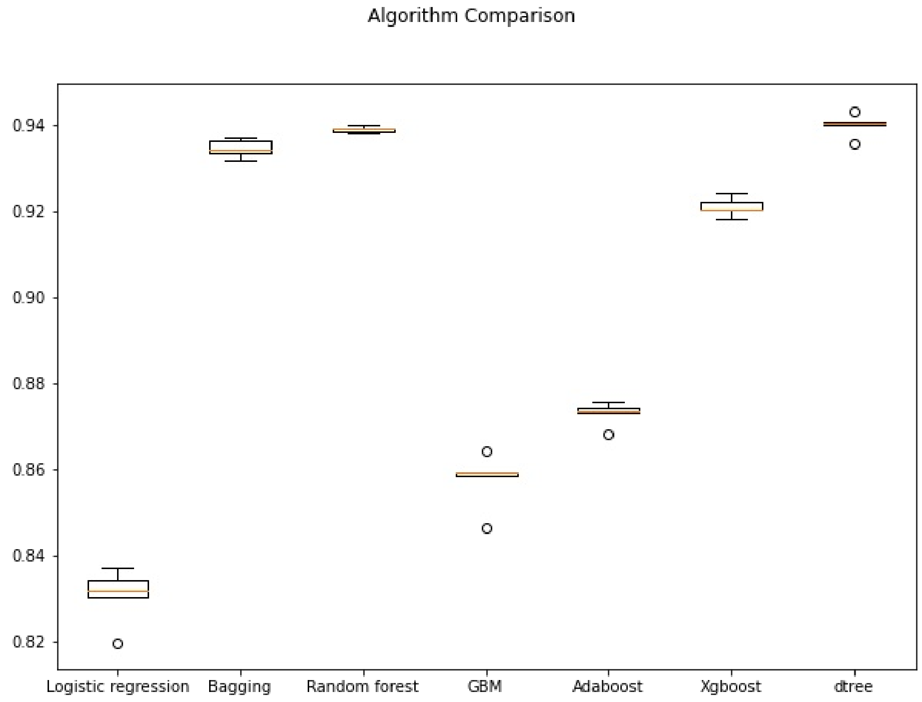
```
%%time
models = []  # Empty list to store all the models

# Appending models into the list
models.append(("Logistic regression", LogisticRegression(random_state=1)))
models.append(("Bagging", BaggingClassifier(random_state=1)))
models.append(("Random forest", RandomForestClassifier(random_state=1)))
models.append(("GBM", GradientBoostingClassifier(random_state=1)))
models.append(("Adaboost", AdaBoostClassifier(random_state=1)))
models.append(("Xgboost", XGBClassifier(random_state=1, eval_metric="logloss")))
models.append(("dtree", DecisionTreeClassifier(random_state=1)))

results2 = []  # Empty list to store all model's CV scores
names = []  # Empty list to store name of the models


# loop through all models to get the mean cross validated score
print("\n" "Cross-Validation Performance:" "\n")

for name, model in models:
    scoring = "recall"
    kfold = StratifiedKFold(
        n_splits=5, shuffle=True, random_state=1
    )  # Setting number of splits equal to 5
    cv_result = cross_val_score(
        estimator=model, X=X_train_over, y=y_train_over, scoring=scoring, cv=kfold, n_jobs=-1
    )
    results2.append(cv_result)
    names.append(name)
    print("{}: {}".format(name, cv_result.mean() * 100))

print("\n" "Validation Performance:" "\n")

for name, model in models:
    model.fit(X_train_over, y_train_over)
    scores = recall_score(y_val, model.predict(X_val))
    print("{}: {}".format(name, scores))
```

```
Cross-Validation Performance:
```

```
Logistic regression: 83.07407160209195
Bagging: 93.46164921905664
Random forest: 93.90373385779299
GBM: 85.76986658368664
Adaboost: 87.30554541388052
Xgboost: 92.10876585490048
dtree: 93.99348731342756

Validation Performance:

Logistic regression: 0.29014989293361887
Bagging: 0.31156316916488225
Random forest: 0.29229122055674517
GBM: 0.37794432548179874
Adaboost: 0.3222698072805139
Xgboost: 0.3747323340471092
dtree: 0.3747323340471092
CPU times: user 40.4 s, sys: 5.32 s, total: 45.7 s
Wall time: 45.2 s
```

In [66]:

```python
# Plotting boxplots for CV scores of all models defined above
fig = plt.figure(figsize=(10, 7))

fig.suptitle("Algorithm Comparison")
ax = fig.add_subplot(111)

plt.boxplot(results2)
ax.set_xticklabels(names)

plt.show()
```



Performance comparison

- Random forest has the best performance followed by bagging
- Performance of all models in the validation set is poor

