

Employee Promotion Prediction

using Decision Tree & Ensemble Learning Algorithms

Introduction



One of the major problem faced by a multinational company is identifying the right employees for promotion. For this purpose, the company created 2 datasets (for training and testing) with 12 input features and 1 output (for training). Using training dataset containing output, the model is to be created and evaluated. This project showcases the implementation of a decision tree and five ensemble learning algorithms.

The goal is to identify the most effective algorithm for determining whether employees in a testing dataset should be promoted.

Here is the feature description for datasets:

Feature	Description
employee_id	Unique ID for 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 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 previous year then 1 else 0
avg_training_score	Average score in current training evaluations
is_promoted	Recommended for promotion

```
In [1]: # basic libraries
import numpy as np
import pandas as pd
from collections import Counter
```

```
In [2]: # data visualization libraries
import matplotlib.pyplot as plt
import seaborn as sns
```

```
In [3]: # sklearn library and imports
from sklearn.utils import resample
from sklearn.preprocessing import OneHotEncoder, MinMaxScaler
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import BaggingClassifier
from sklearn.ensemble import AdaBoostClassifier, GradientBoostingClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import MultinomialNB
from sklearn.svm import SVC
from sklearn.ensemble import VotingClassifier
from sklearn.metrics import confusion_matrix, classification_report
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
```

```
In [4]: # library for model saving
import joblib
```

```
In [5]: # other imports
import warnings
warnings.filterwarnings('ignore')
```

1. Data Collection

```
In [6]: # read csv files
df_train = pd.read_csv("datasets/train.csv")
df_test = pd.read_csv("datasets/test.csv")
```

2. Data Preprocessing

2.1. General Data Exploration

```
In [7]: # top 10 rows of df_train
df_train.head(10)
```

Out[7]:	employee_id	department	region	education	gender	recruitment_channel	no_of_tra
0	65438	Sales & Marketing	region_7	Master's & above	f	sourcing	
1	65141	Operations	region_22	Bachelor's	m	other	
2	7513	Sales & Marketing	region_19	Bachelor's	m	sourcing	
3	2542	Sales & Marketing	region_23	Bachelor's	m	other	
4	48945	Technology	region_26	Bachelor's	m	other	
5	58896	Analytics	region_2	Bachelor's	m	sourcing	
6	20379	Operations	region_20	Bachelor's	f	other	
7	16290	Operations	region_34	Master's & above	m	sourcing	
8	73202	Analytics	region_20	Bachelor's	m	other	
9	28911	Sales & Marketing	region_1	Master's & above	m	sourcing	

```
In [8]: # top 10 rows of df_test
df_test.head(10)
```

Out[8]:	employee_id	department	region	education	gender	recruitment_channel	no_of_tra
0	8724	Technology	region_26	Bachelor's	m	sourcing	
1	74430	HR	region_4	Bachelor's	f	other	
2	72255	Sales & Marketing	region_13	Bachelor's	m	other	
3	38562	Procurement	region_2	Bachelor's	f	other	
4	64486	Finance	region_29	Bachelor's	m	sourcing	
5	46232	Procurement	region_7	Bachelor's	m	sourcing	
6	54542	Finance	region_2	Bachelor's	m	other	
7	67269	Analytics	region_22	Bachelor's	m	sourcing	
8	66174	Technology	region_7	Master's & above	m	other	
9	76303	Technology	region_22	Bachelor's	m	sourcing	

```
In [9]: # check rows and columns
print(df_train.shape)
print(df_test.shape)
```

```
(54808, 13)
```

```
(23490, 12)
```

```
In [10]: # checking null values, count and datatypes in df_train
df_train.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       54808 non-null  int64
12  is_promoted              54808 non-null  int64
dtypes: float64(1), int64(7), object(5)
memory usage: 5.4+ MB
```

```
In [11]: # checking null values, count and datatypes in df_test
df_test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 23490 entries, 0 to 23489
Data columns (total 12 columns):
#   Column                Non-Null Count  Dtype
---  -
0   employee_id            23490 non-null  int64
1   department              23490 non-null  object
2   region                  23490 non-null  object
3   education                22456 non-null  object
4   gender                  23490 non-null  object
5   recruitment_channel      23490 non-null  object
6   no_of_trainings         23490 non-null  int64
7   age                     23490 non-null  int64
8   previous_year_rating    21678 non-null  float64
9   length_of_service       23490 non-null  int64
10  awards_won?             23490 non-null  int64
11  avg_training_score       23490 non-null  int64
dtypes: float64(1), int64(6), object(5)
memory usage: 2.2+ MB
```

```
In [12]: # check statistics of non-boolean df_train features
df_train.drop(['employee_id', 'awards_won?', 'is_promoted'], axis=1).describe()
```

Out[12]:

	no_of_trainings	age	previous_year_rating	length_of_service	avg_training_s
count	54808.000000	54808.000000	50684.000000	54808.000000	54808.00
mean	1.253011	34.803915	3.329256	5.865512	63.38
std	0.609264	7.660169	1.259993	4.265094	13.37
min	1.000000	20.000000	1.000000	1.000000	39.00
25%	1.000000	29.000000	3.000000	3.000000	51.00
50%	1.000000	33.000000	3.000000	5.000000	60.00
75%	1.000000	39.000000	4.000000	7.000000	76.00
max	10.000000	60.000000	5.000000	37.000000	99.00

In [13]: *# check statistics of non-boolean df_test features*
df_test.drop(['employee_id', 'awards_won?'], axis=1).describe()

Out[13]:

	no_of_trainings	age	previous_year_rating	length_of_service	avg_training_s
count	23490.000000	23490.000000	21678.000000	23490.000000	23490.00
mean	1.254236	34.782929	3.339146	5.810387	63.26
std	0.600910	7.679492	1.263294	4.207917	13.41
min	1.000000	20.000000	1.000000	1.000000	39.00
25%	1.000000	29.000000	3.000000	3.000000	51.00
50%	1.000000	33.000000	3.000000	5.000000	60.00
75%	1.000000	39.000000	4.000000	7.000000	76.00
max	9.000000	60.000000	5.000000	34.000000	99.00

2.2. Handling Missing Values

In [14]: *# check missing values in df_train*
df_train.isna().sum()

```
Out[14]: employee_id      0
          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  0
          is_promoted      0
          dtype: int64
```

```
In [15]: # check missing values of df_test
df_test.isna().sum()
```

```
Out[15]: employee_id      0
          department      0
          region          0
          education      1034
          gender          0
          recruitment_channel  0
          no_of_trainings  0
          age            0
          previous_year_rating  1812
          length_of_service  0
          awards_won?      0
          avg_training_score  0
          dtype: int64
```

```
In [16]: # check value counts for education
print(df_train['education'].value_counts())
print(df_test['education'].value_counts())
```

```
Bachelor's      36669
Master's & above  14925
Below Secondary   805
Name: education, dtype: int64
Bachelor's      15578
Master's & above  6504
Below Secondary   374
Name: education, dtype: int64
```

```
In [17]: # replace null values in education by mode
df_train['education'].fillna(df_train['education'].mode()[0], inplace=True)
df_test['education'].fillna(df_test['education'].mode()[0], inplace=True)
```

```
In [18]: # check value counts for previous_year_rating
print(df_train['previous_year_rating'].value_counts())
print(df_test['previous_year_rating'].value_counts())
```

```

3.0    18618
5.0    11741
4.0     9877
1.0     6223
2.0     4225
Name: previous_year_rating, dtype: int64
3.0     7921
5.0     5097
4.0     4249
1.0     2680
2.0     1731
Name: previous_year_rating, dtype: int64

```

```

In [19]: # replace null values in previous_year_rating by mode
df_train['previous_year_rating'].fillna(df_train['previous_year_rating'].mode()[0],
df_test['previous_year_rating'].fillna(df_test['previous_year_rating'].mode()[0], i

```

2.3. Handling Duplicates

```

In [20]: # check duplicates of df_train
print(len(df_train))
print(len(df_train.drop_duplicates()))

```

```

54808
54808

```

```

In [21]: # check duplicates of df_test
print(len(df_test))
print(len(df_test.drop_duplicates()))

```

```

23490
23490

```

```

In [22]: # drop duplicates of df_train
df_train = df_train.drop_duplicates()

```

```

In [23]: # drop duplicates of df_test
df_test = df_test.drop_duplicates()

```

2.4. Handling Outliers

```

In [24]: # define columns for distribution
dist_cols = ['no_of_trainings', 'age', 'length_of_service', 'avg_training_score']

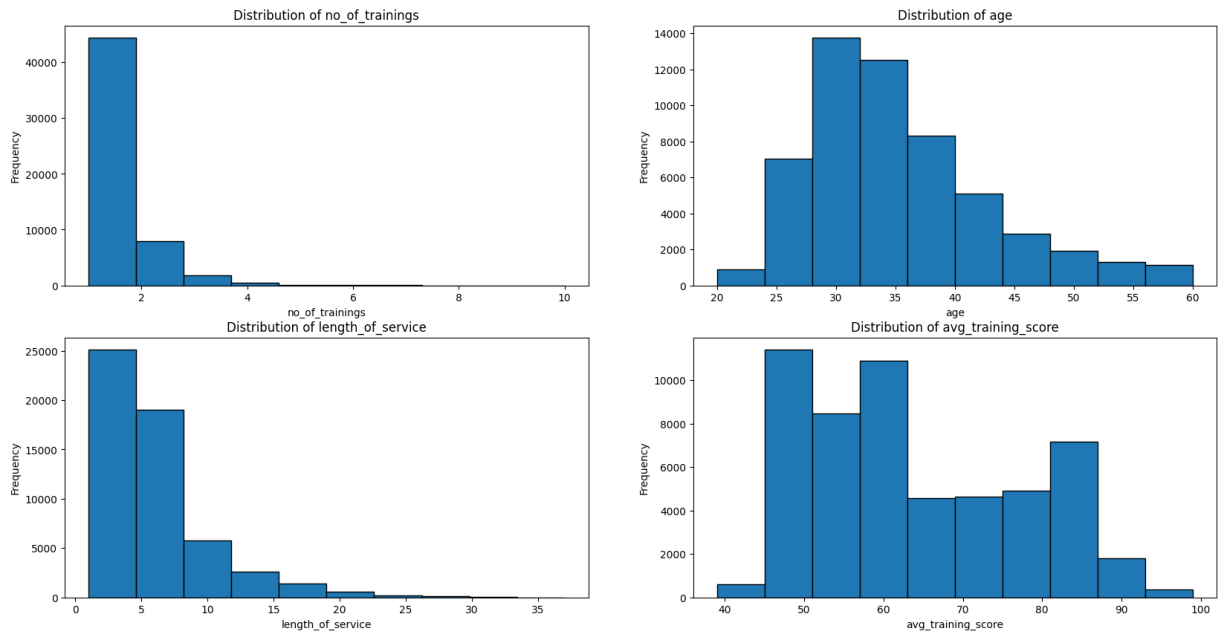
```

```

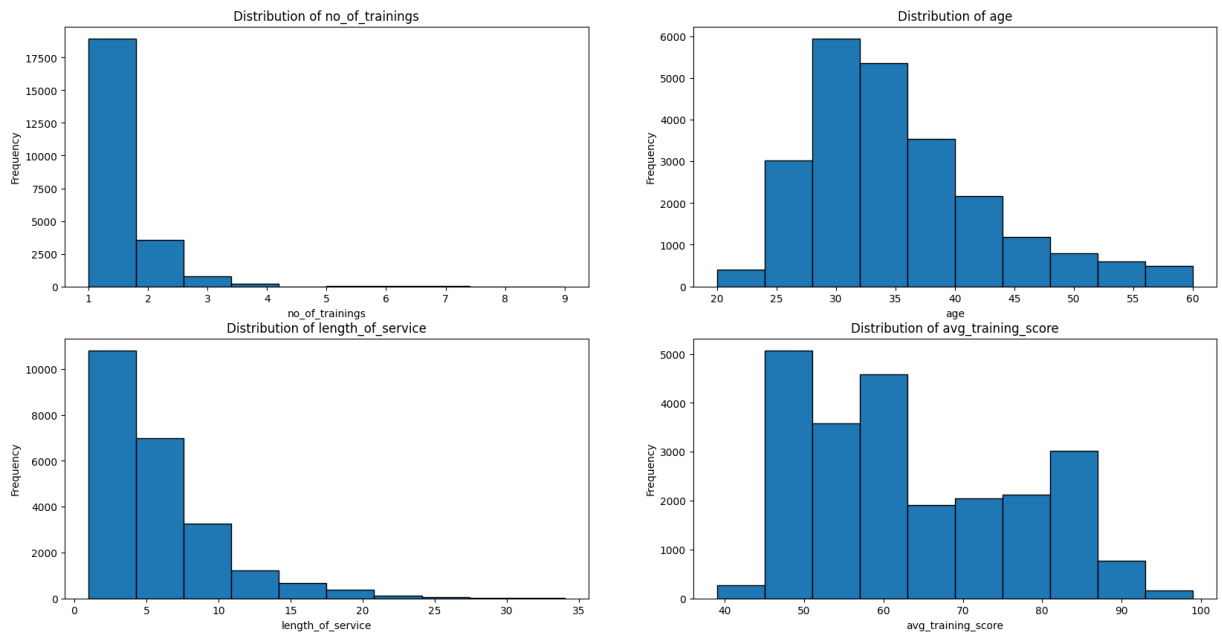
In [25]: # histogram for outliers in df_train
i = 1
plt.figure(figsize=(20, 10))
for col in dist_cols:
    plt.subplot(2, 2, i)
    plt.hist(df_train[col], bins=10, edgecolor='black')
    plt.title(f'Distribution of {col}')
    plt.xlabel(col)
    plt.ylabel('Frequency')

