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 Loading

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_trai
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]:
```python
# 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]:
```python
# 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]:
```python
# 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())
```

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

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

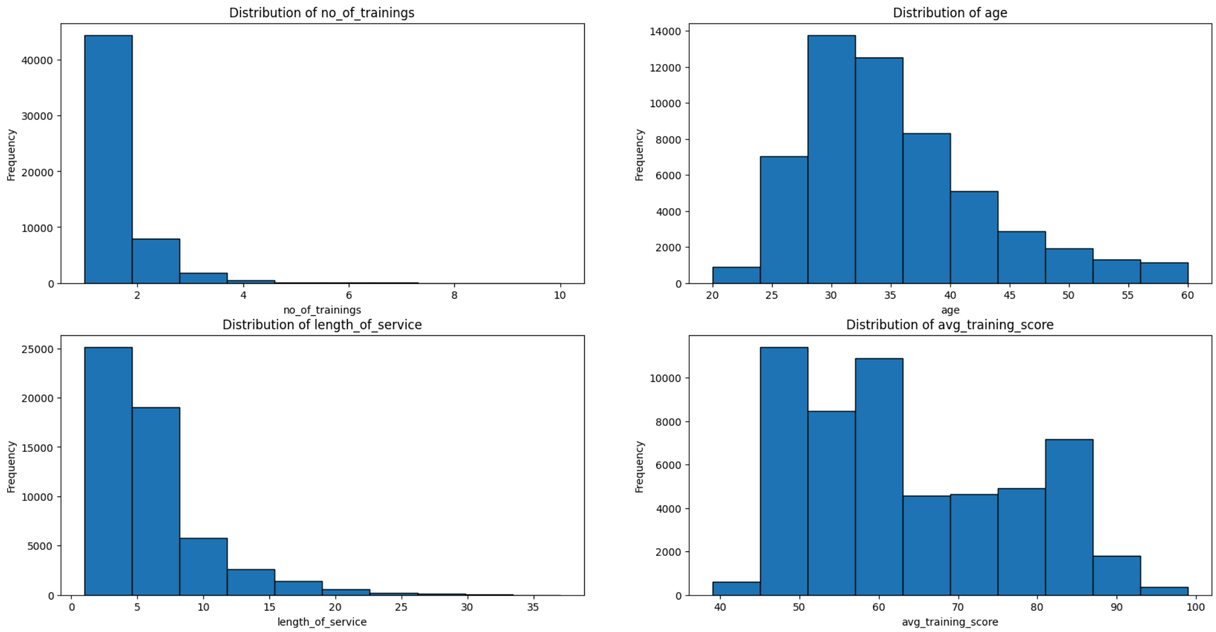
In [23]:
```
# drop duplicates of df_test
df_test = df_test.drop_duplicates()
```

2.4. Handling Outliers

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

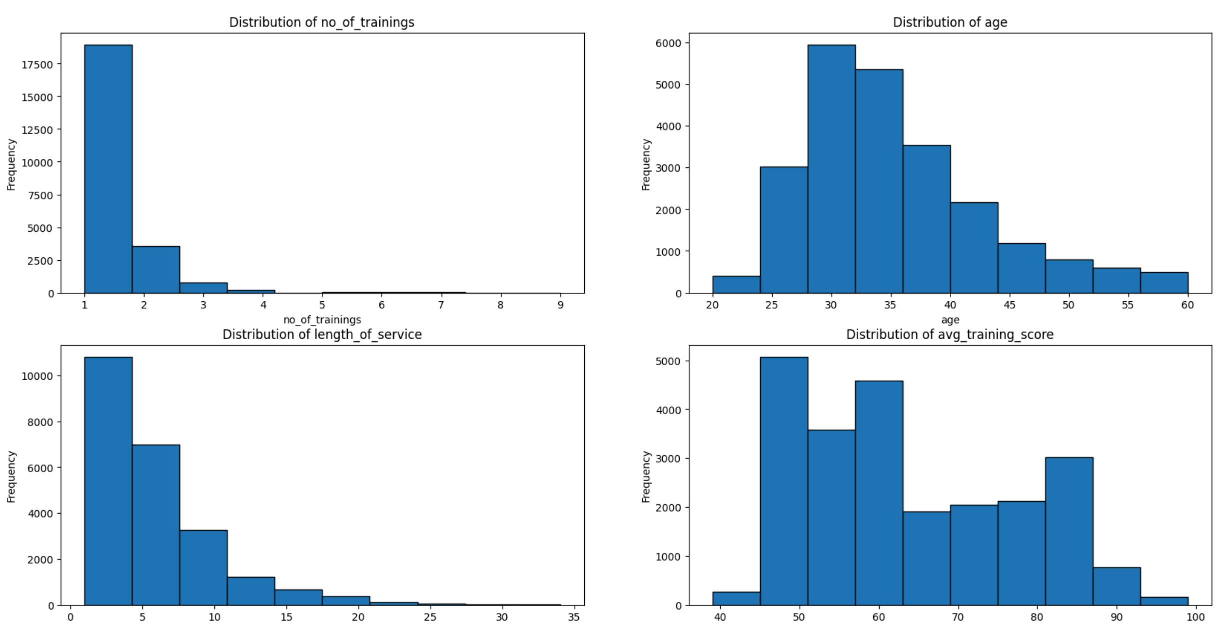
In [25]:
```
# histogram for outliers in df_train
i = 1
plt.figure(figsize=(20, 10))
for col in dist_cols:
    plt.subplot(2, 2, i)
    plt.hist(df_train[col], bins=10, edgecolor='black')
    plt.title(f'Distribution of {col}')
```

```
    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_test
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'>
RangeIndex: 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: 5.0+ MB
```

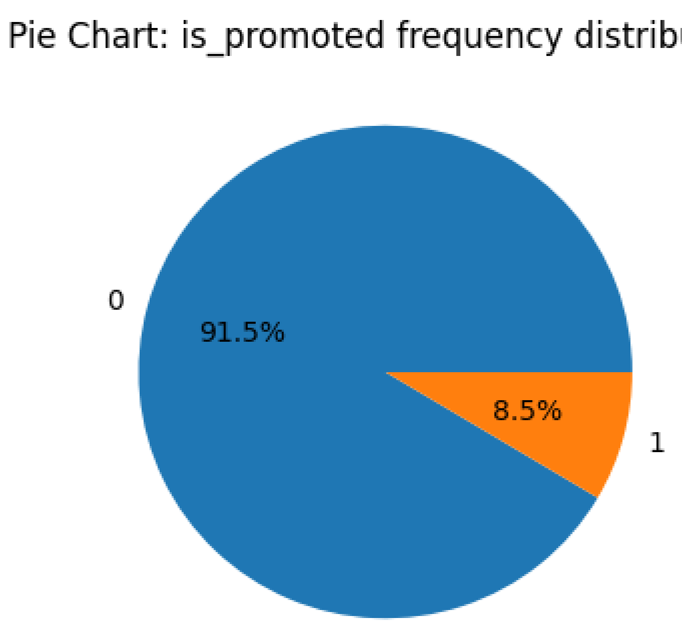
In [32]:
```
# checking preprocessed df_test
df_test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 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: 2.0+ 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()
```



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

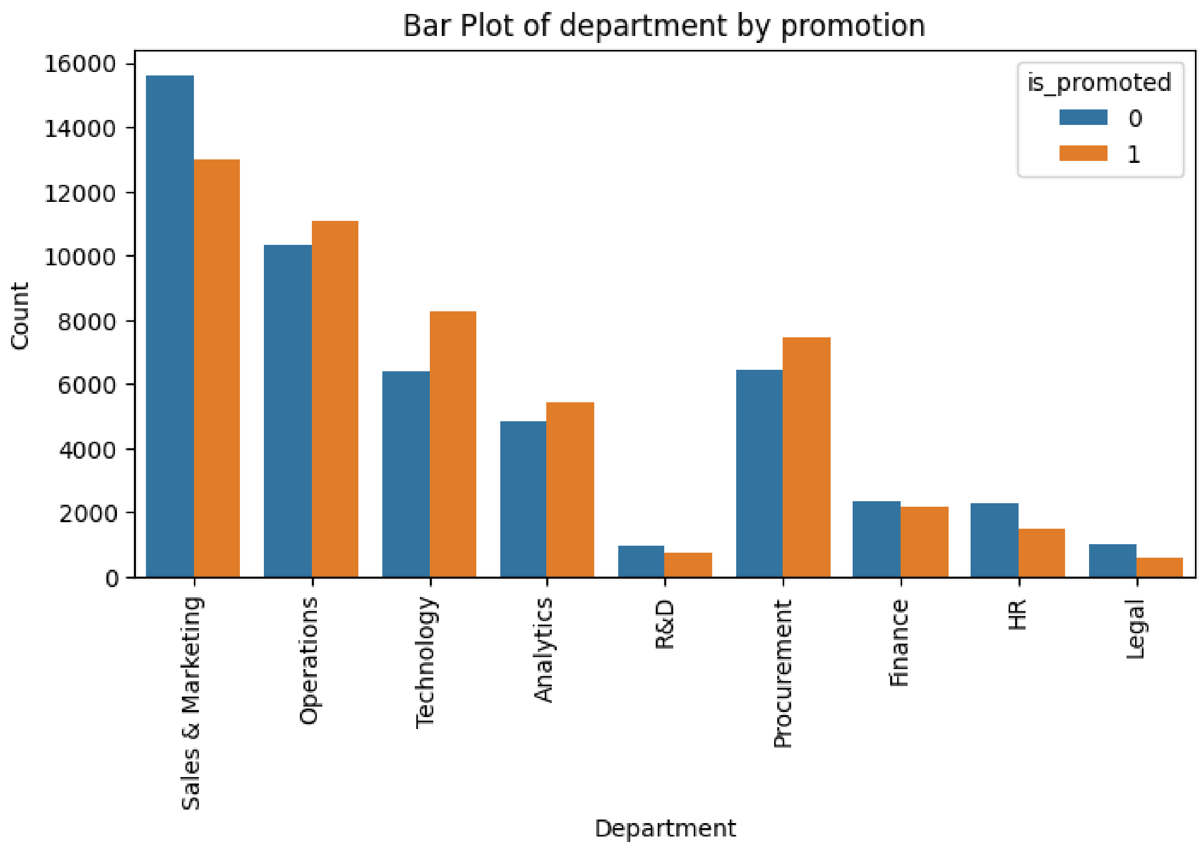
In [34]:
```
# dividing minority and majority classes
minority_class = df_train[df_train['is_promoted'] == 1]
majority_class = df_train[df_train['is_promoted'] == 0]
```