Models with Undersampled data

In [67]:

```python
rus = RandomUnderSampler(random_state=1)
X_train_un, y_train_un = rus.fit_resample(X_train, y_train)
```

In [68]:

```python
print("Before Under Sampling, counts of label 'Yes': {}".format(sum(y_train == 1)))
print("Before Under Sampling, counts of label 'No': {} \n".format(sum(y_train == 0)))
```

```
print("After Under Sampling, counts of label 'Yes': {}".format(sum(y_train_un == 1)))
print("After Under Sampling, counts of label 'No': {} \n".format(sum(y_train_un == 0)))

print("After Under Sampling, the shape of train_X: {}".format(X_train_un.shape))
print("After Under Sampling, the shape of train_y: {} \n".format(y_train_un.shape))
```

```
Before Under Sampling, counts of label 'Yes': 2800
Before Under Sampling, counts of label 'No': 30084

After Under Sampling, counts of label 'Yes': 2800
After Under Sampling, counts of label 'No': 2800

After Under Sampling, the shape of train_X: (5600, 52)
After Under Sampling, the shape of train_y: (5600,)
```

In [69]:

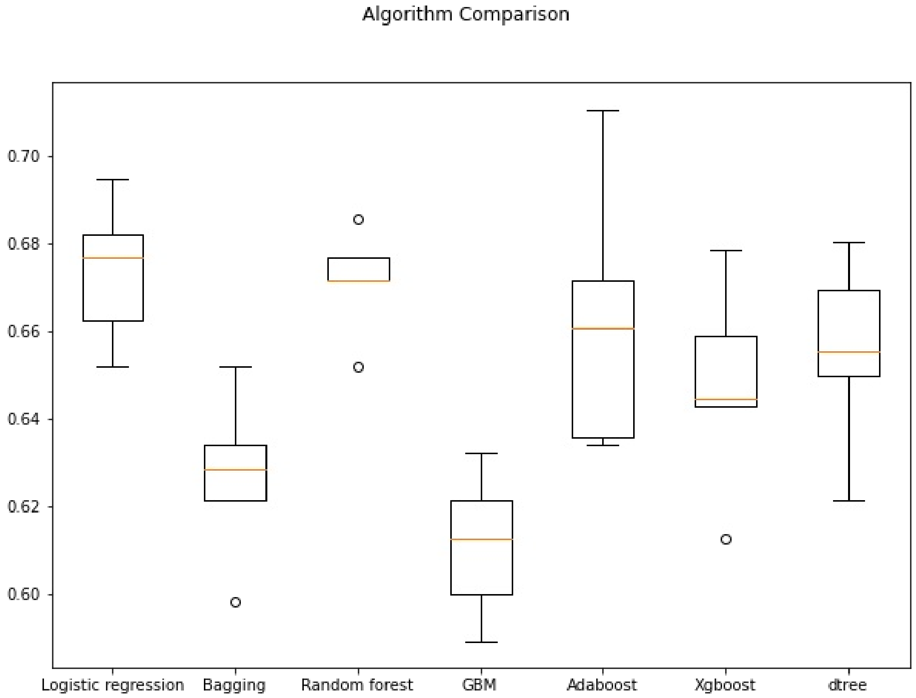
```
models = []  # Empty list to store all the models

# Appending models into the list
models.append(("Logistic regression", LogisticRegression(random_state=1, max_iter=200)))
models.append(("Bagging", BaggingClassifier(random_state=1)))
models.append(("Random forest", RandomForestClassifier(random_state=1)))
models.append(("GBM", GradientBoostingClassifier(random_state=1)))
models.append(("Adaboost", AdaBoostClassifier(random_state=1)))
models.append(("Xgboost", XGBClassifier(random_state=1, eval_metric="logloss")))
models.append(("dtree", DecisionTreeClassifier(random_state=1)))

results3 = []  # Empty list to store all model's CV scores
names = []  # Empty list to store name of the models


# loop through all models to get the mean cross validated score
print("\n" "Cross-Validation Performance:" "\n")

for name, model in models:
    scoring = "recall"
    kfold = StratifiedKFold(
        n_splits=5, shuffle=True, random_state=1
    )  # Setting number of splits equal to 5
    cv_result = cross_val_score(
        estimator=model, X=X_train_un, y=y_train_un, scoring=scoring, cv=kfold
    )
    results3.append(cv_result)
    names.append(name)
    print("{}: {}".format(name, cv_result.mean() * 100))

print("\n" "Validation Performance:" "\n")

for name, model in models:
    model.fit(X_train_un, y_train_un)
    scores = recall_score(y_val, model.predict(X_val))
    print("{}: {}".format(name, scores))
```

```
Cross-Validation Performance:

Logistic regression: 67.35714285714286
Bagging: 62.67857142857143
Random forest: 67.14285714285715
GBM: 61.10714285714286
Adaboost: 66.25
Xgboost: 64.75000000000001
dtree: 65.53571428571429

Validation Performance:

Logistic regression: 0.6852248394004282
Bagging: 0.6124197002141327
Random forest: 0.6702355460385439
GBM: 0.6231263383297645
Adaboost: 0.6702355460385439
Xgboost: 0.6541755888650964
dtree: 0.6413276231263383
```