```

```
i += 1
plt.show()
```



```
In [26]: # histogram plot for outliers in df_test
i = 1
plt.figure(figsize=(20, 10))
for col in dist_cols:
    plt.subplot(2, 2, i)
    plt.hist(df_test[col], bins=10, edgecolor='black')
    plt.title(f'Distribution of {col}')
    plt.xlabel(col)
    plt.ylabel('Frequency')
    i += 1
plt.show()
```



2.5. Index Removal


```
In [27]: # remove employee_id from both dataframes
df_train.drop(['employee_id'], axis=1, inplace=True)
df_test.drop(['employee_id'], axis=1, inplace=True)
```

2.6. Checking Feature Values

```
In [28]: # check unique values for all columns in df_train
for col in df_train.columns:
    print(col)
    print(f"Values: \n{df_train[col].unique()}")
    print(f"Number of Values: {len(df_train[col].unique())}")
    print(f"Datatype: {df_train[col].dtype}")
    print("=====")
```

```

department
Values:
['Sales & Marketing' 'Operations' 'Technology' 'Analytics' 'R&D'
 'Procurement' 'Finance' 'HR' 'Legal']
Number of Values: 9
Datatype: object
=====
region
Values:
['region_7' 'region_22' 'region_19' 'region_23' 'region_26' 'region_2'
 'region_20' 'region_34' 'region_1' 'region_4' 'region_29' 'region_31'
 'region_15' 'region_14' 'region_11' 'region_5' 'region_28' 'region_17'
 'region_13' 'region_16' 'region_25' 'region_10' 'region_27' 'region_30'
 'region_12' 'region_21' 'region_8' 'region_32' 'region_6' 'region_33'
 'region_24' 'region_3' 'region_9' 'region_18']
Number of Values: 34
Datatype: object
=====
education
Values:
["Master's & above" "Bachelor's" 'Below Secondary']
Number of Values: 3
Datatype: object
=====
gender
Values:
['f' 'm']
Number of Values: 2
Datatype: object
=====
recruitment_channel
Values:
['sourcing' 'other' 'referred']
Number of Values: 3
Datatype: object
=====
no_of_trainings
Values:
[ 1  2  3  4  7  5  6  8 10  9]
Number of Values: 10
Datatype: int64
=====
age
Values:
[35 30 34 39 45 31 33 28 32 49 37 38 41 27 29 26 24 57 40 42 23 59 44 50
 56 20 25 47 36 46 60 43 22 54 58 48 53 55 51 52 21]
Number of Values: 41
Datatype: int64
=====
previous_year_rating
Values:
[5. 3. 1. 4. 2.]
Number of Values: 5
Datatype: float64
=====
length_of_service

```

```

Values:
[ 8  4  7 10  2  5  6  1  3 16  9 11 26 12 17 14 13 19 15 23 18 20 22 25
 28 24 31 21 29 30 34 27 33 32 37]
Number of Values: 35
Datatype: int64
=====
awards_won?
Values:
[0 1]
Number of Values: 2
Datatype: int64
=====
avg_training_score
Values:
[49 60 50 73 85 59 63 83 54 77 80 84 51 46 75 57 70 68 79 44 72 61 48 58
 87 47 52 88 71 65 62 53 78 91 82 69 55 74 86 90 92 67 89 56 76 81 45 64
 39 94 93 66 95 42 96 40 99 43 97 41 98]
Number of Values: 61
Datatype: int64
=====
is_promoted
Values:
[0 1]
Number of Values: 2
Datatype: int64
=====

```

```

In [29]: # check unique values for all columns in df_train
for col in df_test.columns:
    print(col)
    print(f"Values: \n{df_test[col].unique()}")
    print(f"Number of Values: {len(df_test[col].unique())}")
    print(f"Datatype: {df_test[col].dtype}")
    print("=====")

```

```

department
Values:
['Technology' 'HR' 'Sales & Marketing' 'Procurement' 'Finance' 'Analytics'
 'Operations' 'Legal' 'R&D']
Number of Values: 9
Datatype: object
=====
region
Values:
['region_26' 'region_4' 'region_13' 'region_2' 'region_29' 'region_7'
 'region_22' 'region_16' 'region_17' 'region_24' 'region_11' 'region_27'
 'region_9' 'region_20' 'region_34' 'region_23' 'region_8' 'region_14'
 'region_31' 'region_19' 'region_5' 'region_28' 'region_15' 'region_3'
 'region_25' 'region_12' 'region_21' 'region_30' 'region_10' 'region_33'
 'region_32' 'region_6' 'region_1' 'region_18']
Number of Values: 34
Datatype: object
=====
education
Values:
["Bachelor's" "Master's & above" 'Below Secondary']
Number of Values: 3
Datatype: object
=====
gender
Values:
['m' 'f']
Number of Values: 2
Datatype: object
=====
recruitment_channel
Values:
['sourcing' 'other' 'referred']
Number of Values: 3
Datatype: object
=====
no_of_trainings
Values:
[1 3 2 4 5 7 6 8 9]
Number of Values: 9
Datatype: int64
=====
age
Values:
[24 31 30 36 33 51 29 40 34 37 26 49 27 25 41 52 43 35 42 57 46 21 32 28
 38 23 58 54 44 48 45 39 59 53 56 47 22 20 50 55 60]
Number of Values: 41
Datatype: int64
=====
previous_year_rating
Values:
[3. 1. 2. 4. 5.]
Number of Values: 5
Datatype: float64
=====
length_of_service

```

```

Values:
[ 1  5  4  9  7  2  3 11 12 10  6 14 18  8 26 13 22 19 21 15 16 17 23 20
 31 24 27 28 25 29 33 30 34 32]
Number of Values: 34
Datatype: int64
=====
awards_won?
Values:
[0 1]
Number of Values: 2
Datatype: int64
=====
avg_training_score
Values:
[77 51 47 65 61 68 57 85 75 76 50 46 52 82 58 56 64 80 83 62 87 55 88 90
 66 45 54 84 59 49 81 79 78 60 74 92 48 86 72 43 69 53 71 73 63 70 67 97
 95 89 94 44 91 93 96 98 99 42 41 40 39]
Number of Values: 61
Datatype: int64
=====

```

2.7. Conversion of Datatypes

```

In [30]: # convert previous_year_rating to int64
df_train['previous_year_rating'] = df_train['previous_year_rating'].astype(np.int64)
df_test['previous_year_rating'] = df_test['previous_year_rating'].astype(np.int64)

```

```

In [31]: # checking preprocessed df_train
df_train.info()

```

```

<class 'pandas.core.frame.DataFrame'>
Int64Index: 54808 entries, 0 to 54807
Data columns (total 12 columns):
#   Column                Non-Null Count  Dtype
---  -
0   department            54808 non-null  object
1   region                54808 non-null  object
2   education             54808 non-null  object
3   gender                54808 non-null  object
4   recruitment_channel    54808 non-null  object
5   no_of_trainings       54808 non-null  int64
6   age                  54808 non-null  int64
7   previous_year_rating  54808 non-null  int64
8   length_of_service     54808 non-null  int64
9   awards_won?          54808 non-null  int64
10  avg_training_score    54808 non-null  int64
11  is_promoted           54808 non-null  int64
dtypes: int64(7), object(5)
memory usage: 5.4+ MB

```

```

In [32]: # checking preprocessed df_test
df_test.info()

```

```

<class 'pandas.core.frame.DataFrame'>
Int64Index: 23490 entries, 0 to 23489
Data columns (total 11 columns):
 #   Column                Non-Null Count  Dtype
---  -
 0   department            23490 non-null  object
 1   region                23490 non-null  object
 2   education              23490 non-null  object
 3   gender                23490 non-null  object
 4   recruitment_channel    23490 non-null  object
 5   no_of_trainings        23490 non-null  int64
 6   age                   23490 non-null  int64
 7   previous_year_rating   23490 non-null  int64
 8   length_of_service      23490 non-null  int64
 9   awards_won?           23490 non-null  int64
10   avg_training_score     23490 non-null  int64
dtypes: int64(6), object(5)
memory usage: 2.2+ MB

```

3. Exploratory Data Analysis

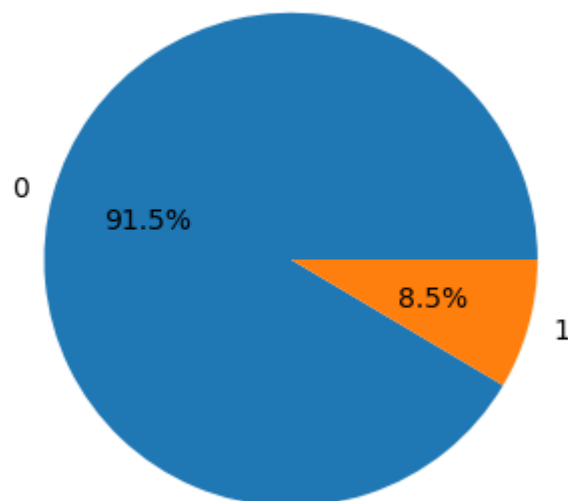
3.1. Frequency Distribution of Target Feature

```

In [33]: # check value counts of is_promoted
counter = Counter(df_train['is_promoted'])
plt.figure(figsize=(4, 4))
plt.pie(list(counter.values()), labels=list(counter.keys()), autopct="%1.1f%")
plt.title('Pie Chart: is_promoted frequency distribution')
plt.show()

```

Pie Chart: is_promoted frequency distribution



Observation: There is 91.5% of employees not promoted compared to minor 8.5%

promoted. For EDA and further analysis, oversampling is important.

3.2. Oversampling for EDA only

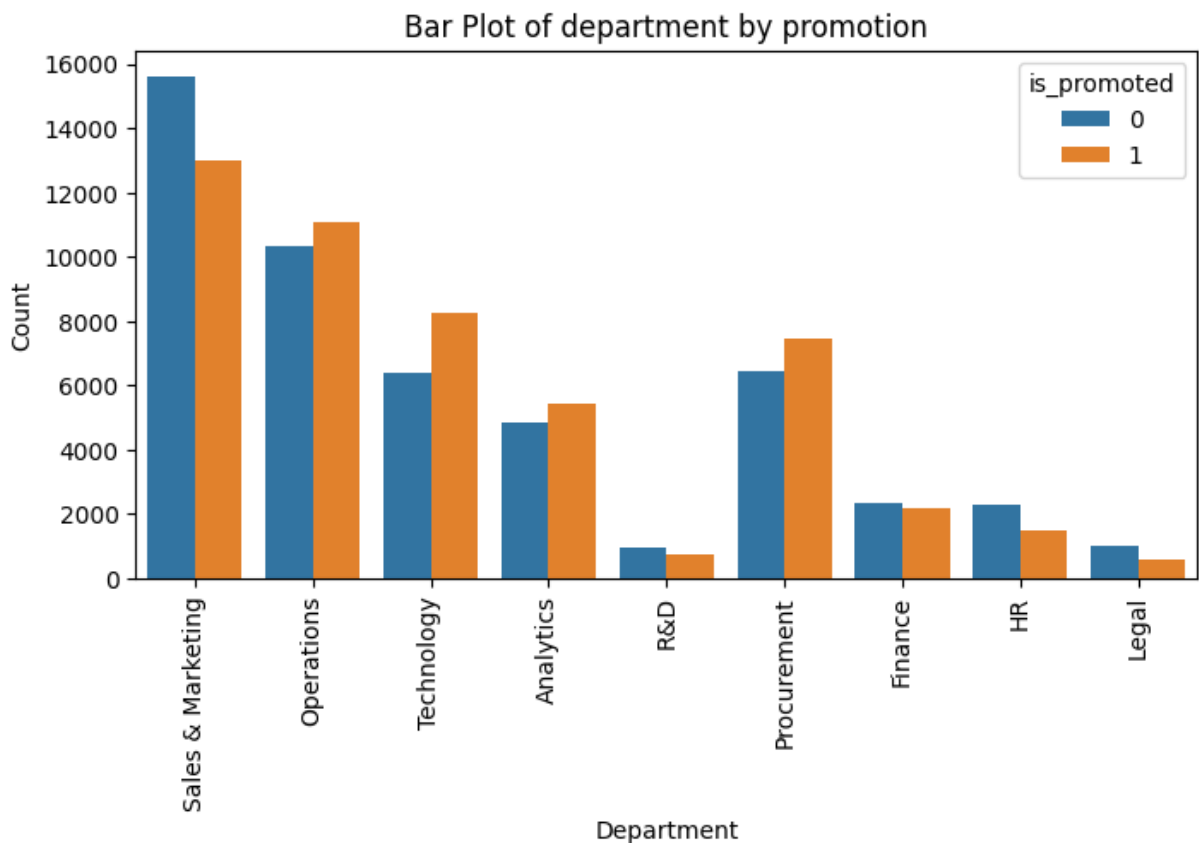
```
In [34]: # dividing minority and majority classes
minority_class = df_train[df_train['is_promoted'] == 1]
majority_class = df_train[df_train['is_promoted'] == 0]
```

```
In [35]: # oversample minority class
oversampled_minority = resample(minority_class, replace=True, n_samples=len(majority_class))
```

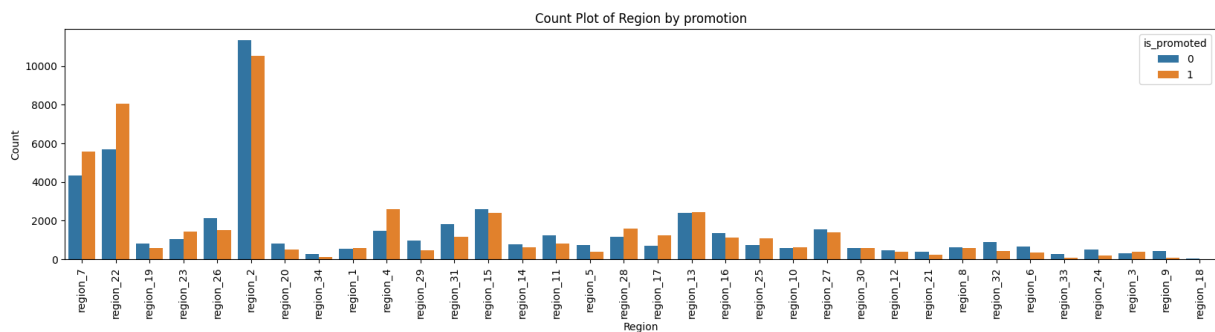
```
In [36]: # combine majority class with oversampled minority class
odf_train = pd.concat([majority_class, oversampled_minority])
```