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

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

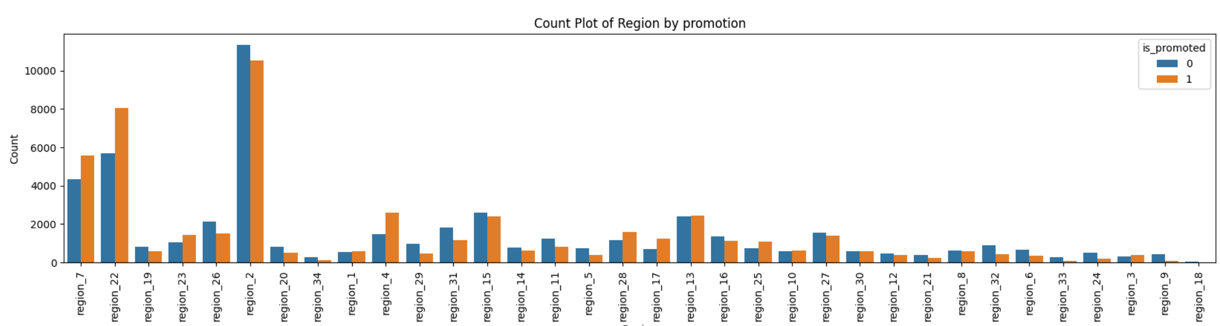
3.3. Data Visualizations after Oversampling

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]:

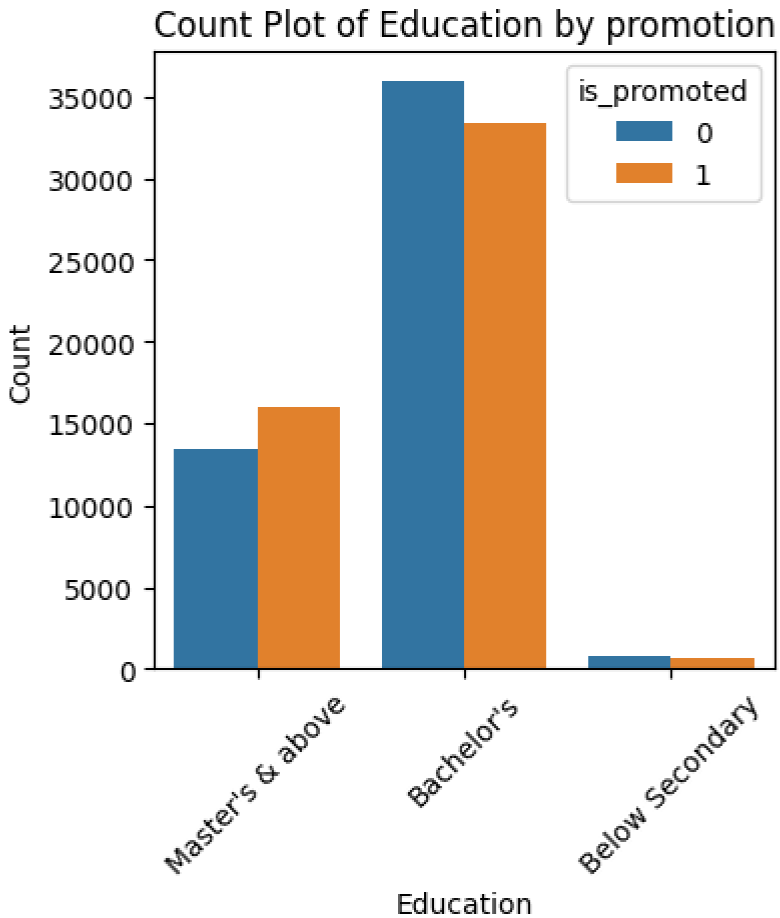
```
# region vs is_promoted
plt.figure(figsize=(20, 4))
sns.countplot(x='region', hue='is_promoted', data=odf_train)
plt.title('Count Plot of Region by promotion')
plt.xlabel('Region')
plt.ylabel('Count')
plt.xticks(rotation=90)
plt.legend(title='is_promoted', labels=[0, 1])
plt.show()
```



In [39]:

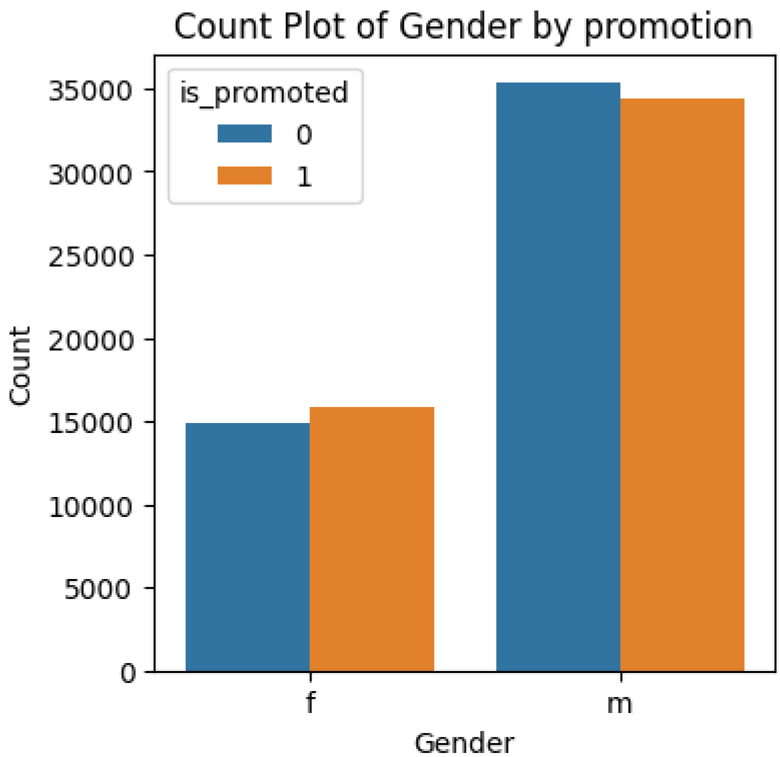
```
# education vs is_promoted count plot
plt.figure(figsize=(4, 4))
sns.countplot(x='education', hue='is_promoted', data=odf_train)
plt.title('Count Plot of Education by promotion')
plt.xlabel('Education')
plt.ylabel('Count')
plt.xticks(rotation=45)
```

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

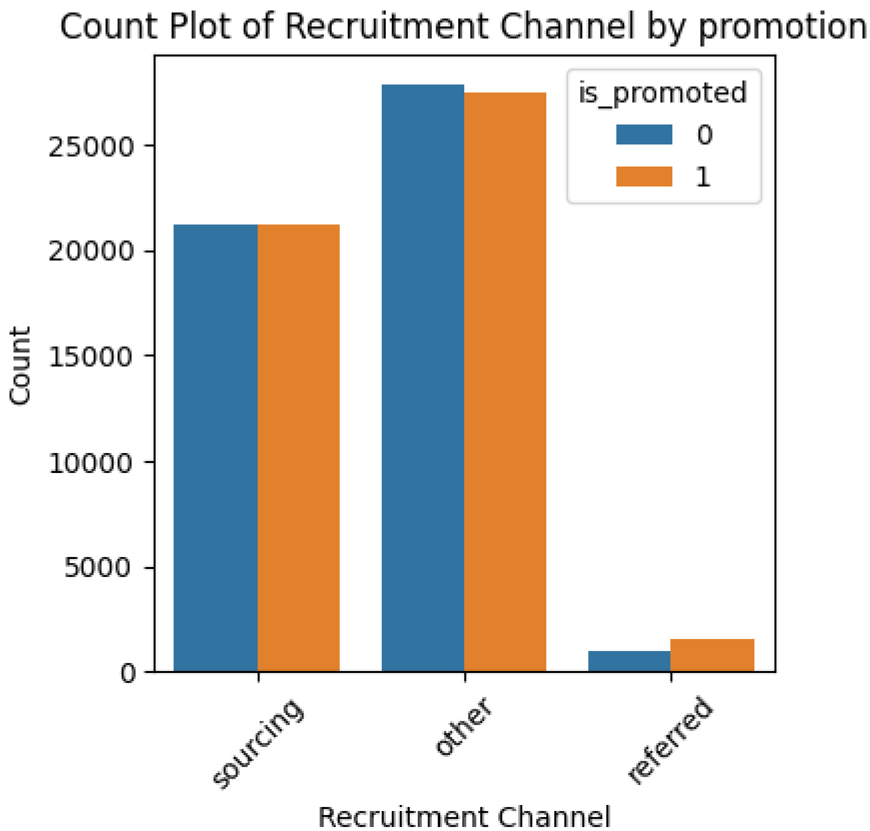


In [40]:

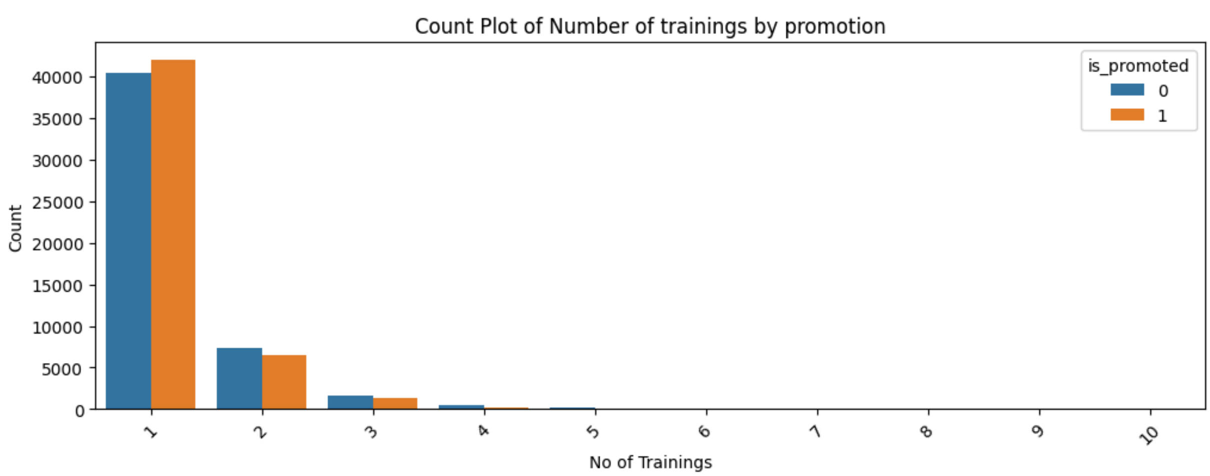
```
# gender vs is_promoted count plot
plt.figure(figsize=(4, 4))
sns.countplot(x='gender', hue='is_promoted', data=odf_train)
plt.title('Count Plot of Gender by promotion')
plt.xlabel('Gender')
plt.ylabel('Count')
plt.xticks()
plt.legend(title='is_promoted', labels=[0, 1])
plt.show()
```



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()
```

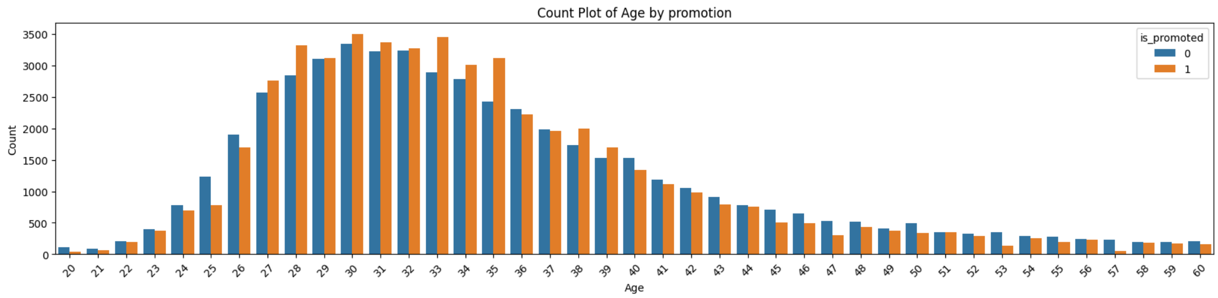


In [42]:
```
# no_of_trainings vs is_promoted count plot
plt.figure(figsize=(12, 4))
sns.countplot(x='no_of_trainings', hue='is_promoted', data=odf_train)
plt.title('Count Plot of Number of trainings by promotion')
plt.xlabel('No of Trainings')
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.legend(title='is_promoted',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

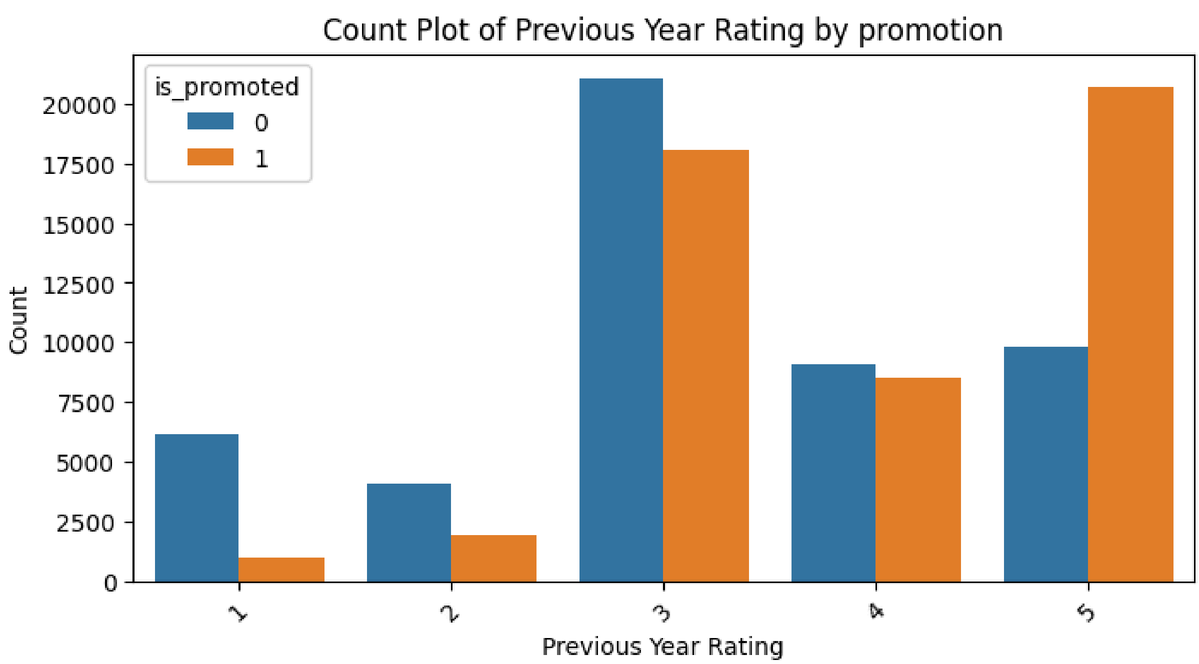


In [43]:
```
# age vs is_promoted count plot
plt.figure(figsize=(20, 4))
sns.countplot(x='age', hue='is_promoted', data=odf_train)
plt.title('Count Plot of Age by promotion')
plt.xlabel('Age')
```