In [70]:

```
# Plotting boxplots for CV scores of all models defined above
fig = plt.figure(figsize=(10, 7))

fig.suptitle("Algorithm Comparison")
ax = fig.add_subplot(111)
```

```
plt.boxplot(results3)
ax.set_xticklabels(names)

plt.show()
```



Performance comparison

- Logistic Regression & random forest are performing equally well as per the validation performance
- It would seem that undersampling is not overfitting the data like in the oversampling case

Which models should be tuned?

- There is a mix and match of models and none are consistent. There is dtree, bagging, random forest and logistic regression
- Tune these 4 models (adding an extra one since the results are ambiguous).
- We will tune these 4 models using undersampled data.
- Sometimes models might overfit after undersampling and oversampling, so it's better to tune models with both undersampled data and original data

Tuning dtree

Tuning with Undersampled data

In [71]:

```
%%time

# defining model
Model = DecisionTreeClassifier(criterion = 'gini', random_state=1)

#Parameter grid to pass in RandomSearchCV
param_grid={'max_depth': np.arange(1,10),
            'min_samples_leaf': [1, 2, 5, 7, 10,15,20],
            'max_leaf_nodes' : [2, 3, 5, 10],
            'min_impurity_decrease': [0.001,0.01,0.1]
           }
from sklearn import metrics

# Type of scoring used to compare parameter combinations
scorer = metrics.make_scorer(metrics.recall_score)

#Calling RandomizedSearchCV
randomized_cv = RandomizedSearchCV(estimator=Model, param_distributions=param_grid, n_iter=50, n_jobs = -1, scori

#Fitting parameters in RandomizedSearchCV
randomized_cv.fit(X_train_un,y_train_un)

print("Best parameters are {} with CV score={}:" .format(randomized_cv.best_params_,randomized_cv.best_score_))
```

```
Best parameters are {'min_samples_leaf': 2, 'min_impurity_decrease': 0.001, 'max_leaf_nodes': 10, 'max_depth': 8}
with CV score=0.5921428571428571:
CPU times: user 267 ms, sys: 73.1 ms, total: 340 ms
Wall time: 353 ms
```

In [72]:

```
%%time

# defining model
Model = DecisionTreeClassifier(criterion = 'gini', random_state=1)

#Parameter grid to pass in RandomSearchCV
param_grid={'max_depth': np.arange(1,10),
              'min_samples_leaf': [1, 2, 5, 7, 10,15,20],
              'max_leaf_nodes' : [2, 3, 5, 10],
              'min_impurity_decrease': [0.001,0.01,0.1]
           }
from sklearn import metrics

# Type of scoring used to compare parameter combinations
scorer = metrics.make_scorer(metrics.recall_score)

#Calling RandomizedSearchCV
randomized_cv = RandomizedSearchCV(estimator=Model, param_distributions=param_grid, n_iter=50, n_jobs = -1, scori

#Fitting parameters in RandomizedSearchCV
randomized_cv.fit(X_train_un,y_train_un)

print("Best parameters are {} with CV score={}:" .format(randomized_cv.best_params_,randomized_cv.best_score_))
```

```
Best parameters are {'min_samples_leaf': 2, 'min_impurity_decrease': 0.001, 'max_leaf_nodes': 10, 'max_depth': 8}
with CV score=0.5921428571428571:
CPU times: user 195 ms, sys: 24.7 ms, total: 220 ms
Wall time: 386 ms
```

In [73]:

```
%%time
tuned_dtree1 = DecisionTreeClassifier(
    random_state=1,
    min_samples_leaf=2,
    min_impurity_decrease=0.001,
    max_leaf_nodes=10,
    max_depth=8,
)
tuned_dtree1.fit(X_train_un, y_train_un)
```

```
CPU times: user 8.63 ms, sys: 689 µs, total: 9.32 ms
Wall time: 8.55 ms
```

Out[73]:

```
DecisionTreeClassifier(max_depth=8, max_leaf_nodes=10,
                       min_impurity_decrease=0.001, min_samples_leaf=2,
                       random_state=1)
```