3.3. Data Visualizations after Oversampling

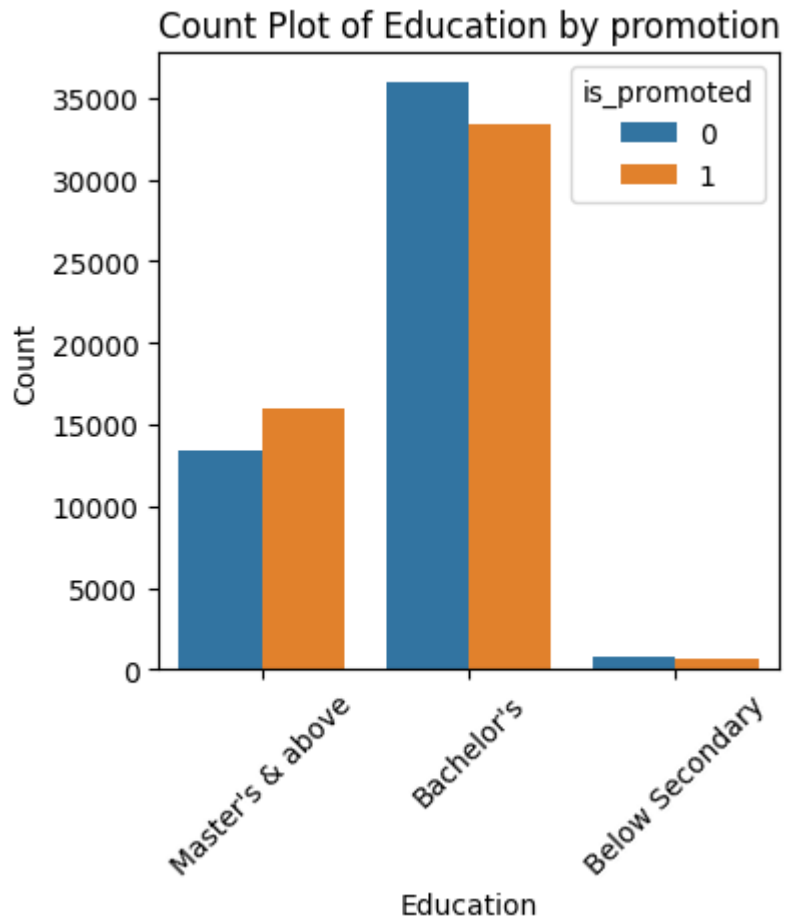
```
In [37]: # department vs is_promoted count plot
plt.figure(figsize=(8, 4))
sns.countplot(x='department', hue='is_promoted', data=odf_train)
plt.title('Bar Plot of department by promotion')
plt.xlabel('Department')
plt.ylabel('Count')
plt.xticks(rotation=90)
plt.legend(title='is_promoted', labels=[0, 1])
plt.show()
```



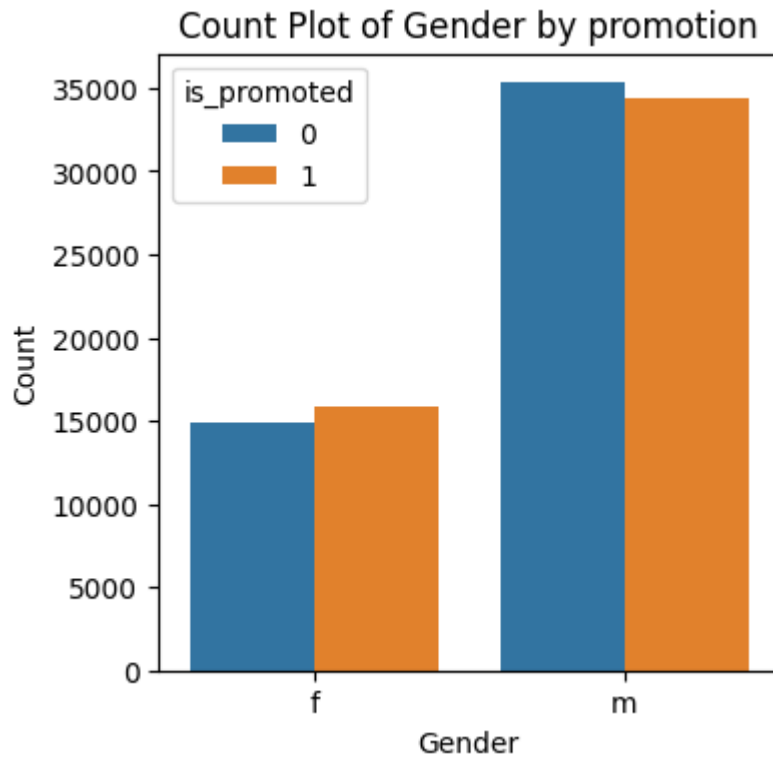
```
In [38]: # region vs is_promoted
plt.figure(figsize=(20, 4))
sns.countplot(x='region', hue='is_promoted', data=odf_train)
plt.title('Count Plot of Region by promotion')
plt.xlabel('Region')
plt.ylabel('Count')
plt.xticks(rotation=90)
plt.legend(title='is_promoted', labels=[0, 1])
plt.show()
```



```
In [39]: # education vs is_promoted count plot
plt.figure(figsize=(4, 4))
sns.countplot(x='education', hue='is_promoted', data=odf_train)
plt.title('Count Plot of Education by promotion')
plt.xlabel('Education')
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.legend(title='is_promoted', labels=[0, 1])
plt.show()
```

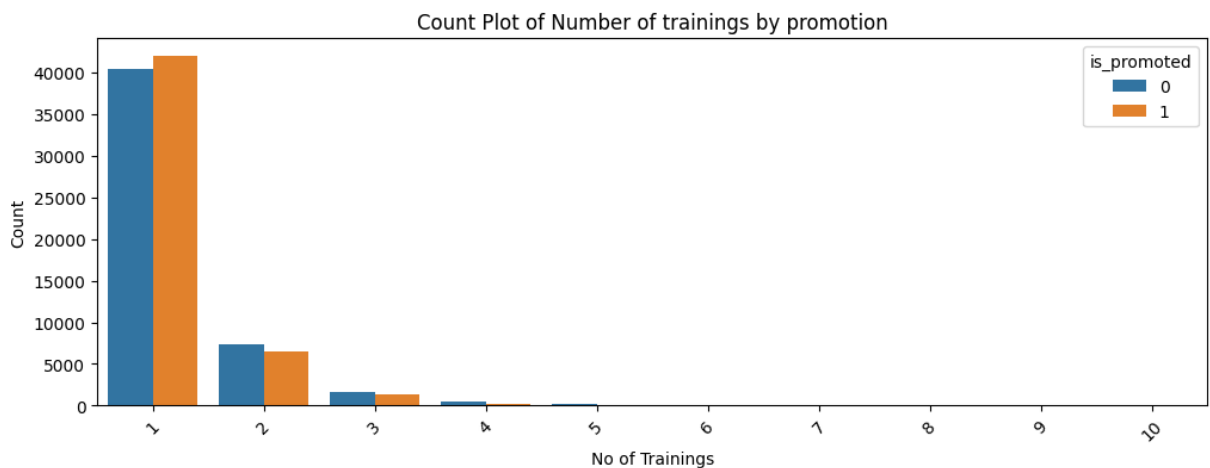
```
In [40]: # gender vs is_promoted count plot
plt.figure(figsize=(4, 4))
sns.countplot(x='gender', hue='is_promoted', data=odf_train)
plt.title('Count Plot of Gender by promotion')
plt.xlabel('Gender')
plt.ylabel('Count')
plt.xticks()
plt.legend(title='is_promoted', labels=[0, 1])
plt.show()
```



```
In [41]: # recruitment_channel vs is_promoted count plot
plt.figure(figsize=(4, 4))
sns.countplot(x='recruitment_channel', hue='is_promoted', data=odf_train)
plt.title('Count Plot of Recruitment Channel by promotion')
plt.xlabel('Recruitment Channel')
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.legend(title='is_promoted', labels=[0, 1])
plt.show()
```

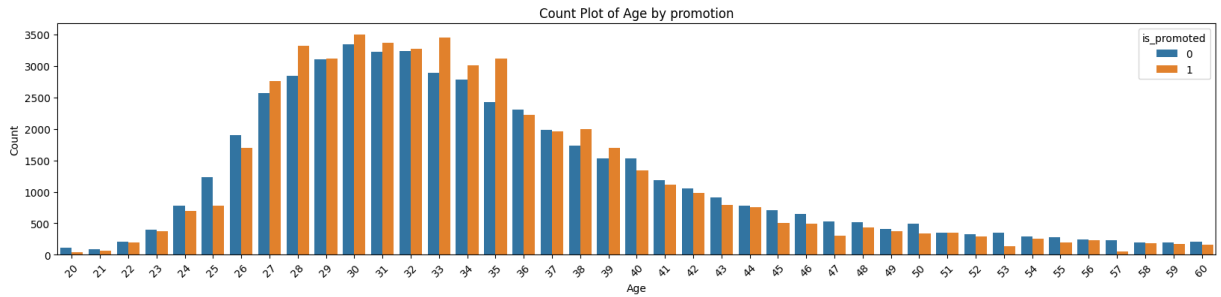


```
In [42]: # no_of_trainings vs is_promoted count plot
plt.figure(figsize=(12, 4))
sns.countplot(x='no_of_trainings', hue='is_promoted', data=odf_train)
plt.title('Count Plot of Number of trainings by promotion')
plt.xlabel('No of Trainings')
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.legend(title='is_promoted', labels=[0, 1])
plt.show()
```

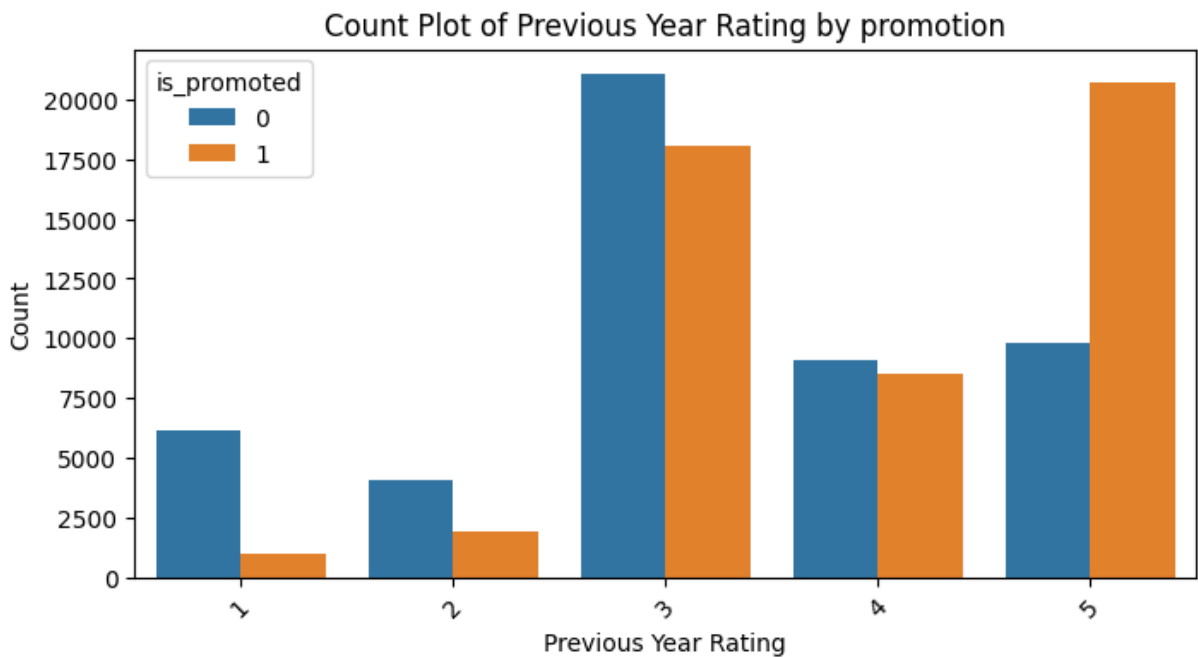


```
In [43]: # age vs is_promoted count plot
plt.figure(figsize=(20, 4))
sns.countplot(x='age', hue='is_promoted', data=odf_train)
plt.title('Count Plot of Age by promotion')
plt.xlabel('Age')
```

```
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.legend(title='is_promoted', labels=[0, 1])
plt.show()
```