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



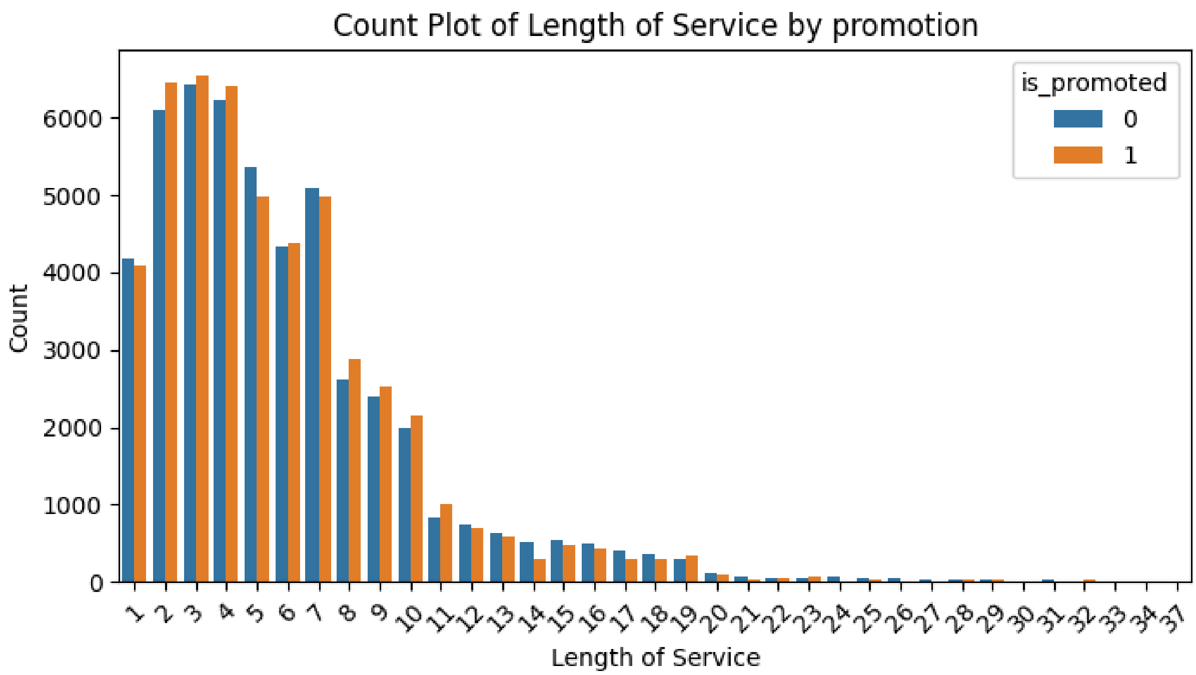
In [44]:
```python
# previous_year_rating vs is_promoted count plot
plt.figure(figsize=(8, 4))
sns.countplot(x='previous_year_rating', hue='is_promoted', data=odf_train)
plt.title('Count Plot of Previous Year Rating by promotion')
plt.xlabel('Previous Year Rating')
plt.ylabel('Count')
plt.xticks(rotation=45)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



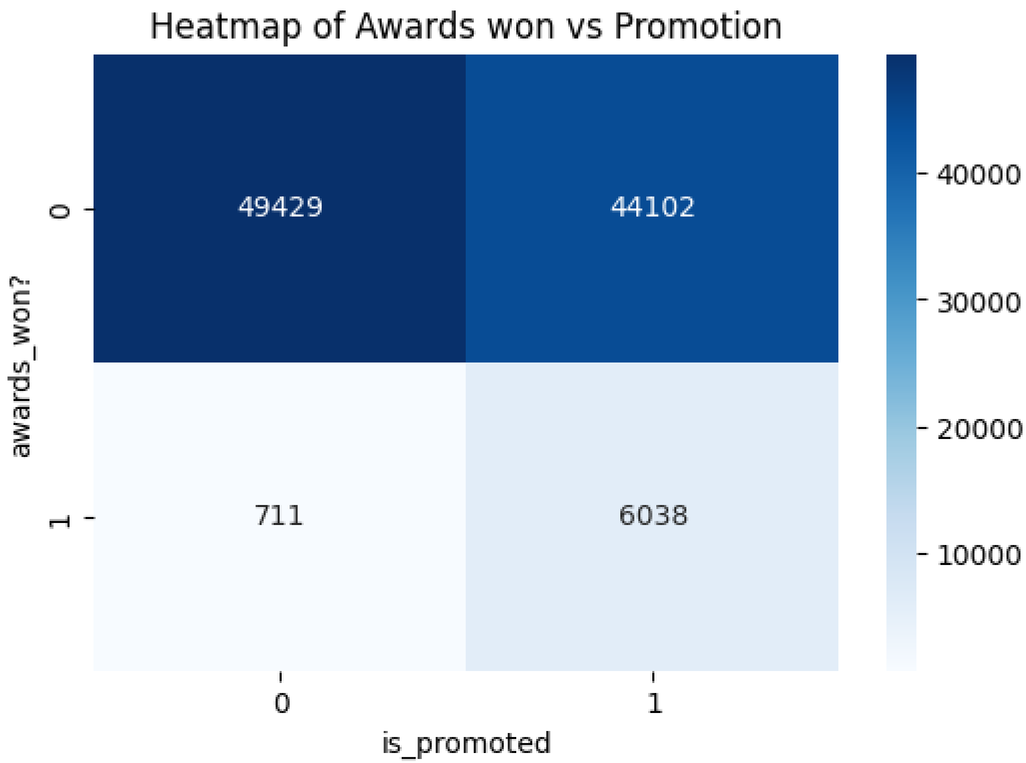
Observation: Employees with 1 previous year rating has minority being promoted which increases upto 5.

In [45]:
```python
# 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()
```

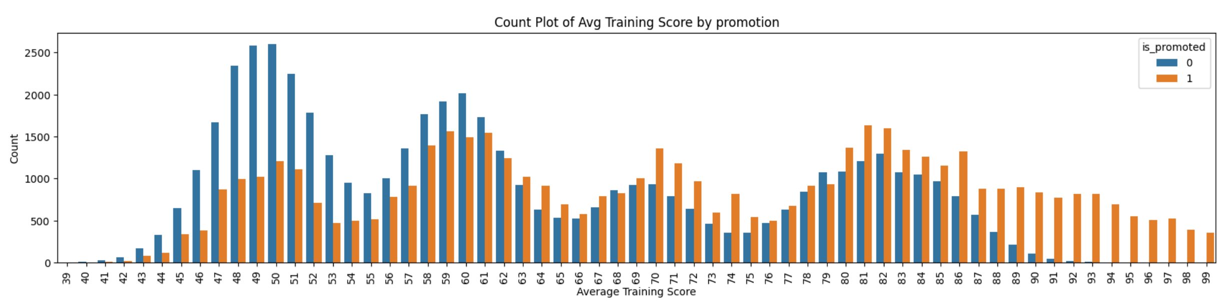


In [46]:
```
# awards_won? vs is_promoted count based heatmap
plt.figure(figsize=(6, 4))
pivot_table = odf_train.pivot_table(index='awards_won?', columns='is_promoted', agg
sns.heatmap(pivot_table, annot=True, cmap='Blues', cbar=True, fmt='g')
plt.title('Heatmap of Awards won vs Promotion')
plt.xlabel('is_promoted')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

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	p
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	p
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 [61]:
```
# get rid of all rows with null values
odf_train.dropna(inplace=True)
df_test.dropna(inplace=True)
```