In [74]:

```
# Checking model's performance on train set
dtree1_train = model_performance_classification_sklearn(
    tuned_dtree1, X_train_un, y_train_un
)
dtree1_train
```

Out[74]:

	Accuracy	Recall	Precision	F1
0	0.688	0.591	0.734	0.655

In [75]:

```
# Checking model's performance on validation set
dtree1_val = model_performance_classification_sklearn(tuned_dtree1, X_val, y_val)
dtree1_val
```

Out[75]:

	Accuracy	Recall	Precision	F1
0	0.770	0.596	0.207	0.307

Tuning with Original data

In [76]:
```
%%time

# defining model
Model = DecisionTreeClassifier(criterion = 'gini', random_state=1)

#Parameter grid to pass in RandomSearchCV
param_grid={'max_depth': np.arange(1,10),
              'min_samples_leaf': [1, 2, 5, 7, 10,15,20],
              'max_leaf_nodes' : [2, 3, 5, 10],
              'min_impurity_decrease': [0.001,0.01,0.1]
           }
from sklearn import metrics

# Type of scoring used to compare parameter combinations
scorer = metrics.make_scorer(metrics.recall_score)

#Calling RandomizedSearchCV
randomized_cv = RandomizedSearchCV(estimator=Model, param_distributions=param_grid, n_iter=50, n_jobs = -1, scori

#Fitting parameters in RandomizedSearchCV
randomized_cv.fit(X_train,y_train)

print("Best parameters are {} with CV score={}:" .format(randomized_cv.best_params_,randomized_cv.best_score_))
```

```
Best parameters are {'min_samples_leaf': 2, 'min_impurity_decrease': 0.001, 'max_leaf_nodes': 10, 'max_depth': 8}
with CV score=0.15035714285714286:
CPU times: user 333 ms, sys: 96.1 ms, total: 429 ms
Wall time: 1.24 s
```

In [77]:
```
tuned_dtree2 = DecisionTreeClassifier(
    random_state=1,
    min_samples_leaf=2,
    min_impurity_decrease=0.001,
    max_leaf_nodes=10,
    max_depth=8,
)
tuned_dtree2.fit(X_train_un, y_train_un)
tuned_dtree2.fit(X_train, y_train)
```

Out[77]:
```
DecisionTreeClassifier(max_depth=8, max_leaf_nodes=10,
                       min_impurity_decrease=0.001, min_samples_leaf=2,
                       random_state=1)
```

In [78]:
```
# Checking model's performance on training set
dtree2_train = model_performance_classification_sklearn(tuned_dtree2, X_train, y_train)
dtree2_train
```

Out[78]:

	Accuracy	Recall	Precision	F1
0	0.925	0.141	0.861	0.242

In [79]:
```
# Checking model's performance on validation set
dtree2_val = model_performance_classification_sklearn(tuned_dtree2, X_val, y_val)
dtree2_val
```

Out[79]:

	Accuracy	Recall	Precision	F1
0	0.924	0.136	0.836	0.234

Tuning Logistic Regression

Tuning with Undersampled data

In [80]:

```
%%time

# defining model
Model = LogisticRegression(random_state=1)

# Parameter grid to pass in RandomSearchCV
param_grid = {
    'penalty': ['l2'],'C':[0.001,.009,0.01,.09,1,5,10,25], 'solver':['newton-cg', 'lbfgs', 'liblinear']
}

# Type of scoring used to compare parameter combinations
scorer = metrics.make_scorer(metrics.recall_score)

#Calling RandomizedSearchCV
randomized_cv = RandomizedSearchCV(estimator=Model, param_distributions=param_grid, n_jobs = -1, n_iter=50, scori

#Fitting parameters in RandomizedSearchCV
randomized_cv.fit(X_train_un,y_train_un)

print("Best parameters are {} with CV score={}:" .format(randomized_cv.best_params_,randomized_cv.best_score_))
```

```
Best parameters are {'solver': 'liblinear', 'penalty': 'l2', 'C': 0.009} with CV score=0.6875:
CPU times: user 196 ms, sys: 19 ms, total: 215 ms
Wall time: 1.83 s
```

In [81]:

```
%%time

# defining model
Model = LogisticRegression(solver="liblinear",random_state=1)

# Parameter grid to pass in RandomSearchCV
param_grid = {
    'penalty': ['l2'],'C':[0.001,.009,0.01,.09,1,5,10,25], 'solver': ['liblinear']
}

# Type of scoring used to compare parameter combinations
scorer = metrics.make_scorer(metrics.recall_score)

#Calling RandomizedSearchCV
randomized_cv = RandomizedSearchCV(estimator=Model, param_distributions=param_grid, n_jobs = -1, n_iter=50, scori

#Fitting parameters in RandomizedSearchCV
randomized_cv.fit(X_train_un,y_train_un)

print("Best parameters are {} with CV score={}:" .format(randomized_cv.best_params_,randomized_cv.best_score_))
```

```
Best parameters are {'solver': 'liblinear', 'penalty': 'l2', 'C': 0.009} with CV score=0.6875:
CPU times: user 60 ms, sys: 6.83 ms, total: 66.9 ms
Wall time: 214 ms
```