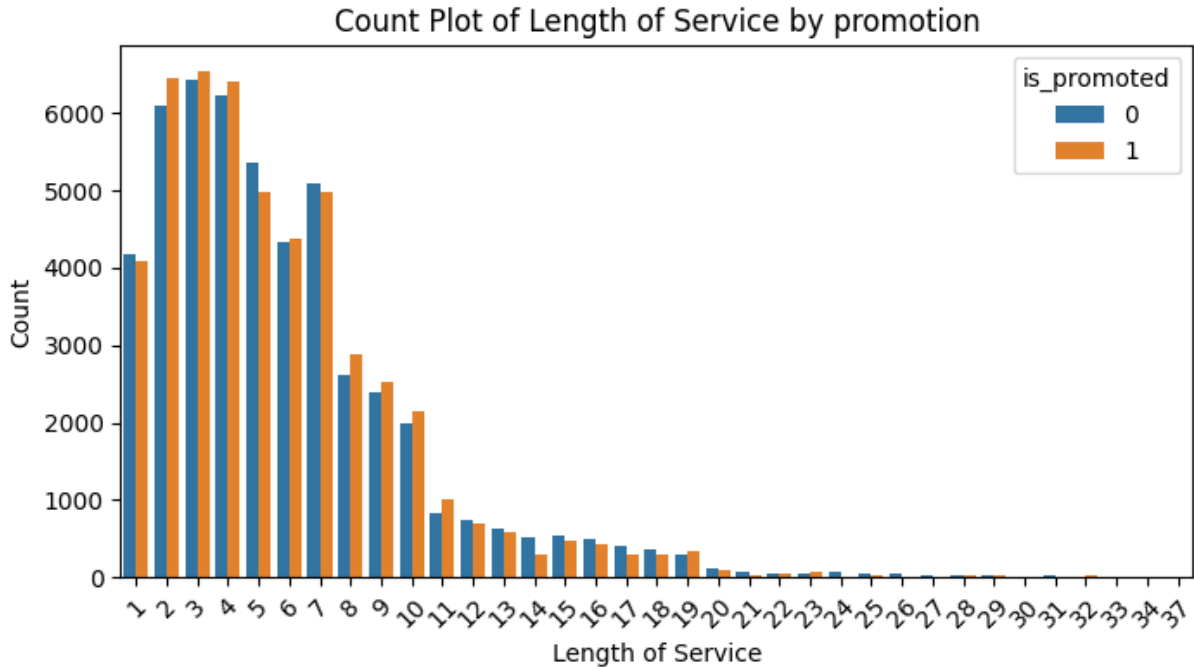
```
In [44]: # previous_year_rating vs is_promoted count plot
plt.figure(figsize=(8, 4))
sns.countplot(x='previous_year_rating', hue='is_promoted', data=odf_train)
plt.title('Count Plot of Previous Year Rating by promotion')
plt.xlabel('Previous Year Rating')
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.legend(title='is_promoted', labels=[0, 1])
plt.show()
```



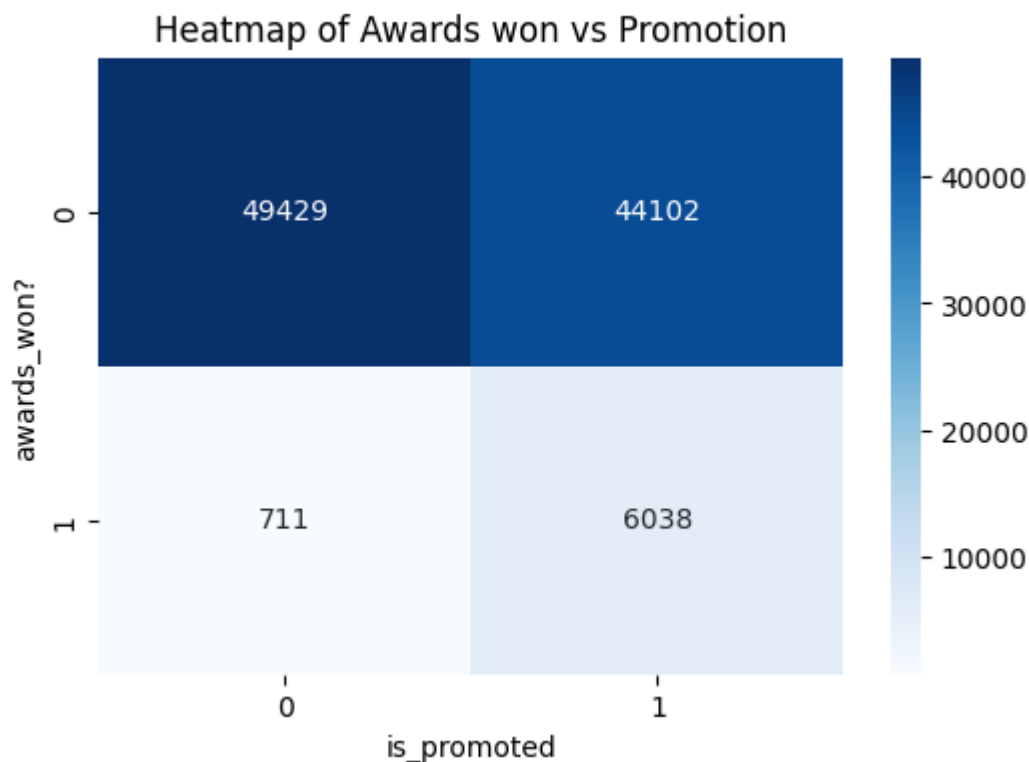
Observation: Employees with 1 previous year rating has minority being promoted which increases upto 5.

```
In [45]: # length_of_service vs is_promoted count plot
plt.figure(figsize=(8, 4))
sns.countplot(x='length_of_service', hue='is_promoted', data=odf_train)
plt.title('Count Plot of Length of Service by promotion')
plt.xlabel('Length of Service')
plt.ylabel('Count')
plt.xticks(rotation=45)
```

```
plt.legend(title='is_promoted', labels=[0, 1])
plt.show()
```

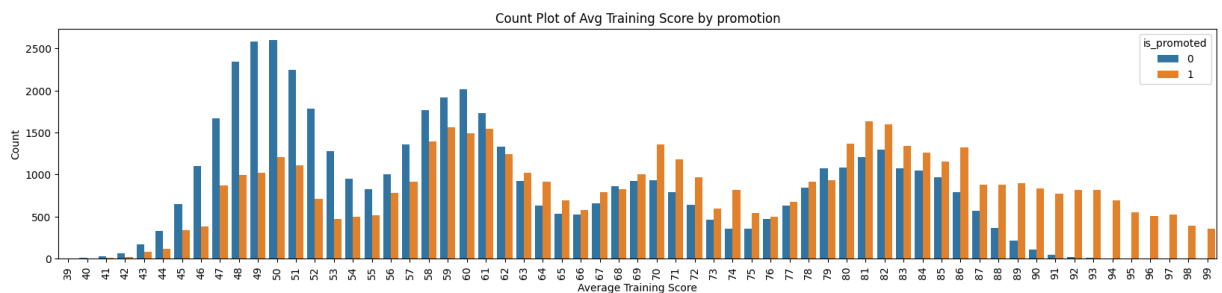


```
In [46]: # awards_won? vs is_promoted count based heatmap
plt.figure(figsize=(6, 4))
pivot_table = odf_train.pivot_table(index='awards_won?', columns='is_promoted', agg
sns.heatmap(pivot_table, annot=True, cmap='Blues', cbar=True, fmt='g')
plt.title('Heatmap of Awards won vs Promotion')
plt.xlabel('is_promoted')
plt.ylabel('awards_won?')
plt.show()
```



Observation: For no award winners, nearly equal % of employees are promoted and not promoted. Whereas award winners, there is more distinction as high % of employees are promoted.

```
In [47]: # avg_training_score vs is_promoted count plot
plt.figure(figsize=(20, 4))
sns.countplot(x='avg_training_score', hue='is_promoted', data=odf_train)
plt.title('Count Plot of Avg Training Score by promotion')
plt.xlabel('Average Training Score')
plt.ylabel('Count')
plt.xticks(rotation=90)
plt.legend(title='is_promoted', labels=[0, 1])
plt.show()
```



Observation: Employees with high avg. training score tends to be more promoted and those with low stay more not promoted.

Results: 'previous_year_rating', 'awards_won?' and 'avg_training_score' have high relationship with target variable 'is_promoted'.

4. Feature Engineering

4.1. Label Encoding

```
In [48]: # define mappings
education_mapping = {"Below Secondary": 0, "Bachelor's": 1, "Master's & above": 2}
gender_mapping = {"m": 0, "f": 1}
```

```
In [49]: # apply mapping for education
odf_train['education'] = odf_train['education'].map(education_mapping)
df_test['education'] = df_test['education'].map(education_mapping)
```

```
In [50]: # apply mapping for gender
odf_train['gender'] = odf_train['gender'].map(gender_mapping)
df_test['gender'] = df_test['gender'].map(gender_mapping)
```

4.2. One-Hot Encoding

```

In [51]: # columns for one-hot encoding
ohe_columns = ['department', 'region', 'recruitment_channel']

In [52]: # define one-hot encoder
ohe = OneHotEncoder(sparse=False)

In [53]: # encode data of ohe_columns
df_test_transformed = ohe.fit_transform(df_test[ohe_columns])
odf_train_transformed = ohe.transform(odf_train[ohe_columns])

In [54]: # convert array to dataframes
odf_train_encoded = pd.DataFrame(odf_train_transformed, columns=ohe.get_feature_names_out())
df_test_encoded = pd.DataFrame(df_test_transformed, columns=ohe.get_feature_names_out())

In [55]: # reset indexes
odf_train = odf_train.reset_index(drop=True)
odf_train_encoded = odf_train_encoded.reset_index(drop=True)
df_test = df_test.reset_index(drop=True)
df_test_encoded = df_test_encoded.reset_index(drop=True)

In [56]: # concatenate original df and encoded df
odf_train = pd.concat([odf_train, odf_train_encoded], axis=1)
df_test = pd.concat([df_test, df_test_encoded], axis=1)

```

4.3. Handling New Columns

```

In [57]: # checking odf_train
odf_train.head(10)

```

Out[57]:

	department	region	education	gender	recruitment_channel	no_of_trainings	age
0	Sales & Marketing	region_7	2	1	sourcing	1	35
1	Operations	region_22	1	0	other	1	30
2	Sales & Marketing	region_19	1	0	sourcing	1	34
3	Sales & Marketing	region_23	1	0	other	2	39
4	Technology	region_26	1	0	other	1	45
5	Analytics	region_2	1	0	sourcing	2	31
6	Operations	region_20	1	1	other	1	31
7	Operations	region_34	2	0	sourcing	1	33
8	Analytics	region_20	1	0	other	1	28
9	Sales & Marketing	region_1	2	0	sourcing	1	32

10 rows × 58 columns

In [58]: `# checking df_test`
`df_test.head(10)`

Out[58]:

	department	region	education	gender	recruitment_channel	no_of_trainings	age
0	Technology	region_26	1	0	sourcing	1	24
1	HR	region_4	1	1	other	1	31
2	Sales & Marketing	region_13	1	0	other	1	31
3	Procurement	region_2	1	1	other	3	31
4	Finance	region_29	1	0	sourcing	1	30
5	Procurement	region_7	1	0	sourcing	1	36
6	Finance	region_2	1	0	other	1	33
7	Analytics	region_22	1	0	sourcing	2	36
8	Technology	region_7	2	0	other	1	51
9	Technology	region_22	1	0	sourcing	1	29

10 rows × 57 columns

In [59]: `# checking null values and datatypes of odf_train`
`odf_train.info()`


```
<class 'pandas.core.frame.DataFrame'>  
RangeIndex: 100280 entries, 0 to 100279  
Data columns (total 58 columns):
```

#	Column	Non-Null Count	Dtype
0	department	100280 non-null	object
1	region	100280 non-null	object
2	education	100280 non-null	int64
3	gender	100280 non-null	int64
4	recruitment_channel	100280 non-null	object
5	no_of_trainings	100280 non-null	int64
6	age	100280 non-null	int64
7	previous_year_rating	100280 non-null	int64
8	length_of_service	100280 non-null	int64
9	awards_won?	100280 non-null	int64
10	avg_training_score	100280 non-null	int64
11	is_promoted	100280 non-null	int64
12	department_Analytics	100280 non-null	float64
13	department_Finance	100280 non-null	float64
14	department_HR	100280 non-null	float64
15	department_Legal	100280 non-null	float64
16	department_Operations	100280 non-null	float64
17	department_Procurement	100280 non-null	float64
18	department_R&D	100280 non-null	float64
19	department_Sales & Marketing	100280 non-null	float64
20	department_Technology	100280 non-null	float64
21	region_region_1	100280 non-null	float64
22	region_region_10	100280 non-null	float64
23	region_region_11	100280 non-null	float64
24	region_region_12	100280 non-null	float64
25	region_region_13	100280 non-null	float64
26	region_region_14	100280 non-null	float64
27	region_region_15	100280 non-null	float64
28	region_region_16	100280 non-null	float64
29	region_region_17	100280 non-null	float64
30	region_region_18	100280 non-null	float64
31	region_region_19	100280 non-null	float64
32	region_region_2	100280 non-null	float64
33	region_region_20	100280 non-null	float64
34	region_region_21	100280 non-null	float64
35	region_region_22	100280 non-null	float64
36	region_region_23	100280 non-null	float64
37	region_region_24	100280 non-null	float64
38	region_region_25	100280 non-null	float64
39	region_region_26	100280 non-null	float64
40	region_region_27	100280 non-null	float64
41	region_region_28	100280 non-null	float64
42	region_region_29	100280 non-null	float64
43	region_region_3	100280 non-null	float64
44	region_region_30	100280 non-null	float64
45	region_region_31	100280 non-null	float64
46	region_region_32	100280 non-null	float64
47	region_region_33	100280 non-null	float64
48	region_region_34	100280 non-null	float64
49	region_region_4	100280 non-null	float64
50	region_region_5	100280 non-null	float64

```
51 region_region_6          100280 non-null float64
52 region_region_7          100280 non-null float64
53 region_region_8          100280 non-null float64
54 region_region_9          100280 non-null float64
55 recruitment_channel_other 100280 non-null float64
56 recruitment_channel_referred 100280 non-null float64
57 recruitment_channel_sourcing 100280 non-null float64
dtypes: float64(46), int64(9), object(3)
memory usage: 44.4+ MB
```

```
In [60]: # checking null values and datatypes of df_test
df_test.info()
```

<class 'pandas.core.frame.DataFrame'>

RangeIndex: 23490 entries, 0 to 23489

Data columns (total 57 columns):