In [62]:
```
# 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 [63]:
```
# 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()
```

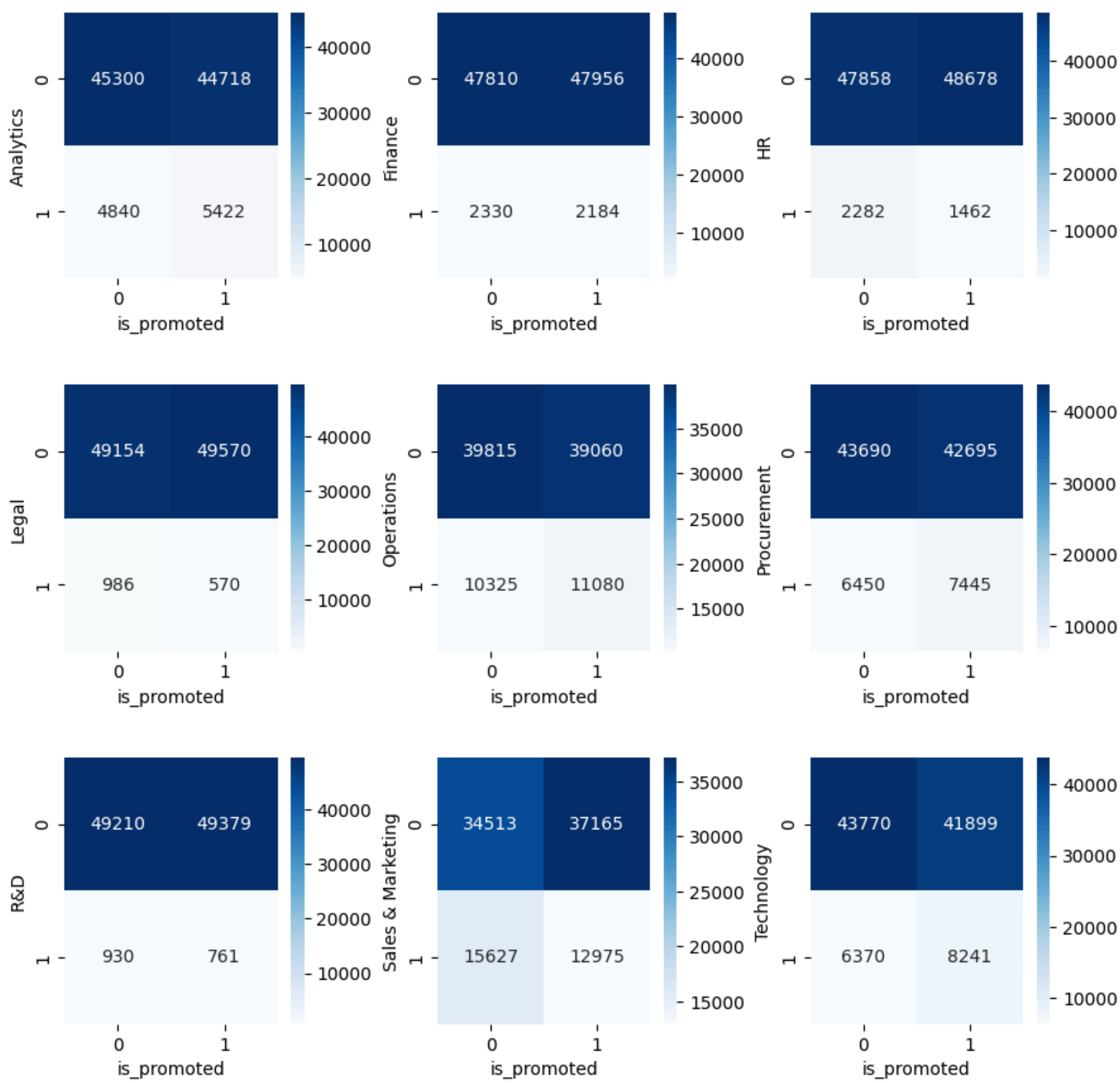
In [70]:
```
# scale mm_scaler_cols
odf_train_scaled = mm_scaler.fit_transform(odf_train[mm_scaler_cols])
df_test_scaled = mm_scaler.transform(df_test[mm_scaler_cols])
```

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

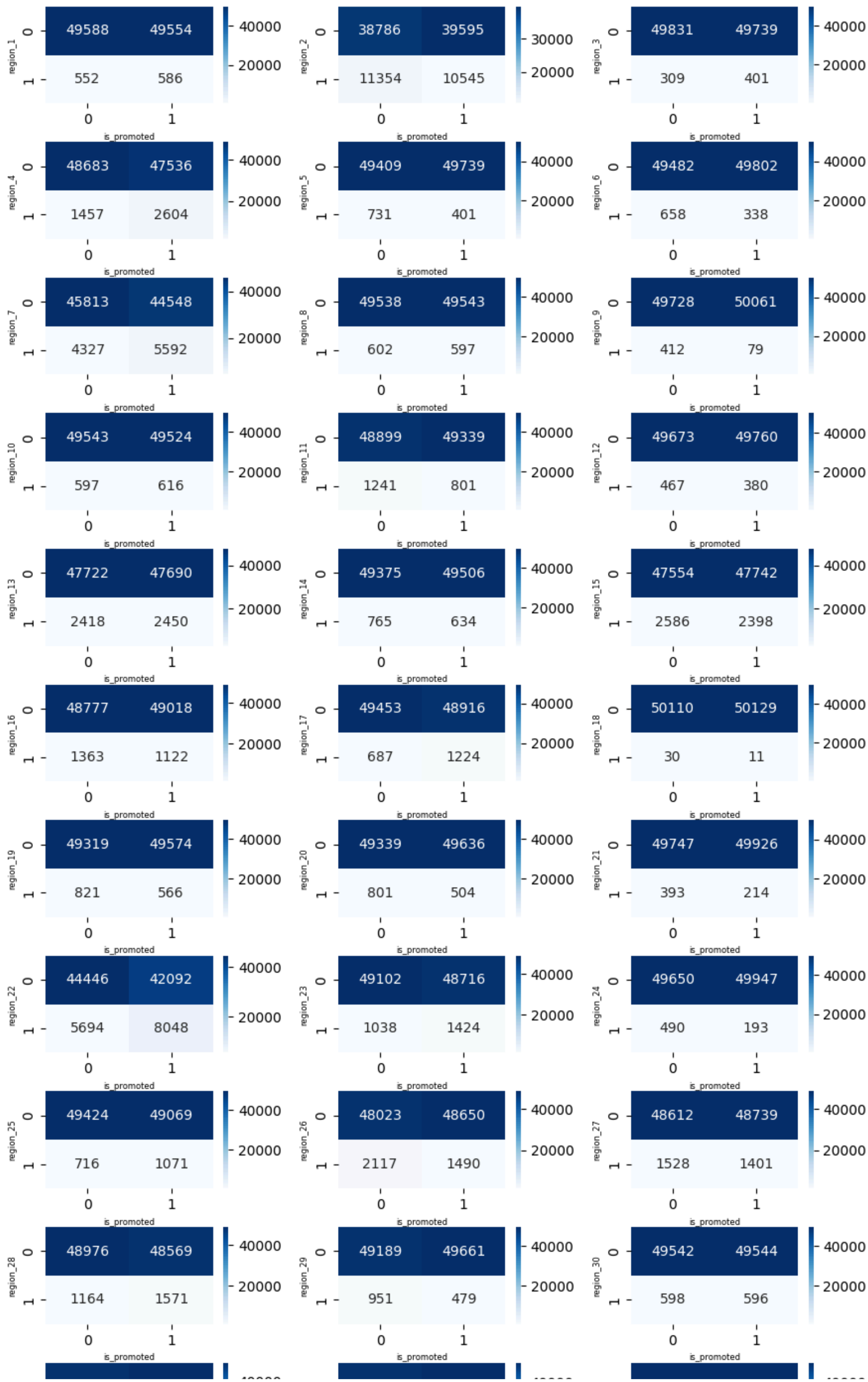
In [72]:

```
# 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()
```

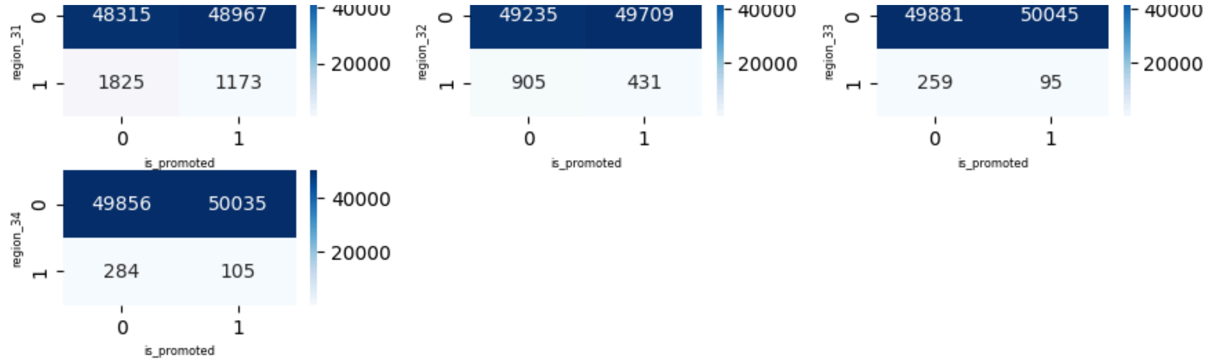


Observation: HR, Legal, Sales & Marketing and Technology are 2 departments that look highly correlated to promotion. Most employees in these 2 departments don't receive promotion. Whereas, those from Sales & Marketing and Technology have inversely proportional relationship to 'is_promoted'.