In [82]:

```
tuned_log1 = LogisticRegression(
    random_state=1, penalty="l2", C=0.009, solver="liblinear"
)

tuned_log1.fit(X_train_un, y_train_un)
```

Out[82]:

```
LogisticRegression(C=0.009, random_state=1, solver='liblinear')
```

In [83]:

```
# Checking model's performance on training set
log1_train = model_performance_classification_sklearn(
    tuned_log1, X_train_un, y_train_un
)
log1_train
```

Out[83]:

	Accuracy	Recall	Precision	F1
0	0.656	0.687	0.647	0.666

In [84]:

```
# Checking model's performance on validation set
log1_val = model_performance_classification_sklearn(tuned_log1, X_val, y_val)
log1_val
```

Out[84]:

	Accuracy	Recall	Precision	F1
0	0.639	0.678	0.148	0.242

Tuning with Original data

In [85]:

```
%%time

# defining model
Model = LogisticRegression(random_state=1)

# Parameter grid to pass in RandomSearchCV
param_grid = {
    'penalty': ['l2'],'C':[0.001,.009,0.01,.09,1,5,10,25],'solver': ['liblinear']

}


# Type of scoring used to compare parameter combinations
scorer = metrics.make_scorer(metrics.recall_score)

#Calling RandomizedSearchCV
randomized_cv = RandomizedSearchCV(estimator=Model, param_distributions=param_grid, n_jobs = -1, n_iter=50, scori

#Fitting parameters in RandomizedSearchCV
randomized_cv.fit(X_train,y_train)

print("Best parameters are {} with CV score={}:" .format(randomized_cv.best_params_,randomized_cv.best_score_))
```

```
Best parameters are {'solver': 'liblinear', 'penalty': 'l2', 'C': 25} with CV score=0.26357142857142857:
CPU times: user 285 ms, sys: 209 ms, total: 494 ms
Wall time: 987 ms
```

In [86]:

```
tuned_log2 = LogisticRegression(random_state=1, penalty="l2", C=25, solver="liblinear")
tuned_log2.fit(X_train, y_train)
```

Out[86]:

```
LogisticRegression(C=25, random_state=1, solver='liblinear')
```

In [87]:

```
# Checking model's performance on validation set
log2_val = model_performance_classification_sklearn(tuned_log2, X_val, y_val)
log2_val
```

Out[87]:

	Accuracy	Recall	Precision	F1
0	0.937	0.283	0.943	0.435

In [88]:

```
# Checking model's performance on training set
log2_train = model_performance_classification_sklearn(tuned_log2, X_train, y_train)
log2_train
```

Out[88]:

	Accuracy	Recall	Precision	F1
0	0.937	0.269	0.954	0.420

Tuning Bagging

Tuning with Undersampled Data

In [89]:

```
%%time

#Creating pipeline
Model = BaggingClassifier(random_state=1)
```

```
#Parameter grid to pass in RandomSearchCV
param_grid = {
    'n_estimators' : [100, 300, 500, 800, 1200],
#max_depth = [5, 10, 15, 25, 30]
'max_samples' : [5, 10, 25, 50, 100],
'max_features' : [1, 2, 5, 10, 13],
}

# Type of scoring used to compare parameter combinations
scorer = metrics.make_scorer(metrics.recall_score)

#Calling RandomizedSearchCV
randomized_cv = RandomizedSearchCV(estimator=Model, param_distributions=param_grid, n_iter=50, scoring=scorer, cv

#Fitting parameters in RandomizedSearchCV
randomized_cv.fit(X_train_un,y_train_un)

print("Best parameters are {} with CV score={}:" .format(randomized_cv.best_params_,randomized_cv.best_score_))
```

```
Best parameters are {'n_estimators': 500, 'max_samples': 5, 'max_features': 1} with CV score=0.7949999999999999:
CPU times: user 1.09 s, sys: 299 ms, total: 1.39 s
Wall time: 21.2 s
```

In [90]:

```
tuned_bag1 = BaggingClassifier(
    random_state=1, n_estimators=500, max_samples=5, max_features=1,
)
tuned_bag1.fit(X_train_un, y_train_un)
```

Out[90]:

```
BaggingClassifier(max_features=1, max_samples=5, n_estimators=500,
                  random_state=1)
```