#	Column	Non-Null Count	Dtype
0	department	23490 non-null	object
1	region	23490 non-null	object
2	education	23490 non-null	int64
3	gender	23490 non-null	int64
4	recruitment_channel	23490 non-null	object
5	no_of_trainings	23490 non-null	int64
6	age	23490 non-null	int64
7	previous_year_rating	23490 non-null	int64
8	length_of_service	23490 non-null	int64
9	awards_won?	23490 non-null	int64
10	avg_training_score	23490 non-null	int64
11	department_Analytics	23490 non-null	float64
12	department_Finance	23490 non-null	float64
13	department_HR	23490 non-null	float64
14	department_Legal	23490 non-null	float64
15	department_Operations	23490 non-null	float64
16	department_Procurement	23490 non-null	float64
17	department_R&D	23490 non-null	float64
18	department_Sales & Marketing	23490 non-null	float64
19	department_Technology	23490 non-null	float64
20	region_region_1	23490 non-null	float64
21	region_region_10	23490 non-null	float64
22	region_region_11	23490 non-null	float64
23	region_region_12	23490 non-null	float64
24	region_region_13	23490 non-null	float64
25	region_region_14	23490 non-null	float64
26	region_region_15	23490 non-null	float64
27	region_region_16	23490 non-null	float64
28	region_region_17	23490 non-null	float64
29	region_region_18	23490 non-null	float64
30	region_region_19	23490 non-null	float64
31	region_region_2	23490 non-null	float64
32	region_region_20	23490 non-null	float64
33	region_region_21	23490 non-null	float64
34	region_region_22	23490 non-null	float64
35	region_region_23	23490 non-null	float64
36	region_region_24	23490 non-null	float64
37	region_region_25	23490 non-null	float64
38	region_region_26	23490 non-null	float64
39	region_region_27	23490 non-null	float64
40	region_region_28	23490 non-null	float64
41	region_region_29	23490 non-null	float64
42	region_region_3	23490 non-null	float64
43	region_region_30	23490 non-null	float64
44	region_region_31	23490 non-null	float64
45	region_region_32	23490 non-null	float64
46	region_region_33	23490 non-null	float64
47	region_region_34	23490 non-null	float64
48	region_region_4	23490 non-null	float64
49	region_region_5	23490 non-null	float64
50	region_region_6	23490 non-null	float64

```
51 region_region_7                23490 non-null float64
52 region_region_8                23490 non-null float64
53 region_region_9                23490 non-null float64
54 recruitment_channel_other      23490 non-null float64
55 recruitment_channel_referred   23490 non-null float64
56 recruitment_channel_sourcing   23490 non-null float64
dtypes: float64(46), int64(8), object(3)
memory usage: 10.2+ MB
```

```
In [63]: # get rid of all rows with null values
odf_train.dropna(inplace=True)
df_test.dropna(inplace=True)
```

```
In [61]: # convert datatypes and names of new columns in odf_train
for col in ohe_columns:
    for val in odf_train[col].unique():
        temp_col = str(col) + "_" + str(val)
        odf_train[temp_col] = odf_train[temp_col].astype(np.int64)
        odf_train.rename(columns={temp_col: val}, inplace=True)
```

```
In [62]: # convert datatypes and names of new columns in df_test
for col in ohe_columns:
    for val in df_test[col].unique():
        temp_col = str(col) + "_" + str(val)
        df_test[temp_col] = df_test[temp_col].astype(np.int64)
        df_test.rename(columns={temp_col: val}, inplace=True)
```

4.4. Handling Unnecessary Columns

```
In [64]: # drop columns used in One-hot encoding
odf_train.drop(ohe_columns, axis=1, inplace=True)
df_test.drop(ohe_columns, axis=1, inplace=True)
```

```
In [65]: # check unnecessary columns
print(odf_train.columns)
print(df_test.columns)
```

```

Index(['education', 'gender', 'no_of_trainings', 'age', 'previous_year_rating',
      'length_of_service', 'awards_won?', 'avg_training_score', 'is_promoted',
      'Analytics', 'Finance', 'HR', 'Legal', 'Operations', 'Procurement',
      'R&D', 'Sales & Marketing', 'Technology', 'region_1', 'region_10',
      'region_11', 'region_12', 'region_13', 'region_14', 'region_15',
      'region_16', 'region_17', 'region_18', 'region_19', 'region_2',
      'region_20', 'region_21', 'region_22', 'region_23', 'region_24',
      'region_25', 'region_26', 'region_27', 'region_28', 'region_29',
      'region_3', 'region_30', 'region_31', 'region_32', 'region_33',
      'region_34', 'region_4', 'region_5', 'region_6', 'region_7', 'region_8',
      'region_9', 'other', 'referred', 'sourcing'],
      dtype='object')
Index(['education', 'gender', 'no_of_trainings', 'age', 'previous_year_rating',
      'length_of_service', 'awards_won?', 'avg_training_score', 'Analytics',
      'Finance', 'HR', 'Legal', 'Operations', 'Procurement', 'R&D',
      'Sales & Marketing', 'Technology', 'region_1', 'region_10', 'region_11',
      'region_12', 'region_13', 'region_14', 'region_15', 'region_16',
      'region_17', 'region_18', 'region_19', 'region_2', 'region_20',
      'region_21', 'region_22', 'region_23', 'region_24', 'region_25',
      'region_26', 'region_27', 'region_28', 'region_29', 'region_3',
      'region_30', 'region_31', 'region_32', 'region_33', 'region_34',
      'region_4', 'region_5', 'region_6', 'region_7', 'region_8', 'region_9',
      'other', 'referred', 'sourcing'],
      dtype='object')

```

4.5. Feature Scaling

In [66]: *# columns for min max scaling*

```

mm_scaler_cols = dist_cols + ['education', 'previous_year_rating']
print(mm_scaler_cols)

```

```

['no_of_trainings', 'age', 'length_of_service', 'avg_training_score', 'education',
'previous_year_rating']

```

In [67]: *# check statistics for odf_train*

```

odf_train.describe()

```

Out[67]:

	education	gender	no_of_trainings	age	previous_year_rating
count	100280.000000	100280.000000	100280.000000	100280.000000	100280.000000
mean	1.278969	0.305525	1.229876	34.607190	3.583556
std	0.479777	0.460632	0.566950	7.402226	1.181526
min	0.000000	0.000000	1.000000	20.000000	1.000000
25%	1.000000	0.000000	1.000000	29.000000	3.000000
50%	1.000000	0.000000	1.000000	33.000000	3.000000
75%	2.000000	1.000000	1.000000	38.000000	5.000000
max	2.000000	1.000000	10.000000	60.000000	5.000000

8 rows × 55 columns

```
In [68]: # check statistics for df_test
df_test.describe()
```

```
Out[68]:
```

	education	gender	no_of_trainings	age	previous_year_rating	len
count	23490.000000	23490.000000	23490.000000	23490.000000	23490.000000	
mean	1.260962	0.293487	1.254236	34.782929	3.312984	
std	0.474040	0.455369	0.600910	7.679492	1.216959	
min	0.000000	0.000000	1.000000	20.000000	1.000000	
25%	1.000000	0.000000	1.000000	29.000000	3.000000	
50%	1.000000	0.000000	1.000000	33.000000	3.000000	
75%	2.000000	1.000000	1.000000	39.000000	4.000000	
max	2.000000	1.000000	9.000000	60.000000	5.000000	

8 rows × 54 columns

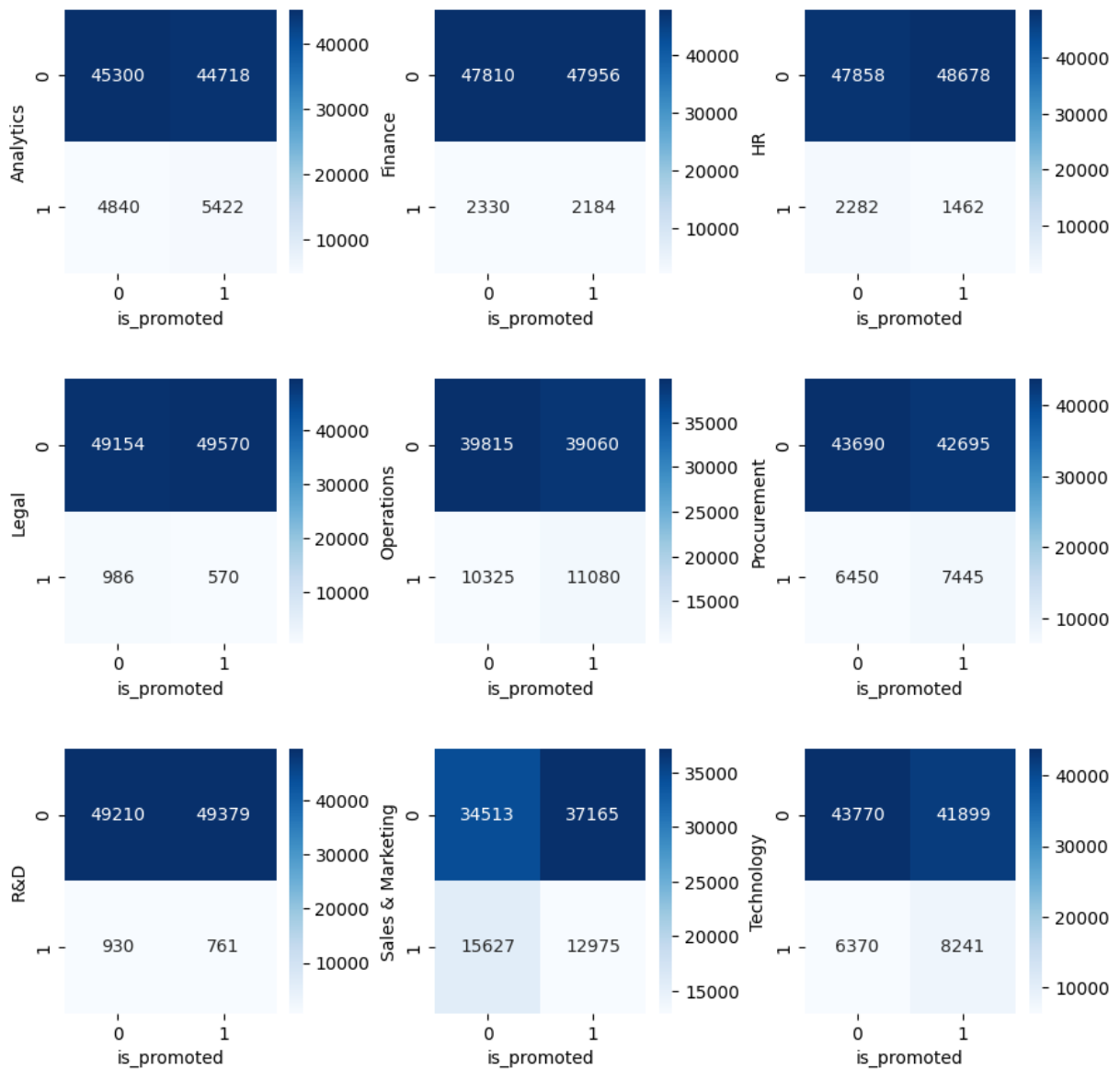
```
In [69]: # define scaler
mm_scaler = MinMaxScaler()
```

```
In [70]: # scale mm_scaler_cols
odf_train_scaled = mm_scaler.fit_transform(odf_train[mm_scaler_cols])
df_test_scaled = mm_scaler.transform(df_test[mm_scaler_cols])
```

```
In [71]: # apply scaled data to original datasets
odf_train[mm_scaler_cols] = pd.DataFrame(odf_train_scaled, columns=mm_scaler_cols)
df_test[mm_scaler_cols] = pd.DataFrame(df_test_scaled, columns=mm_scaler_cols)
```

4.6. Feature Selection

```
In [74]: # checking relationships of different departments to is_promoted
departments = ['Analytics', 'Finance', 'HR', 'Legal', 'Operations', 'Procurement',
i = 1
plt.figure(figsize=(10, 10))
for col in departments:
    plt.subplot(3, 3, i)
    pivot_table = odf_train.pivot_table(index=col, columns='is_promoted', aggfunc='
sns.heatmap(pivot_table, annot=True, cmap='Blues', cbar=True, fmt='g')
    plt.xlabel('is_promoted', fontsize=10)
    plt.ylabel(col, fontsize=10)
    i += 1
plt.subplots_adjust(left=0.1, right=0.9, bottom=0.1, top=0.9, wspace=0.4, hspace=0.
plt.show()
```