```
In [73]: # checking relationships of different regions to is_promoted
regions = ['region_1', 'region_2','region_3', 'region_4', 'region_5', 'region_6', '
           'region_9', 'region_10', 'region_11', 'region_12', 'region_13', 'region_
           'region_17', 'region_18', 'region_19', 'region_20', 'region_21', 'region
           'region_25', 'region_26', 'region_27', 'region_28', 'region_29', 'region
           '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='
    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.
plt.show()
```

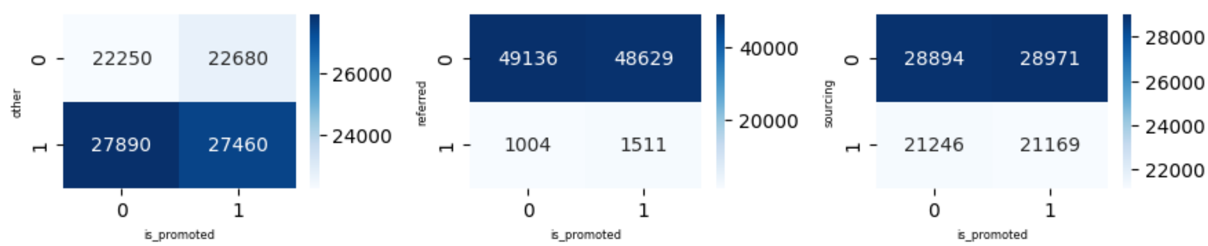


region_1
49588 49554
552 586
region_2
38786 39595
11354 10545
region_3
49831 49739
309 401
region_4
48683 47536
1457 2604
region_5
49409 49739
731 401
region_6
49482 49802
658 338
region_7
45813 44548
4327 5592
region_8
49538 49543
602 597
region_9
49728 50061
412 79
region_10
49543 49524
597 616
region_11
48899 49339
1241 801
region_12
49673 49760
467 380
region_13
47722 47690
2418 2450
region_14
49375 49506
765 634
region_15
47554 47742
2586 2398
region_16
48777 49018
1363 1122
region_17
49453 48916
687 1224
region_18
50110 50129
30 11
region_19
49319 49574
821 566
region_20
49339 49636
801 504
region_21
49747 49926
393 214
region_22
44446 42092
5694 8048
region_23
49102 48716
1038 1424
region_24
49650 49947
490 193
region_25
49424 49069
716 1071
region_26
48023 48650
2117 1490
region_27
48612 48739
1528 1401
region_28
48976 48569
1164 1571
region_29
49189 49661
951 479
region_30
49542 49544
598 596
is_promoted
0 1
40000
30000
20000



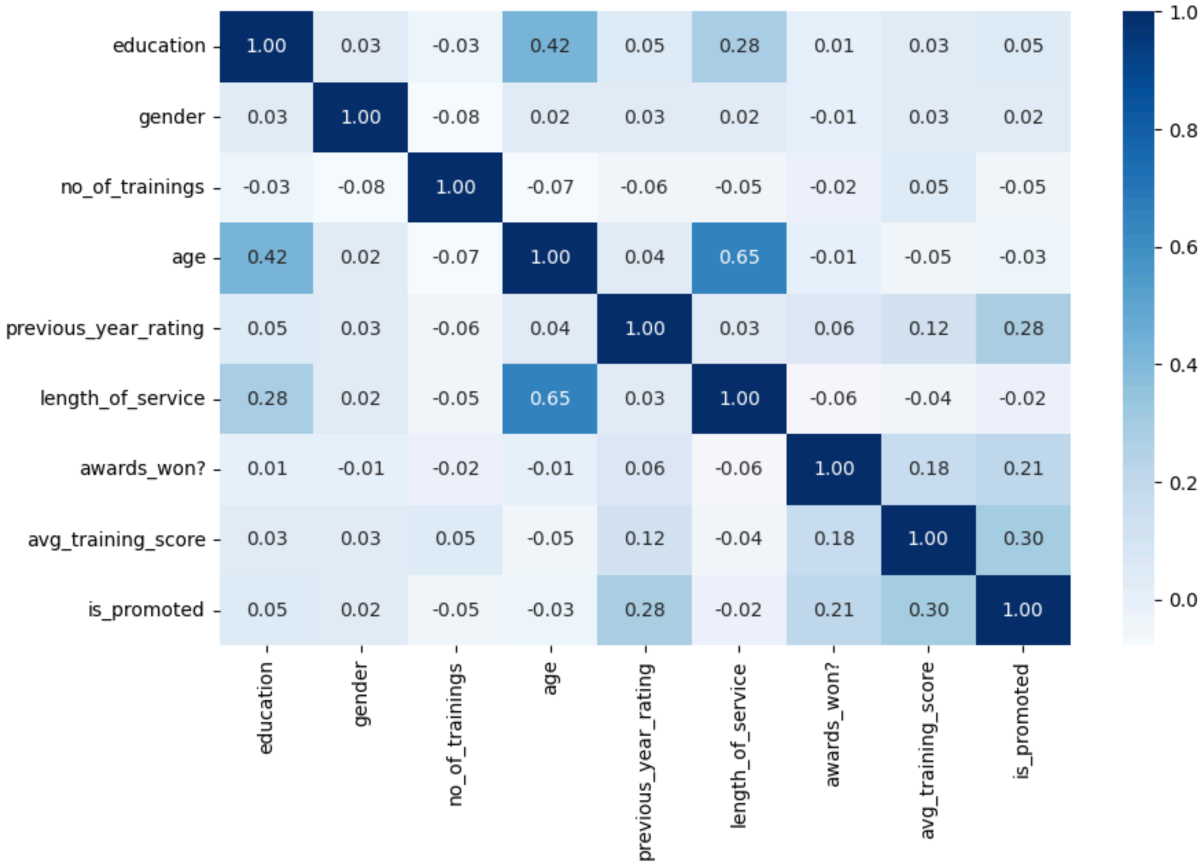
Observation: Employees from regions 3-7, 9, 11, 12, 17, 18-26, 28, 29 and 31-34 have high correlation to promotion.

In [74]:
```
# 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='
    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.
plt.show()
```



Observation: Referred employees enjoy high correlation.

In [75]:
```
# checking relationships of other features to is_promoted
df_train_others = odf_train[['education', 'gender', 'no_of_trainings', 'age', 'prev
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 [76]:
```
# 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 [77]:
```
# define X and y
X = odf_train[important_features]
y = odf_train['is_promoted']
```

In [78]:
```
# 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 [79]:
```
# replace null values by 0
X_train.fillna(0, inplace=True)
X_test.fillna(0, inplace=True)
```

6. Model Building and Evaluation

In [80]:
```
# defining empty dictionary for comparing evaluation
evaluation = dict()
```

6.1. Decision Tree Classifier

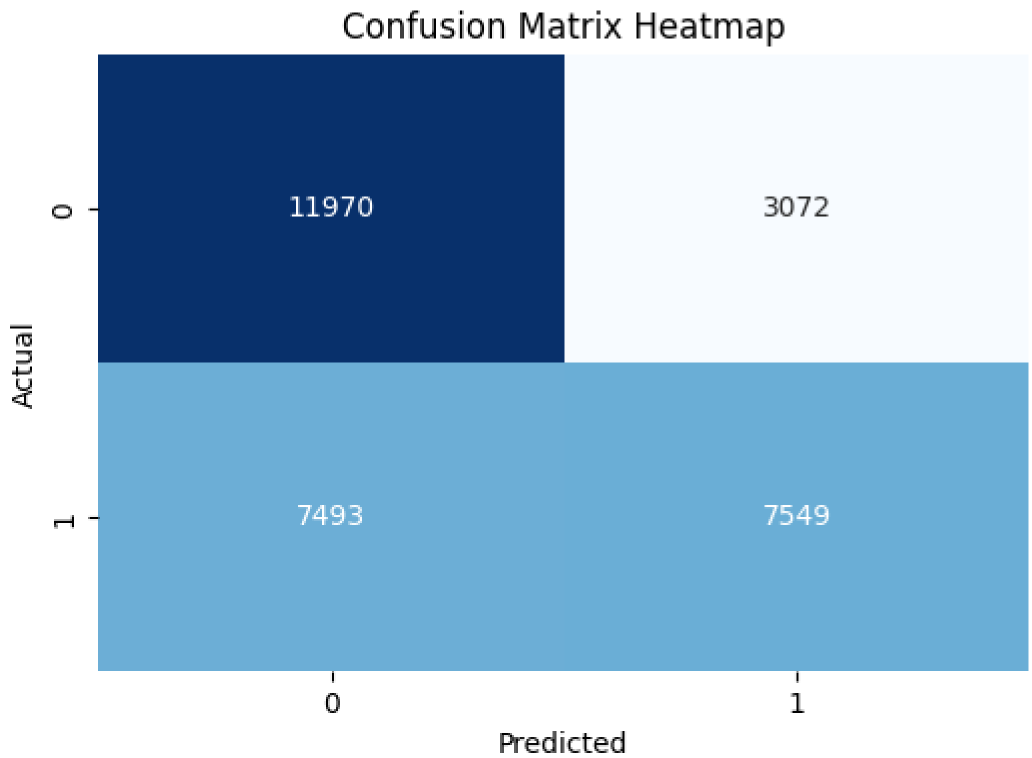
In [81]:
```
# defining classifier
dt_classifier = DecisionTreeClassifier(min_samples_split=10,max_depth=3)
```

In [82]:
```
# model fitting
dt_classifier.fit(X_train, y_train)
```

Out[82]:
```
DecisionTreeClassifier
DecisionTreeClassifier(max_depth=3, min_samples_split=10)
```

In [83]:
```
# model prediction
y_pred = dt_classifier.predict(X_test)
```

In [84]:
```
# 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 [85]:
```
# 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

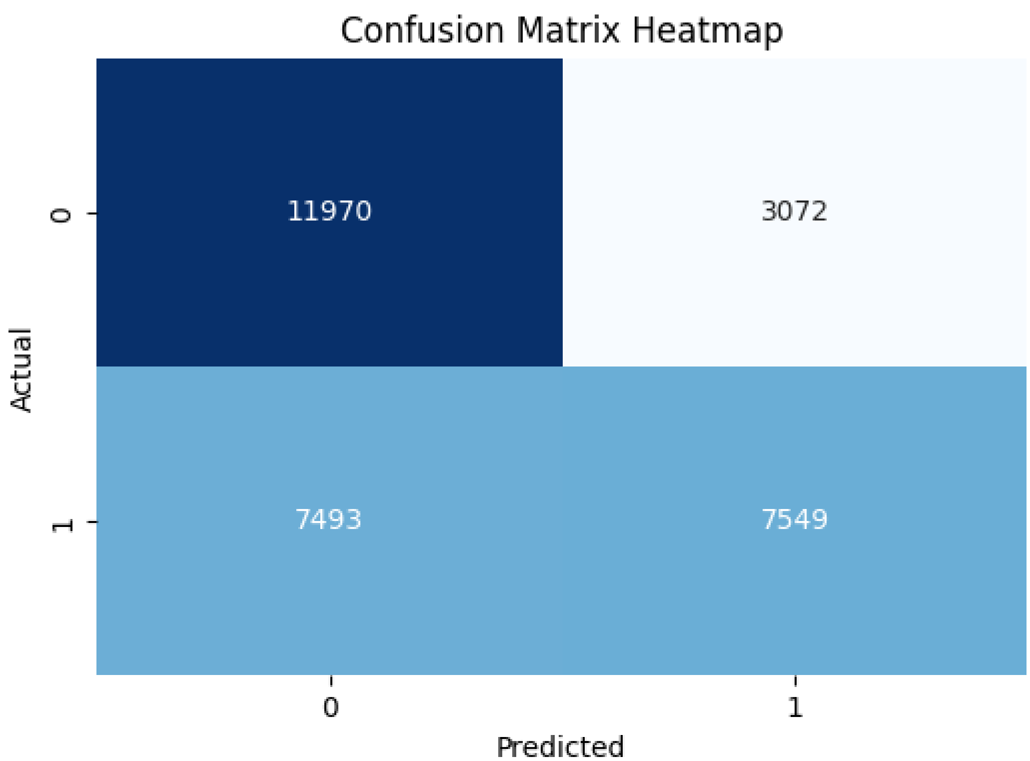
In [86]:
```
# defining classifier
bg_classifier = BaggingClassifier(DecisionTreeClassifier(min_samples_split=10,max_d
```