In [91]:

```
# Checking model's performance on training set
bag1_train = model_performance_classification_sklearn(
    tuned_bag1, X_train_un, y_train_un
)
bag1_train
```

Out[91]:

	Accuracy	Recall	Precision	F1
0	0.548	0.840	0.530	0.650

In [92]:

```
# Checking model's performance on validation set
bag1_val = model_performance_classification_sklearn(tuned_bag1, X_val, y_val)
bag1_val
```

Out[92]:

	Accuracy	Recall	Precision	F1
0	0.321	0.849	0.098	0.176

Tuning with Original data

In [93]:

```
%%time

#defining model
Model = BaggingClassifier(random_state=1)

#Parameter grid to pass in RandomSearchCV
param_grid = {
    'n_estimators' : [100, 300, 500, 800, 1200],
#max_depth = [5, 10, 15, 25, 30]
'max_samples' : [5, 10, 25, 50, 100],
'max_features' : [1, 2, 5, 10, 13],
}

# Type of scoring used to compare parameter combinations
scorer = metrics.make_scorer(metrics.recall_score)

#Calling RandomizedSearchCV
randomized_cv = RandomizedSearchCV(estimator=Model, param_distributions=param_grid, n_iter=50, scoring=scorer, cv
```

```
#Fitting parameters in RandomizedSearchCV
randomized_cv.fit(X_train,y_train)

print("Best parameters are {} with CV score={}:" .format(randomized_cv.best_params_,randomized_cv.best_score_))
```

```
Best parameters are {'n_estimators': 1200, 'max_samples': 100, 'max_features': 5} with CV score=0.0:
CPU times: user 2.85 s, sys: 278 ms, total: 3.13 s
Wall time: 43 s
```

In [94]:

```
tuned_bag2 = BaggingClassifier(
    random_state=1, n_estimators=1200, max_samples=100, max_features=5,
)
tuned_bag2.fit(X_train, y_train)
```

Out[94]:

```
BaggingClassifier(max_features=5, max_samples=100, n_estimators=1200,
                  random_state=1)
```

In [95]:

```
# Checking model's performance on training set
bag2_train = model_performance_classification_sklearn(tuned_bag2, X_train, y_train)
bag2_train
```

Out[95]:

	Accuracy	Recall	Precision	F1
0	0.915	0.000	0.000	0.000

In [96]:

```
# Checking model's performance on validation set
bag2_val = model_performance_classification_sklearn(tuned_bag2, X_val, y_val)
bag2_val
```

Out[96]:

	Accuracy	Recall	Precision	F1
0	0.915	0.000	0.000	0.000

Tuning Random Forest

Tuning with Undersampled Data

In [ ]:

```
%%time

#Creating pipeline
Model = RandomForestClassifier(random_state=1)

#Parameter grid to pass in RandomSearchCV
param_grid = {
   'n_estimators' : [100, 300, 500, 800, 1200],
'max_depth' : [5, 10, 15, 25, 30],
'min_samples_split' :[2, 5, 10, 15, 100],
'min_samples_leaf' : [1, 2, 5, 10]
}

# Type of scoring used to compare parameter combinations
scorer = metrics.make_scorer(metrics.recall_score)

#Calling RandomizedSearchCV
randomized_cv = RandomizedSearchCV(estimator=Model, param_distributions=param_grid, n_iter=50, scoring=scorer, cv

#Fitting parameters in RandomizedSearchCV
randomized_cv.fit(X_train_un,y_train_un)

print("Best parameters are {} with CV score={}:" .format(randomized_cv.best_params_,randomized_cv.best_score_))
```

In [ ]:

```
tuned_forest1 = RandomForestClassifier(
    random_state=1,
    n_estimators=100,
    min_samples_split=5,
    min_samples_leaf=2,
    max_depth=30
```

```
)
tuned_forest1.fit(X_train_un, y_train_un)
```

In [ ]:
```
# Checking model's performance on training set
forest1_train = model_performance_classification_sklearn(
    tuned_forest1, X_train_un, y_train_un
)
forest1_train
```

In [ ]:
```
# Checking model's performance on validation set
forest1_val = model_performance_classification_sklearn(tuned_forest1, X_val, y_val)
forest1_val
```