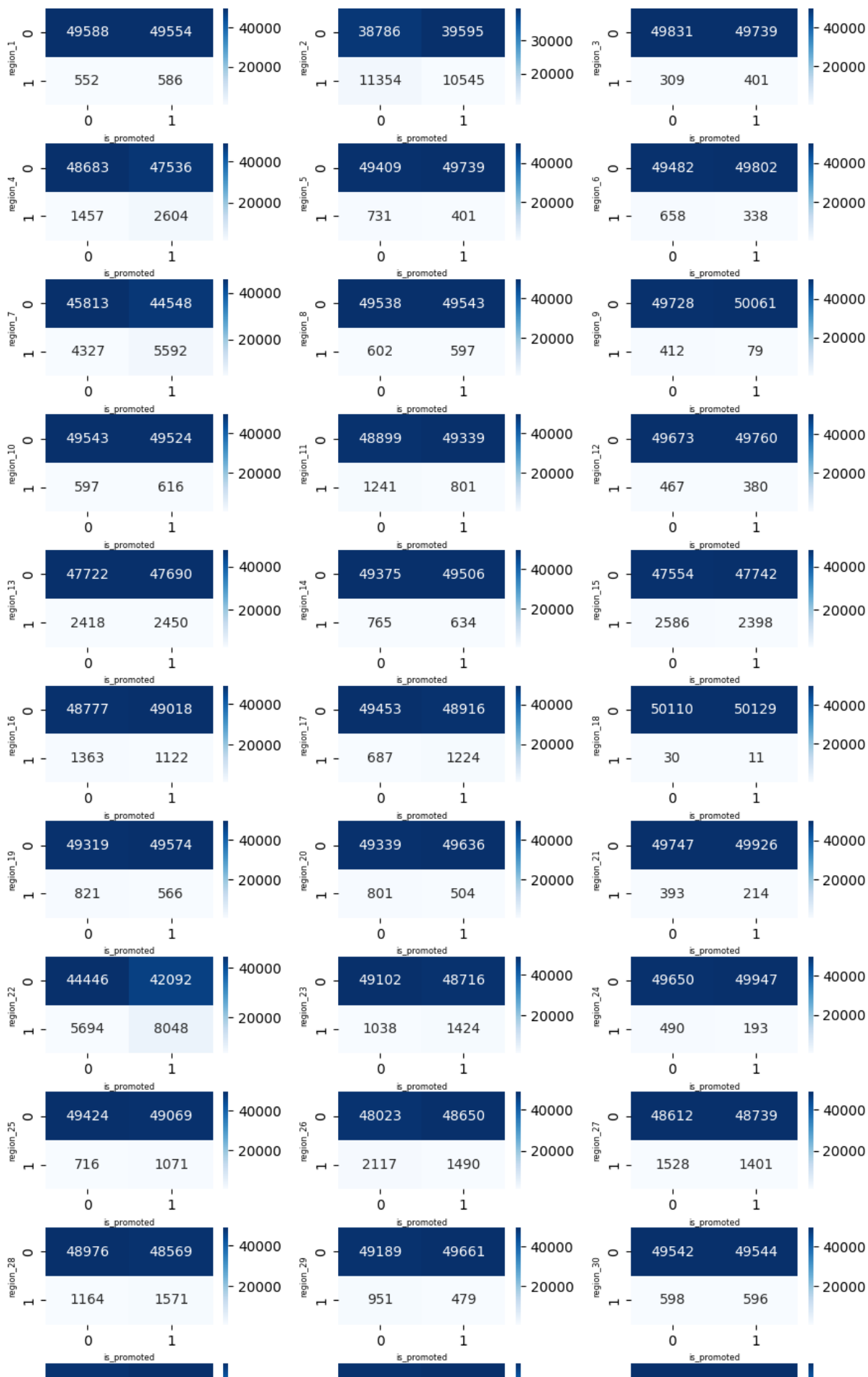


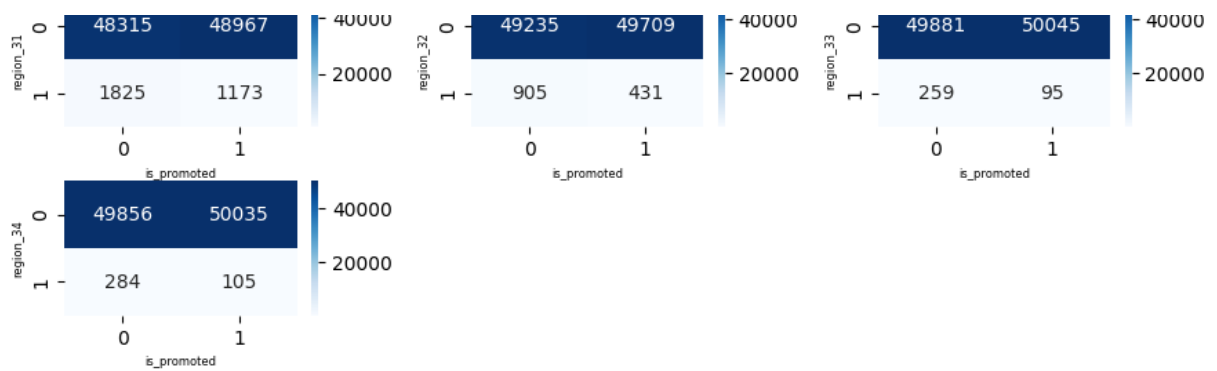
Observation: HR, Legal, Sales & Marketing and Technology are 2 departments that look highly correlated to promotion. Most employees in these 2 departments don't receive promotion. Whereas, those from Sales & Marketing and Technology have inversely proportional relationship to 'is_promoted'.

```
In [76]: # checking relationships of different regions to is_promoted
regions = ['region_1', 'region_2', 'region_3', 'region_4', 'region_5', 'region_6', 'region_7', 'region_8', 'region_9', 'region_10', 'region_11', 'region_12', 'region_13', 'region_14', 'region_15', 'region_16', 'region_17', 'region_18', 'region_19', 'region_20', 'region_21', 'region_22', 'region_23', 'region_24', 'region_25', 'region_26', 'region_27', 'region_28', 'region_29', 'region_30', 'region_31', 'region_32', 'region_33', 'region_34']

i = 1
plt.figure(figsize=(10, 20))
for col in regions:
    plt.subplot(12, 3, i)
    pivot_table = odf_train.pivot_table(index=col, columns='is_promoted', aggfunc='count')
    sns.heatmap(pivot_table, annot=True, cmap='Blues', cbar=True, fmt='g')
    plt.xlabel('is_promoted', fontsize=6)
    plt.ylabel(col, fontsize=6)
    i += 1
```

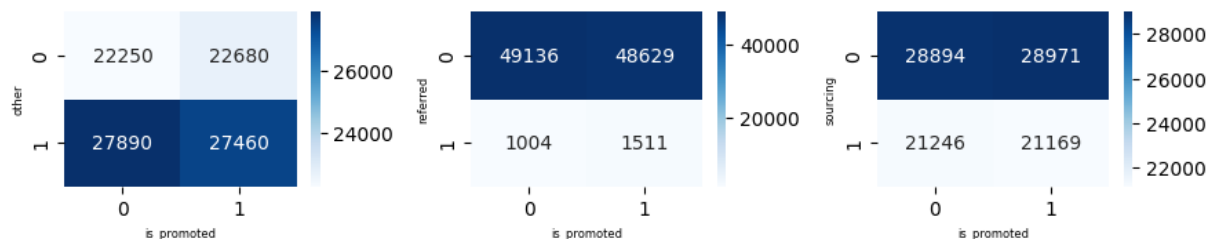
```
    i += 1  
plt.subplots_adjust(left=0.1, right=0.9, bottom=0.1, top=0.9, wspace=0.4, hspace=0.  
plt.show()
```



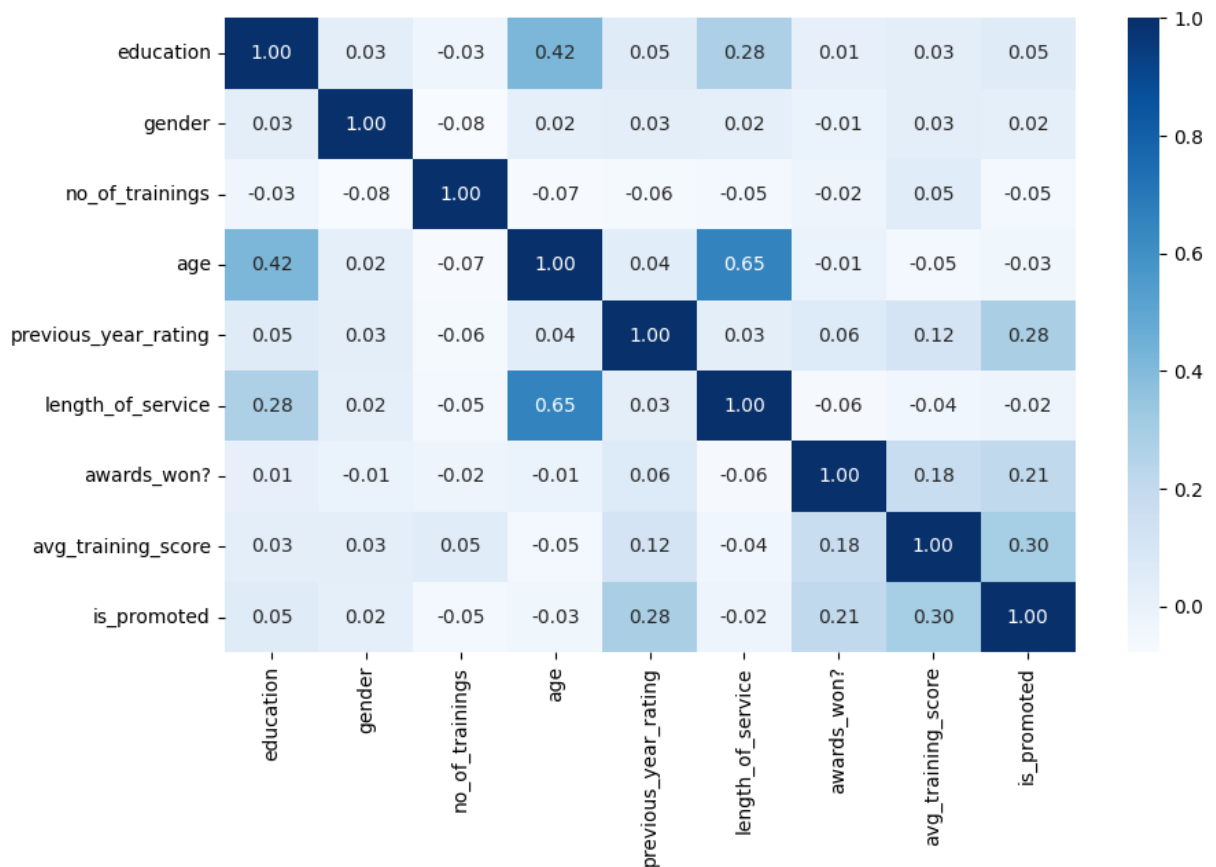
Observation: Employees from regions 3-7, 9, 11, 12, 17, 18-26, 28, 29 and 31-34 have high correlation to promotion.

```
In [77]: # checking relationships of different recruitment_channels to is_promoted
recruitment_channels = ['other', 'referred', 'sourcing']
i = 1
plt.figure(figsize=(10, 6))
for col in recruitment_channels:
    plt.subplot(3, 3, i)
    pivot_table = odf_train.pivot_table(index=col, columns='is_promoted', aggfunc='count')
    sns.heatmap(pivot_table, annot=True, cmap='Blues', cbar=True, fmt='g')
    plt.xlabel('is_promoted', fontsize=6)
    plt.ylabel(col, fontsize=6)
    i += 1
plt.subplots_adjust(left=0.1, right=0.9, bottom=0.1, top=0.9, wspace=0.4, hspace=0.4)
plt.show()
```



Observation: Referred employees enjoy high correlation.

```
In [78]: # checking relationships of other features to is_promoted
df_train_others = odf_train[['education', 'gender', 'no_of_trainings', 'age', 'prev_experience']]
plt.figure(figsize=(10, 6))
sns.heatmap(df_train_others.corr(), annot=True, fmt=".2f", cmap='Blues')
plt.show()
```



Observation: 'previous_year_rating', 'length_of_service' and 'avg_training_score' are correlated with 'is_promoted'.

```
In [79]: # defining most important features
important_features = [
    'HR', 'Legal', 'Sales & Marketing', 'Technology',
    'region_3', 'region_4', 'region_5', 'region_6', 'region_7',
    'region_9', 'region_11', 'region_12', 'region_17',
    'region_18', 'region_19', 'region_20', 'region_21', 'region_22', 'region_23', 'reg
    'region_28', 'region_29',
    'region_31', 'region_32', 'region_33', 'region_34',
    'referred',
    'previous_year_rating', 'length_of_service', 'avg_training_score'
]
```

5. Train Test Split

```
In [81]: # define X and y
X = odf_train[important_features]
y = odf_train['is_promoted']
```

```
In [82]: # splitting data after stratification into train and test
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, stratify=y)
```

```
In [83]: # replace null values by 0
```

```
X_train.fillna(0, inplace=True)
X_test.fillna(0, inplace=True)
```

6. Model Building and Evaluation

```
In [84]: # defining empty dictionary for comparing evaluation
evaluation = dict()
```

6.1. Decision Tree Classifier

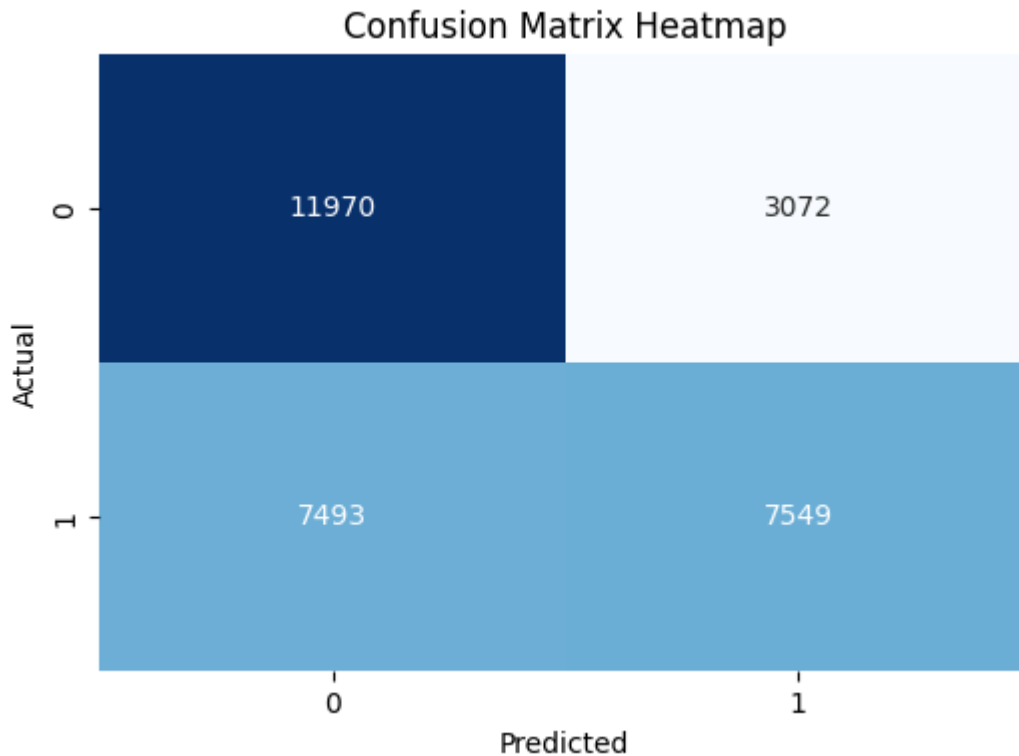
```
In [85]: # defining classifier
dt_classifier = DecisionTreeClassifier(min_samples_split=10,max_depth=3)
```

```
In [86]: # model fitting
dt_classifier.fit(X_train, y_train)
```

```
Out[86]: DecisionTreeClassifier(max_depth=3, min_samples_split=10)
```

```
In [87]: # model prediction
y_pred = dt_classifier.predict(X_test)
```

```
In [88]: # confusion matrix
plt.figure(figsize=(6, 4))
sns.heatmap(confusion_matrix(y_test, y_pred), annot=True, fmt='d', cmap='Blues', cb
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix Heatmap')
plt.show()
```



```
In [89]: # evaluation metrics
evaluation['dt_classifier'] = {
    'classification_report': classification_report(y_test, y_pred),
    'accuracy': accuracy_score(y_test, y_pred),
    'precision': precision_score(y_test, y_pred),
    'recall': recall_score(y_test, y_pred),
    'f1_score': f1_score(y_test, y_pred)
}
```