In [87]:
```
# model fitting
bg_classifier.fit(X_train, y_train)
```

Out[87]:
```
BaggingClassifier
estimator: DecisionTreeClassifier
DecisionTreeClassifier
```

In [88]:
```
# model prediction
y_pred = bg_classifier.predict(X_test)
```

In [89]:
```
# 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 [90]:
```
# 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 [91]:
```
# defining classifier
adab_classifier = AdaBoostClassifier(DecisionTreeClassifier(max_depth=3),n_estimato
```

In [92]:
```
# model fitting
adab_classifier.fit(X_train, y_train)
```

Out[92]:

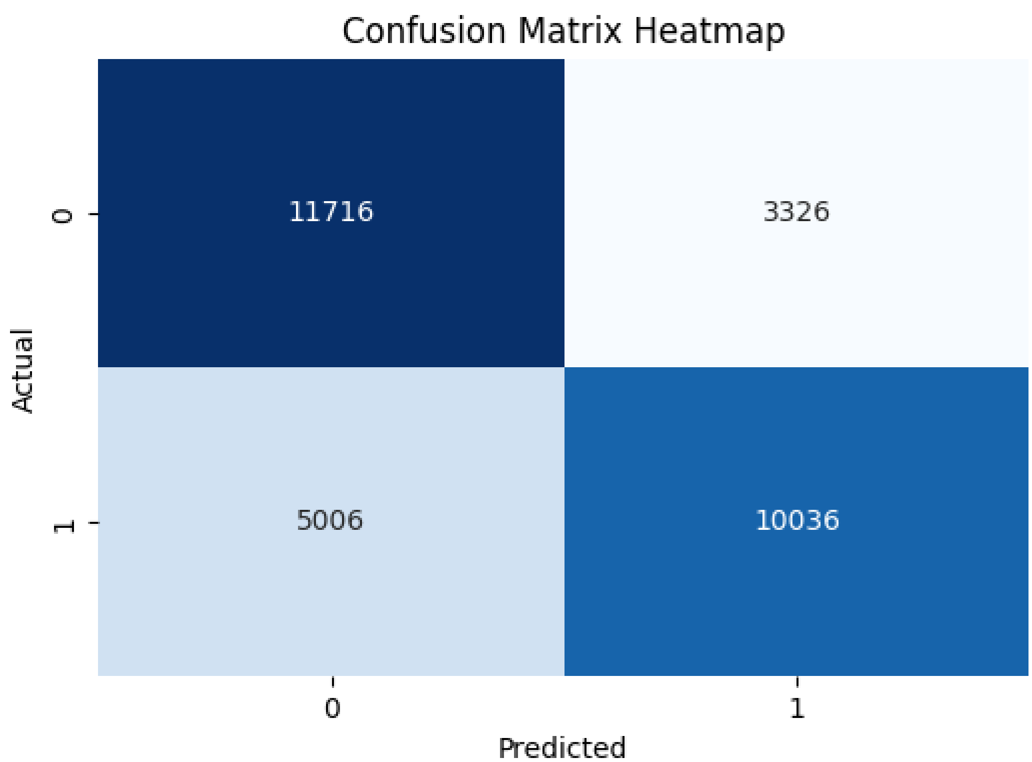
```
▸ AdaBoostClassifier
▸ estimator: DecisionTreeClassifier
  ▸ DecisionTreeClassifier
```

In [93]:

```python
# model prediction
y_pred = adab_classifier.predict(X_test)
```

In [94]:

```python
# 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 [95]:

```python
# 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

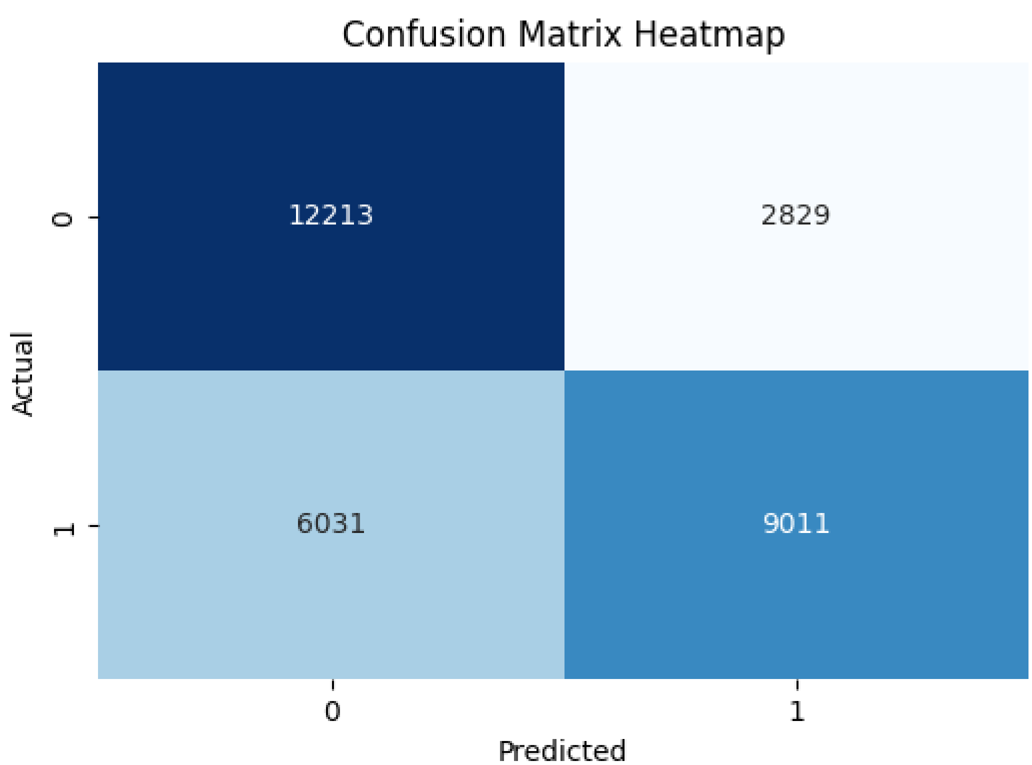
In [96]:
```
# defining classifier
gb_classifier = GradientBoostingClassifier(n_estimators=100)
```

In [97]:
```
# model fitting
gb_classifier.fit(X_train, y_train)
```

Out[97]:
```
GradientBoostingClassifier
GradientBoostingClassifier()
```

In [98]:
```
# model prediction
y_pred = gb_classifier.predict(X_test)
```

In [99]:
```
# 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 [100…
```
# 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

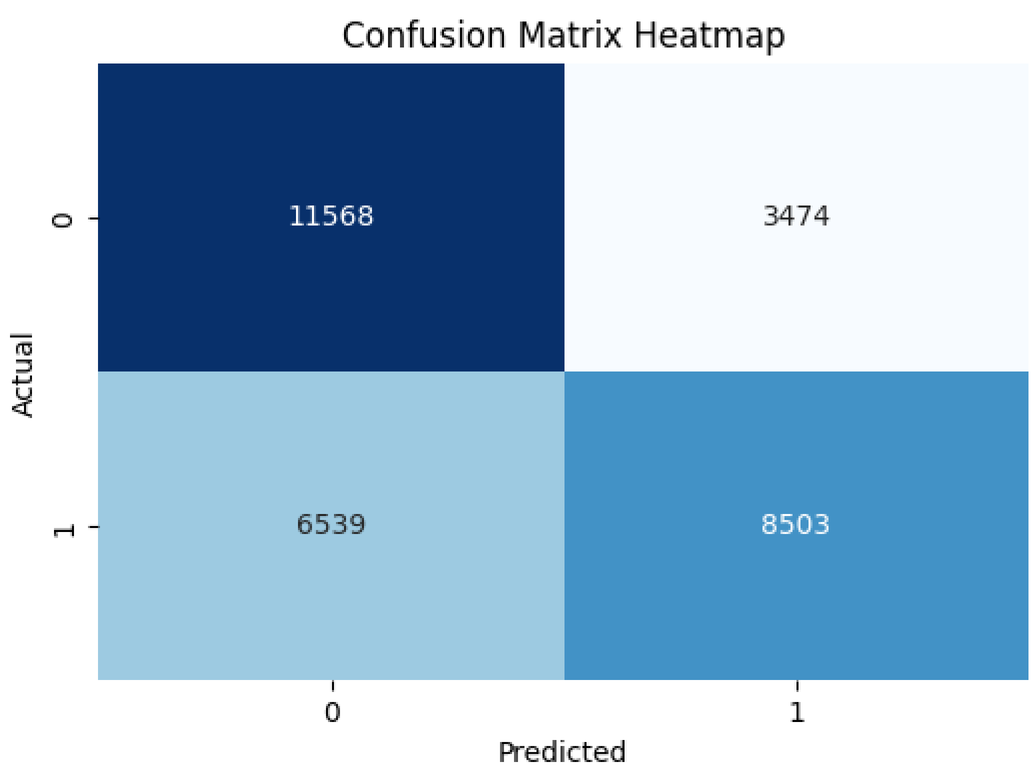
In [101…
```
# defining classifier
rf_classifier = RandomForestClassifier(n_estimators=300,max_depth=3)
```