Tuning with Original data

In [ ]:
```
%%time

#defining model
Model = RandomForestClassifier(random_state=1)

#Parameter grid to pass in RandomSearchCV
param_grid = {
   'n_estimators' : [100, 300, 500, 800, 1200],
'max_depth' : [5, 10, 15, 25, 30],
'min_samples_split' :[2, 5, 10, 15, 100],
'min_samples_leaf' : [1, 2, 5, 10]
}

# Type of scoring used to compare parameter combinations
scorer = metrics.make_scorer(metrics.recall_score)

#Calling RandomizedSearchCV
randomized_cv = RandomizedSearchCV(estimator=Model, param_distributions=param_grid, n_iter=50, scoring=scorer, cv

#Fitting parameters in RandomizedSearchCV
randomized_cv.fit(X_train,y_train)

print("Best parameters are {} with CV score={}:" .format(randomized_cv.best_params_,randomized_cv.best_score_))
```

In [ ]:
```
tuned_forest2 = RandomForestClassifier(
    random_state=1,
    n_estimators=300,
    min_samples_split=2,
    min_samples_leaf=1,
    max_depth=30

)
tuned_forest2.fit(X_train_un, y_train_un)
```

In [ ]:
```
# Checking model's performance on training set
forest2_train = model_performance_classification_sklearn(
    tuned_forest2, X_train_un, y_train_un
)
forest2_train
```

In [ ]:
```
# Checking model's performance on validation set
forest2_val = model_performance_classification_sklearn(tuned_forest2, X_val, y_val)
forest2_val
```

In [ ]:
```

```

Model Performance comparison

In [ ]:
```
# training performance comparison

models_train_comp_df = pd.concat(
    [
        dtree1_train.T,
        dtree2_train.T,
        log1_train.T,
        log2_train.T,
        bag1_train.T,
        bag2_train.T,
```

```
        forest1_train.T,
        forest2_train.T
    ],
    axis=1,
)
models_train_comp_df.columns = [
    "Decision Tree trained with Undersampled data",
    "Decision Tree trained with Original data",
    "Logistic Regression trained with Undersampled data",
    "Logistic Regression trained with Original data",
    "Bagging trained with Undersampled data",
    "Bagging trained with Original data",
    "Random forest trained with Undersampled data",
    "Random forest trained with Original data"
]
print("Training performance comparison:")
models_train_comp_df
```

In [ ]:

```
# Validation performance comparison

models_train_comp_df = pd.concat(
    [dtree1_val.T, dtree2_val.T, log1_val.T, log2_val.T, bag1_val.T, bag2_val.T, forest1_val.T, forest2_val.T],
    axis=1,
)
models_train_comp_df.columns = [
    "Decision Tree trained with Undersampled data",
    "Decision Tree trained with Original data",
    "Logistic Regression trained with Undersampled data",
    "Logistic Regression trained with Original data",
    "Bagging trained with Undersampled data",
    "Bagging trained with Original data",
    "Random forest trained with Undersampled data",
    "Random forest trained with Original data"]

print("Validation performance comparison:")
models_train_comp_df
```

- Random Forest model trained with original data has generalised performance

In [ ]:

```
# Let's check the performance on test set
forest2_test = model_performance_classification_sklearn(tuned_forest2, X_test, y_test)
forest2_test
```

- The model has given generalised performance on test set.

In [ ]:

```
feature_names = X_train.columns
importances = tuned_forest2.feature_importances_
indices = np.argsort(importances)

plt.figure(figsize=(12, 12))
plt.title("Feature Importances")
plt.barh(range(len(indices)), importances[indices], color="violet", align="center")
plt.yticks(range(len(indices)), [feature_names[i] for i in indices])
plt.xlabel("Relative Importance")
plt.show()
```

- Avg_training_score is the most important variable in predicting employee promotion followed by age, length_of_service, previous_year_rating and awards_won

Final Pipelin/Model

In [ ]:

```
# creating a list of numerical variables
numerical_features = [
     'no_of_trainings', 'age',
       'previous_year_rating', 'length_of_service',
       'awards_won', 'avg_training_score']

# creating a transformer for numerical variables, which will apply simple imputer on the numerical variables
numeric_transformer = Pipeline(steps=[("imputer", SimpleImputer(strategy="median"))])


# creating a list of categorical variables
categorical_features = ['department',
       'region', 'education', 'gender',
       'recruitment_channel']
```

```
# creating a transformer for categorical variables, which will first apply simple imputer and
#then do one hot encoding for categorical variables
categorical_transformer = Pipeline(
    steps=[
        ("imputer", SimpleImputer(strategy="most_frequent")),
        ("onehot", OneHotEncoder(handle_unknown="ignore")),
    ]
)
# handle_unknown = "ignore", allows model to handle any unknown category in the test data

# combining categorical transformer and numerical transformer using a column transformer

preprocessor = ColumnTransformer(
    transformers=[
        ("num", numeric_transformer, numerical_features),
        ("cat", categorical_transformer, categorical_features),
    ],
    remainder="drop",
)
# remainder = "drop" has been used, it will drop the variables that are not present in "numerical_features"
# and "categorical_features"
```