6.2. Bagging Classifier

```
In [90]: # defining classifier
bg_classifier = BaggingClassifier(DecisionTreeClassifier(min_samples_split=10,max_d
```

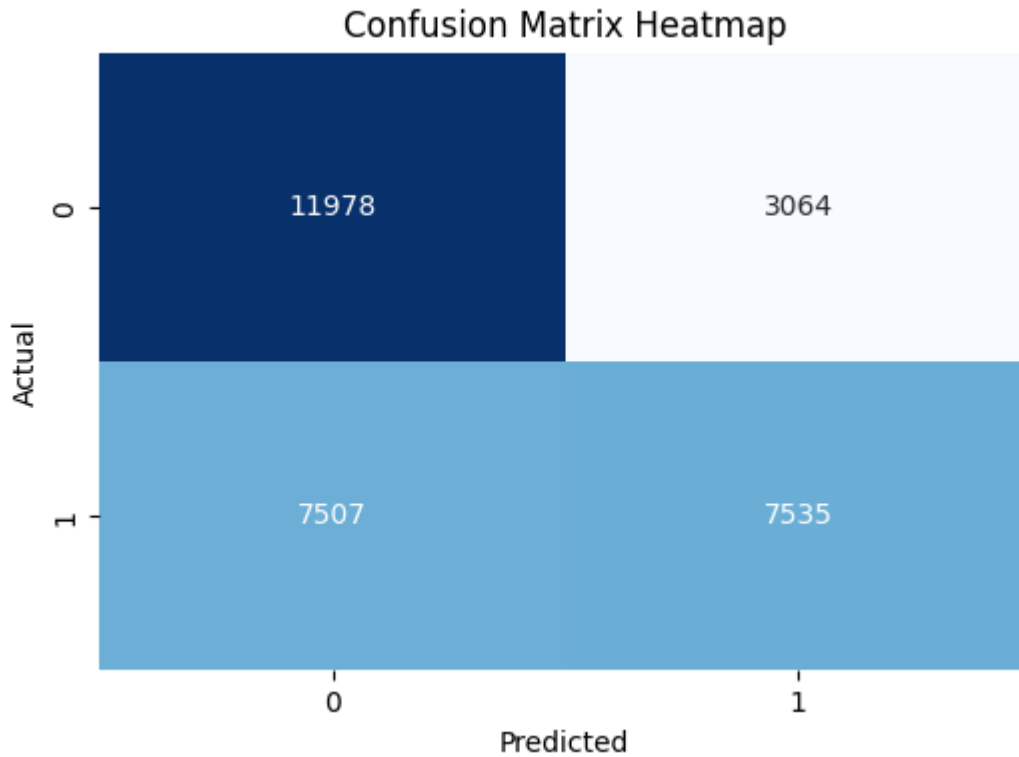
```
In [91]: # model fitting
bg_classifier.fit(X_train, y_train)
```

```
Out[91]: BaggingClassifier(base_estimator=DecisionTreeClassifier(max_depth=3,
                                                                min_samples_split=10),
                          max_samples=0.5)
```

```
In [92]: # model prediction
y_pred = bg_classifier.predict(X_test)
```

```
In [93]: # confusion matrix
plt.figure(figsize=(6, 4))
sns.heatmap(confusion_matrix(y_test, y_pred), annot=True, fmt='d', cmap='Blues', cb
plt.xlabel('Predicted')
plt.ylabel('Actual')
```

```
plt.title('Confusion Matrix Heatmap')
plt.show()
```



```
In [94]: # evaluation metrics
evaluation['bg_classifier'] = {
    'classification_report': classification_report(y_test, y_pred),
    'accuracy': accuracy_score(y_test, y_pred),
    'precision': precision_score(y_test, y_pred),
    'recall': recall_score(y_test, y_pred),
    'f1_score': f1_score(y_test, y_pred)
}
```

6.3. AdaBoost Classifier

```
In [95]: # defining classifier
adab_classifier = AdaBoostClassifier(DecisionTreeClassifier(max_depth=3), n_estimators=100)
```

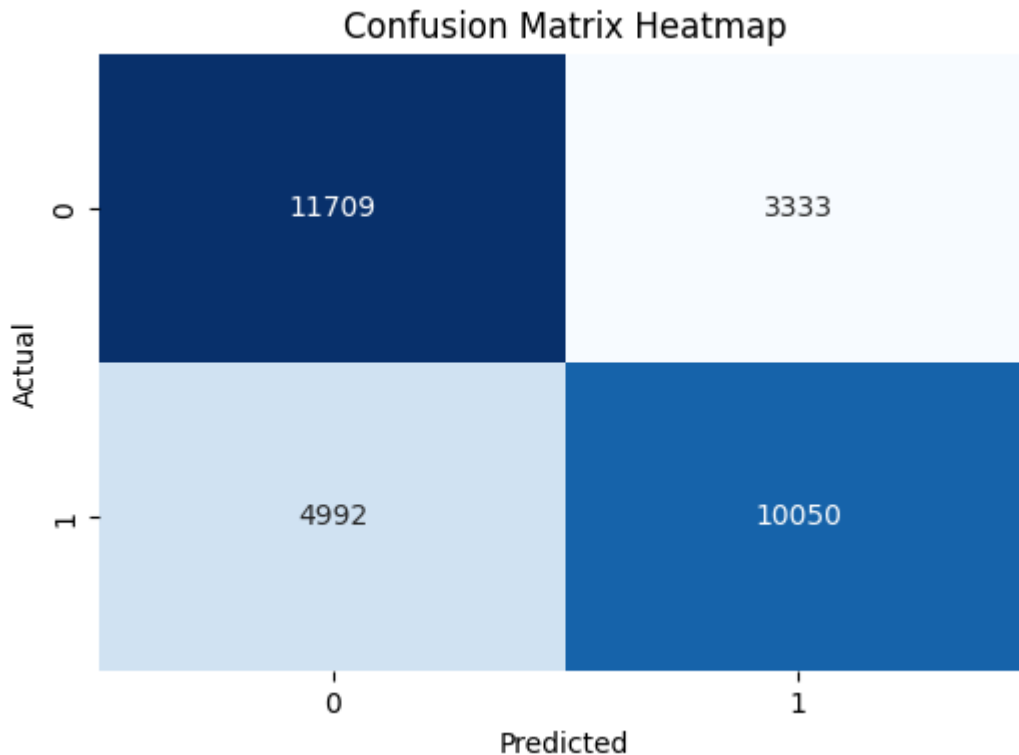
```
In [96]: # model fitting
adab_classifier.fit(X_train, y_train)
```

```
Out[96]: AdaBoostClassifier(base_estimator=DecisionTreeClassifier(max_depth=3),
                             learning_rate=0.5, n_estimators=100)
```

```
In [97]: # model prediction
y_pred = adab_classifier.predict(X_test)
```

```
In [98]: # confusion matrix
plt.figure(figsize=(6, 4))
sns.heatmap(confusion_matrix(y_test, y_pred), annot=True, fmt='d', cmap='Blues', cb
```

```
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix Heatmap')
plt.show()
```



```
In [99]: # evaluation metrics
evaluation['adab_classifier'] = {
    'classification_report': classification_report(y_test, y_pred),
    'accuracy': accuracy_score(y_test, y_pred),
    'precision': precision_score(y_test, y_pred),
    'recall': recall_score(y_test, y_pred),
    'f1_score': f1_score(y_test, y_pred)
}
```

6.4. Gradient Boosting Classifier

```
In [100]: # defining classifier
gb_classifier = GradientBoostingClassifier(n_estimators=100)
```

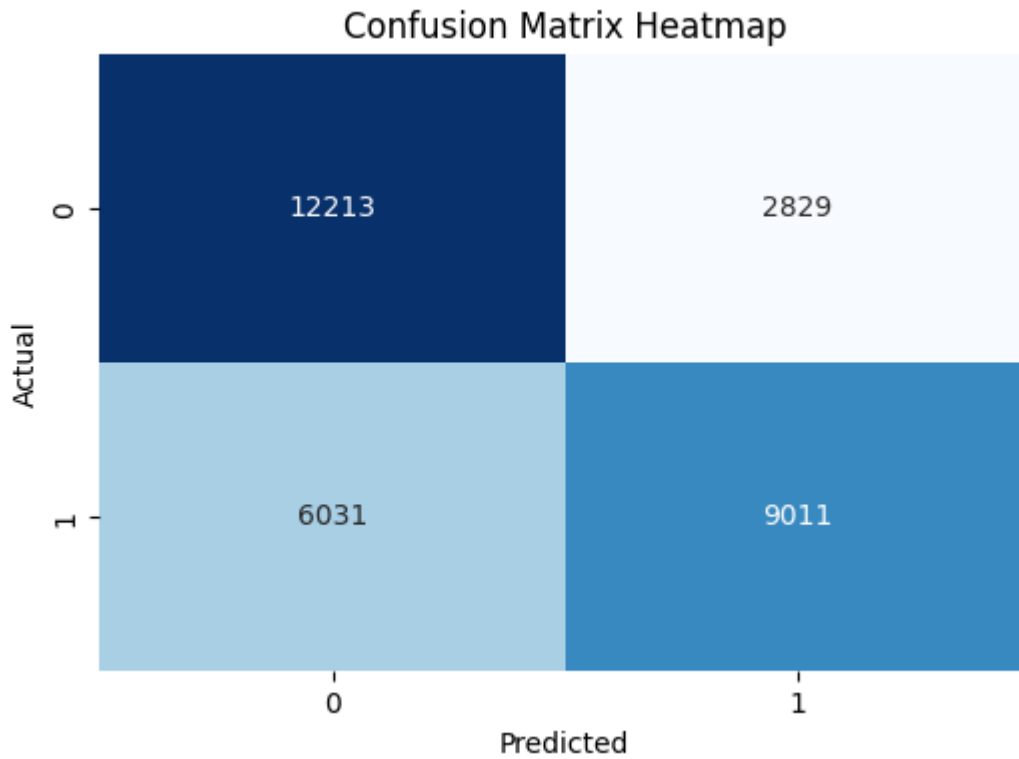
```
In [101]: # model fitting
gb_classifier.fit(X_train, y_train)
```

Out[101]: GradientBoostingClassifier()

```
In [102]: # model prediction
y_pred = gb_classifier.predict(X_test)
```

```
In [103]: # confusion matrix
plt.figure(figsize=(6, 4))
```

```
sns.heatmap(confusion_matrix(y_test, y_pred), annot=True, fmt='d', cmap='Blues', cb
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix Heatmap')
plt.show()
```



```
In [104... # evaluation metrics
evaluation['gb_classifier'] = {
    'classification_report': classification_report(y_test, y_pred),
    'accuracy': accuracy_score(y_test, y_pred),
    'precision': precision_score(y_test, y_pred),
    'recall': recall_score(y_test, y_pred),
    'f1_score': f1_score(y_test, y_pred)
}
```

6.5. Random Forest Classifier

```
In [106... # defining classifier
rf_classifier = RandomForestClassifier(n_estimators=300, max_depth=3)
```

```
In [107... # model fitting
rf_classifier.fit(X_train, y_train)
```