In [102…
```
# model fitting
rf_classifier.fit(X_train, y_train)
```

Out[102…
```
RandomForestClassifier
RandomForestClassifier(max_depth=3, n_estimators=300)
```

In [103…
```
# model prediction
y_pred = rf_classifier.predict(X_test)
```

In [104…
```
# 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 [105…

```
# 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

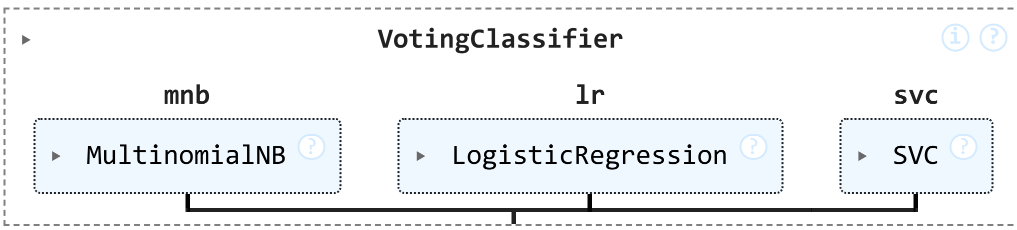
In [106…

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

In [107…

```
# model fitting
vot_classifier.fit(X_train, y_train)
```

Out[107…

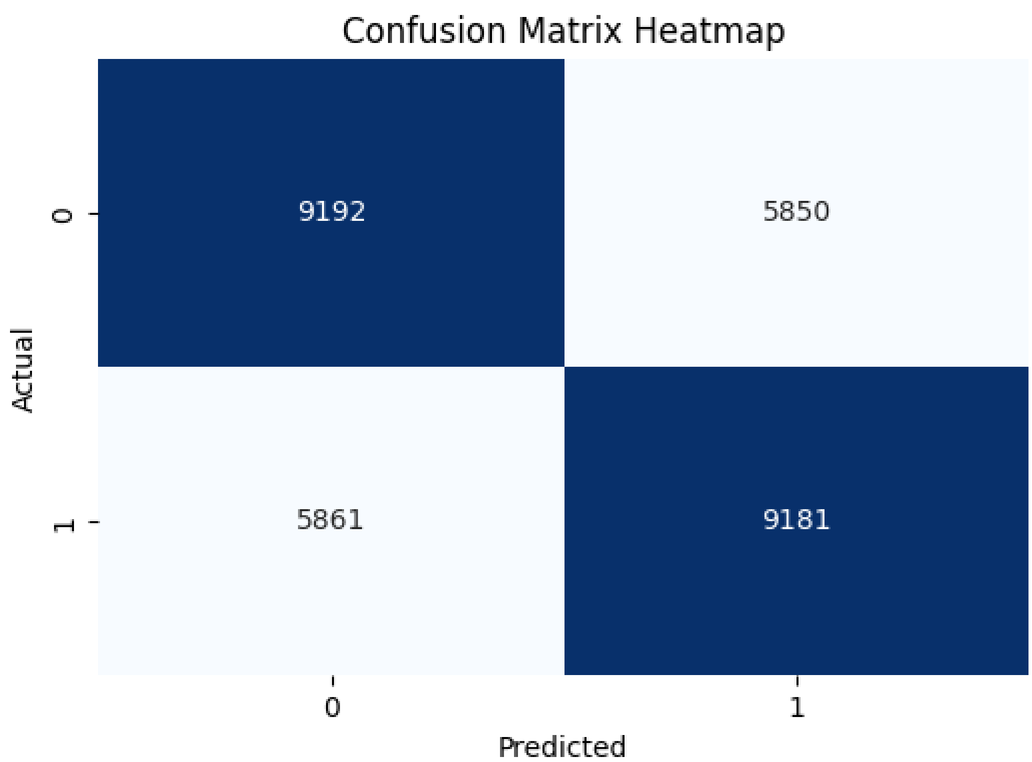


In [108…

```
# model prediction
y_pred = vot_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['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 Comparison

In [111…

```
# 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	0.62	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

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	0.77	0.70	15042
1	0.71	0.57	0.63	15042
accuracy			0.67	30084
macro avg	0.67	0.67	0.66	30084
weighted avg	0.67	0.67	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 [112…

```
# 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: 0.5883178116354284
===========================================
bg_classifier
accuracy: 0.6488166467225103
precision: 0.7107616985217965
recall: 0.501861454593804
f1-score: 0.5883178116354284
===========================================
adab_classifier
accuracy: 0.7230421486504455
precision: 0.751085166891184
recall: 0.667198510836325
f1-score: 0.7066610336572314
===========================================
gb_classifier
accuracy: 0.7054912910517218
precision: 0.7610641891891892
recall: 0.5990559765988566
f1-score: 0.6704114277211517
===========================================
rf_classifier
accuracy: 0.6671652705757213
precision: 0.7099440594472739
recall: 0.5652838718255551
f1-score: 0.6294089344535327
===========================================
vot_classifier
accuracy: 0.6107233080707353
precision: 0.6108043377020823
recall: 0.6103576652040952
f1-score: 0.6105809197619126
===========================================
```

In [113…

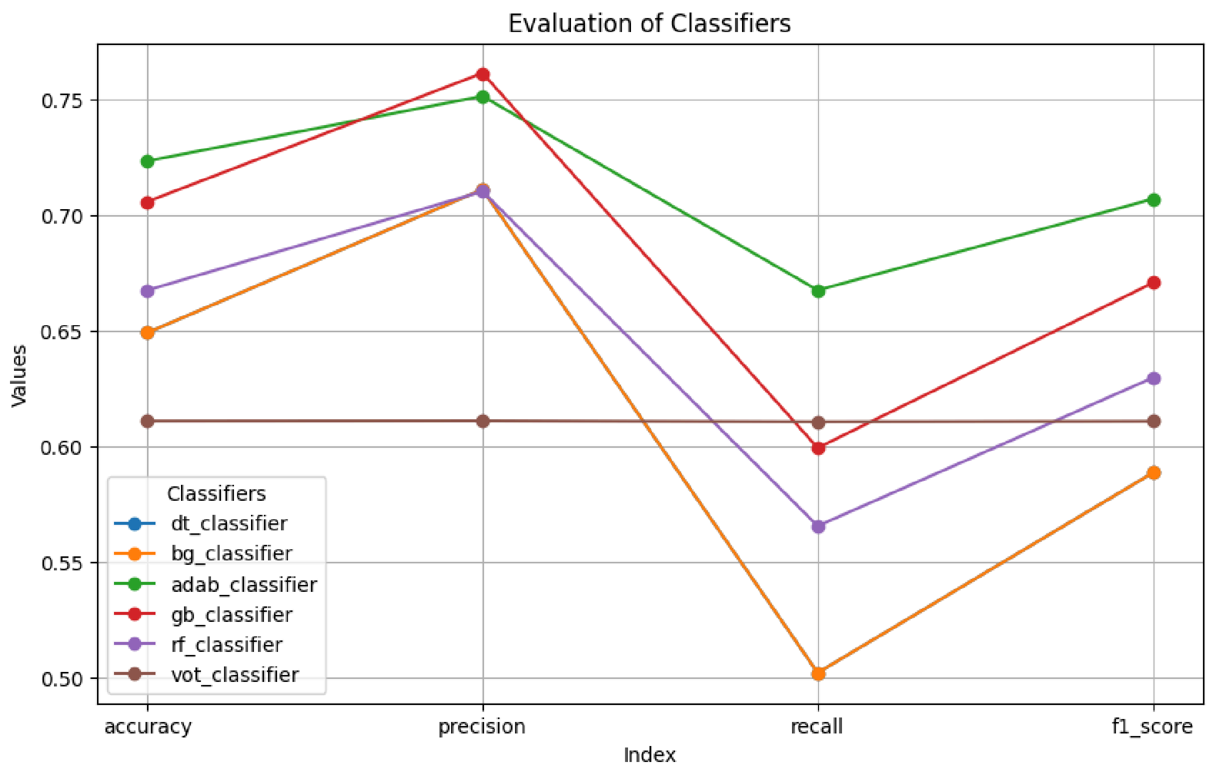
```
# convert evaluation data into dataframe
df_evaluation = pd.DataFrame({key: {
    'accuracy': value['accuracy'],
    'precision': value['precision'],
    'recall': value['recall'],
```

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

In [114…

```
# 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 [115…

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

In [116…

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

Out[116...

	education	gender	no_of_trainings	age	previous_year_rating	length_of_service	awarc
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 [117...

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

Out[117...

```
is_promoted
0    17551
1     5939
Name: count, dtype: int64
```

8. Model Saving

In [118...

```
# saving model
joblib.dump(adab_classifier, 'final_model.sav')
```

Out[118...

```
['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.