In [ ]:

```
# Separating target variable and other variables
X = prediction.drop(columns="is_promoted")
Y = prediction["is_promoted"]
```

- pre-processing

In [ ]:

```
# employee ID are unique values and will not add value to the modeling
X.drop(["employee_id"], axis=1, inplace=True)
```

- Using the best model random forest

In [ ]:

```
# Splitting the data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(
    X, Y, test_size=0.30, random_state=1, stratify=Y
)
print(X_train.shape, X_test.shape)
```

In [ ]:

```
# Creating new pipeline with best parameters
model = Pipeline(
    steps=[
        ("pre", preprocessor),
        (
            "RF",RandomForestClassifier(
    random_state=1,
    n_estimators=300,
    min_samples_split=2,
    min_samples_leaf=1,
    max_depth=30

            ),
        ),
    ]
)
# Fit the model on training data
model.fit(X_train, y_train)
```

Key Insights:

Important Factors Influencing Promotion:

Average Training Score: Higher training scores significantly improve the likelihood of promotion. Previous Year Rating: Higher ratings in the previous year positively correlate with promotions. Length of Service: Employees with longer service are more likely to be promoted. Awards Won: Winning awards in the previous year significantly increases the chances of promotion. Age: There is a noticeable trend where certain age groups have higher promotion rates. Departmental Influence:

Employees in the Technology, Procurement, and Analytics departments have a higher likelihood of being promoted compared to other departments. Gender and Promotion:

There is no significant difference in promotion rates between male and female employees, indicating gender neutrality in promotions. Education Level:

Employees with a Master's degree or higher have a slightly better chance of being promoted compared to those with a Bachelor's degree or below. Region Impact:

Certain regions, like Region 2 and Region 22, have higher promotion rates, suggesting potential regional biases or differences in performance standards. Recommendations: Focus on Training and Development:

Enhance Training Programs: Invest in training programs to improve average training scores. Employees with higher training scores are more likely to be promoted. Regular Assessments: Conduct regular assessments and provide feedback to help employees improve their training scores. Reward and Recognition:

Incentivize Awards: Encourage and incentivize employees to participate in award programs, as winning awards significantly boosts promotion chances. Transparent Criteria: Clearly communicate the criteria for winning awards to all employees. Performance Ratings:

Objective Evaluation: Ensure performance ratings are objective and consistent across departments to avoid biases. Regular Reviews: Conduct regular performance reviews and provide constructive feedback to help employees improve their ratings. Tenure and Experience:

Career Path Planning: Develop clear career paths that outline the progression opportunities for employees based on their tenure and performance. Mentorship Programs: Implement mentorship programs to support employees' career development and readiness for promotion. Age and Promotion:

Age Diversity: Ensure that promotion policies do not inadvertently favor or disadvantage certain age groups. Promote age diversity and inclusivity in the workplace. Departmental Balance:

Cross-Departmental Opportunities: Provide opportunities for employees in lower-promotion departments to participate in projects or roles in higher-promotion departments. Standardize Criteria: Standardize promotion criteria across departments to ensure fairness and consistency. Regional Considerations:

Uniform Standards: Implement uniform performance standards across all regions to ensure equal opportunities for promotion. Regional Training Programs: Address regional disparities by providing additional support and training programs in regions with lower promotion rates. Implementation Steps: Model Deployment:

Deploy the Random Forest model with the best parameters to predict promotions. Integrate the model into the HR system to assist in making informed promotion decisions. Continuous Monitoring and Improvement:

Regularly monitor the model's performance and update it with new data to ensure its accuracy and relevance. Use feedback from the promotion process to refine and improve the model. Employee Feedback:

Gather feedback from employees on the promotion process to identify areas for improvement. Ensure transparency and communication about how promotions are decided and what employees can do to enhance their chances.* We have been able to build a predictive model:

- The company can utilize this model to predicte employee promotion
- The analysis can be used to distinguish and effect factors that drive promotion
- THe company can use the information to build "better" paths to promotion. Interestingly the random forest using original data gave us "age" as a factor that influences promotion, this should be investigated further in order to institue policies that promote fairness in all age groups

- Factors that help promotion - length_of_service, awards_won, previous_year_rating, age, avg_training_score

- awards_won. This factor influences prmotion positively, in other words if the employee has won an award it means that the likelihood of promotion is higher

- previous_year_rating. The factor influences promotion the higher the ranking the higher the chances of promotion

- length_of_service. This factor is somewhat intuitive as the longer the tenure of an employee the higher the chances for promotion

- There was an important factor potentially missing from the model which is department. The data analysis shows a correlation of people belonging to Technology to have a propensity of promotion over other groups

In [ ]:

```

```