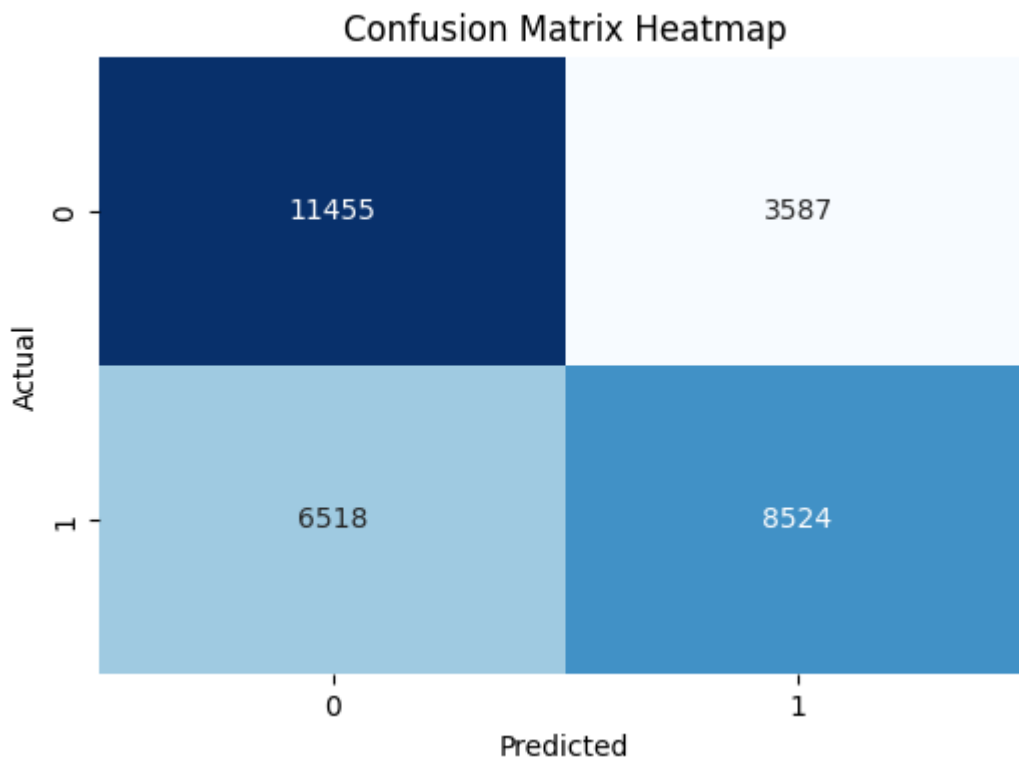
```
Out[107]: RandomForestClassifier(max_depth=3, n_estimators=300)
```

```
In [108... # model prediction
y_pred = rf_classifier.predict(X_test)
```

```
In [109... # confusion matrix
```



```
plt.figure(figsize=(6, 4))
sns.heatmap(confusion_matrix(y_test, y_pred), annot=True, fmt='d', cmap='Blues', cb
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix Heatmap')
plt.show()
```



```
In [110... # evaluation metrics
evaluation['rf_classifier'] = {
    'classification_report': classification_report(y_test, y_pred),
    'accuracy': accuracy_score(y_test, y_pred),
    'precision': precision_score(y_test, y_pred),
    'recall': recall_score(y_test, y_pred),
    'f1_score': f1_score(y_test, y_pred)
}
```

6.6.Voting Classifier

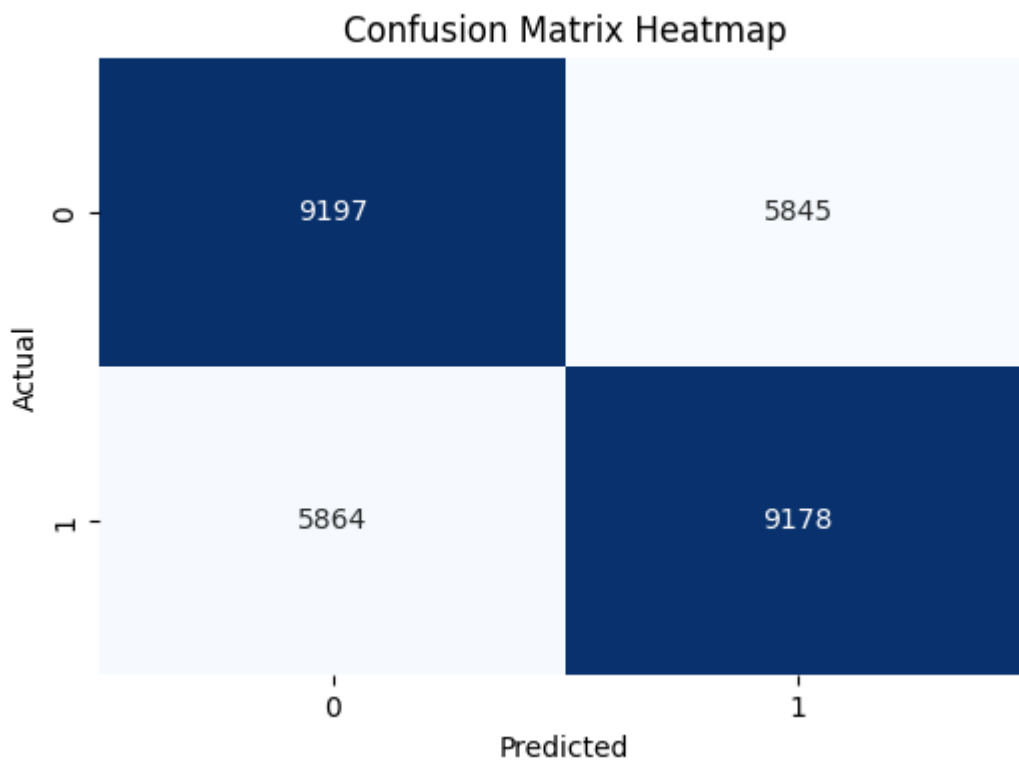
```
In [111... # defining classifier
mnbc = MultinomialNB()
lr = LogisticRegression(max_iter=5000)
svc = SVC(max_iter=5000)
vot_classifier = VotingClassifier(estimators=[('mnbc', mnbc), ('lr', lr), ('svc', svc)])
```

```
In [112]: # model fitting
vot_classifier.fit(X_train, y_train)
```

[illegible]

```
In [113... # model prediction
y_pred = vot_classifier.predict(X_test)
```

```
In [114... # confusion matrix
plt.figure(figsize=(6, 4))
sns.heatmap(confusion_matrix(y_test, y_pred), annot=True, fmt='d', cmap='Blues', cb
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix Heatmap')
plt.show()
```



```
In [115... # evaluation metrics
evaluation['vot_classifier'] = {
    'classification_report': classification_report(y_test, y_pred),
    'accuracy': accuracy_score(y_test, y_pred),
    'precision': precision_score(y_test, y_pred),
    'recall': recall_score(y_test, y_pred),
    'f1_score': f1_score(y_test, y_pred)
}
```

6.7. Models Comparisons

```
In [116... # classification reports of all models
for key, value in evaluation.items():
    print(key)
    print(value['classification_report'])
```

dt_classifier					
	precision	recall	f1-score	support	
0	0.62	0.80	0.69	15042	
1	0.71	0.50	0.59	15042	
accuracy			0.65	30084	
macro avg	0.66	0.65	0.64	30084	
weighted avg	0.66	0.65	0.64	30084	
bg_classifier					
	precision	recall	f1-score	support	
0	0.61	0.80	0.69	15042	
1	0.71	0.50	0.59	15042	
accuracy			0.65	30084	
macro avg	0.66	0.65	0.64	30084	
weighted avg	0.66	0.65	0.64	30084	
adab_classifier					
	precision	recall	f1-score	support	
0	0.70	0.78	0.74	15042	
1	0.75	0.67	0.71	15042	
accuracy			0.72	30084	
macro avg	0.73	0.72	0.72	30084	
weighted avg	0.73	0.72	0.72	30084	
gb_classifier					
	precision	recall	f1-score	support	
0	0.67	0.81	0.73	15042	
1	0.76	0.60	0.67	15042	
accuracy			0.71	30084	
macro avg	0.72	0.71	0.70	30084	
weighted avg	0.72	0.71	0.70	30084	
rf_classifier					
	precision	recall	f1-score	support	
0	0.64	0.76	0.69	15042	
1	0.70	0.57	0.63	15042	
accuracy			0.66	30084	
macro avg	0.67	0.66	0.66	30084	
weighted avg	0.67	0.66	0.66	30084	
vot_classifier					
	precision	recall	f1-score	support	
0	0.61	0.61	0.61	15042	
1	0.61	0.61	0.61	15042	

accuracy			0.61	30084
macro avg	0.61	0.61	0.61	30084
weighted avg	0.61	0.61	0.61	30084

```
In [117... # evaluation metrics of all models
for key, value in evaluation.items():
    print(key)
    print(f"accuracy: {value['accuracy']}")
    print(f"precision: {value['precision']}")
    print(f"recall: {value['recall']}")
    print(f"f1-score: {value['f1_score']}")
    print("=====")
```

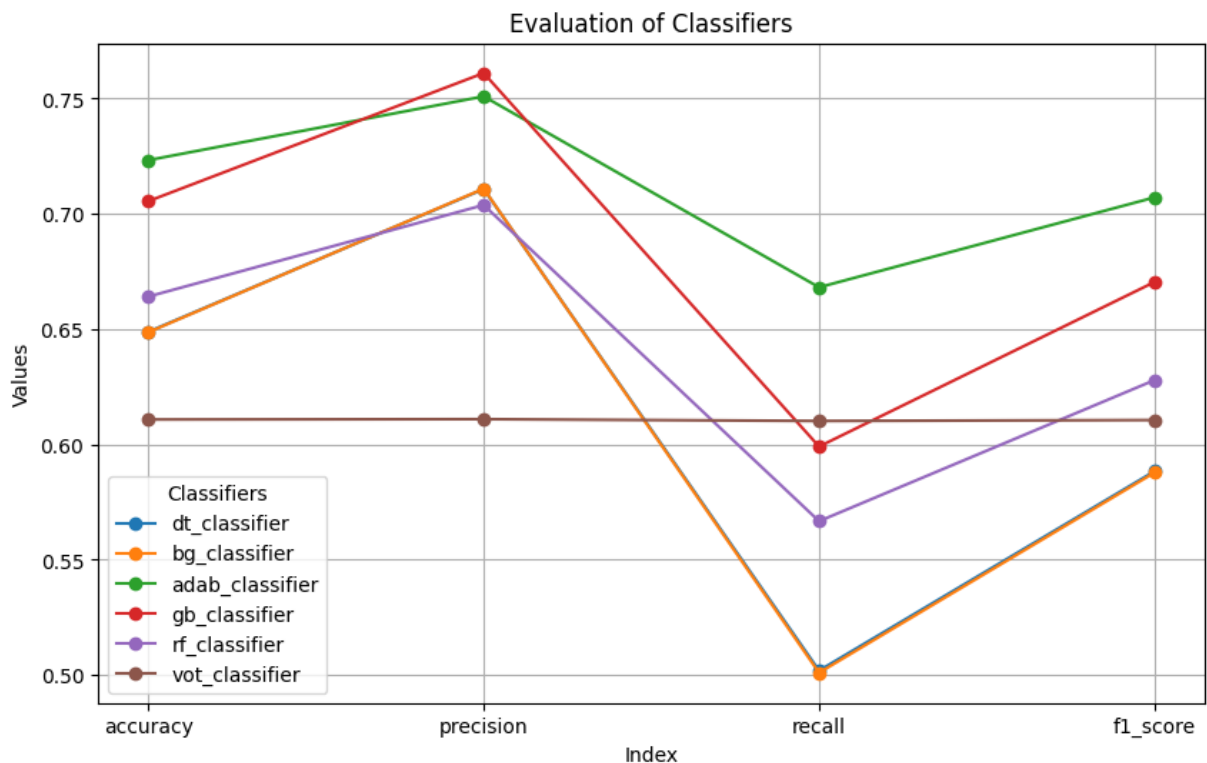
```
dt_classifier
accuracy: 0.6488166467225103
precision: 0.7107616985217965
recall: 0.501861454593804
f1-score: 0.5883178116354285
=====
bg_classifier
accuracy: 0.6486172051588884
precision: 0.7109161241626568
recall: 0.500930727296902
f1-score: 0.5877305877305877
=====
adab_classifier
accuracy: 0.7232748304746709
precision: 0.7509527011880744
recall: 0.668129238133227
f1-score: 0.7071240105540898
=====
gb_classifier
accuracy: 0.7054912910517218
precision: 0.7610641891891892
recall: 0.5990559765988566
f1-score: 0.6704114277211517
=====
rf_classifier
accuracy: 0.6641071666001861
precision: 0.7038229708529437
recall: 0.5666799627709082
f1-score: 0.6278495930468089
=====
vot_classifier
accuracy: 0.6107897885919426
precision: 0.6109299074752047
recall: 0.6101582236404733
f1-score: 0.6105438217196075
=====
```

```
In [118... # convert evaluation data into dataframe
df_evaluation = pd.DataFrame({key: {
    'accuracy': value['accuracy'],
    'precision': value['precision'],
    'recall': value['recall'],
```

```
'f1_score': value['f1_score']
} for key, value in evaluation.items()})
```

```
In [119... # show line plots for all classifiers
plt.figure(figsize=(10, 6))
for column in df_evaluation.columns:
    plt.plot(df_evaluation.index, df_evaluation[column], marker='o', label=column)

plt.title('Evaluation of Classifiers')
plt.xlabel('Index')
plt.ylabel('Values')
plt.legend(title='Classifiers')
plt.grid(True)
plt.show()
```



Results: Adaboost Classifier show highest results in evaluation metrics with second lowest variation.

7. Model Testing

```
In [120... # using adaboost classifier for prediction
df_test['is_promoted'] = adab_classifier.predict(df_test[important_features])
```

```
In [121... # top 10 elements with is_promoted
df_test.head(10)
```

Out[121]:	education	gender	no_of_trainings	age	previous_year_rating	length_of_service	awar
0	0.5	0	0.000000	0.100	0.50	0.000000	
1	0.5	1	0.000000	0.275	0.50	0.111111	
2	0.5	0	0.000000	0.275	0.00	0.083333	
3	0.5	1	0.222222	0.275	0.25	0.222222	
4	0.5	0	0.000000	0.250	0.75	0.166667	
5	0.5	0	0.000000	0.400	0.50	0.027778	
6	0.5	0	0.000000	0.325	1.00	0.055556	
7	0.5	0	0.111111	0.400	0.50	0.055556	
8	1.0	0	0.000000	0.775	0.75	0.277778	
9	0.5	0	0.000000	0.225	1.00	0.027778	

10 rows × 55 columns

```
In [122]: # checking value counts
df_test['is_promoted'].value_counts()
```

```
Out[122]: 0    17506
          1     5984
          Name: is_promoted, dtype: int64
```

8. Model Saving

```
In [123]: # saving model
joblib.dump(adab_classifier, 'final_model.sav')
```

```
Out[123]: ['final_model.sav']
```

References

- “HR Analytics: Employee Promotion Data.” Www.kaggle.com, www.kaggle.com/datasets/arashnic/hr-ana.
- Nature.com, 2024, www.nature.com/nature-index/article/image/615b9add4e229320e10253a6.

```
In [ ]:
```