Developing Staff Promotion Algorithm

> **CASE STUDY: YAKUB TRADING GROUP ALGORITHMIC STAFF PROMOTION**

Objectives:

1. Analyze the data and see the differnt variables that can affect an employees promotion
2. Build a predictive model to determine the employees that are likely to be promoted

Exploratory Data Analysis

Importing the libraries for the analysis

In [5]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
print('All libraries imported')
```

```
All libraries imported
```

Settings (Optional)

In [29]:
```
# setting up default plotting parameters
%matplotlib inline

plt.rcParams['figure.figsize'] = [20.0, 7.0]
plt.rcParams.update({'font.size': 22,})

sns.set_palette('viridis')
sns.set_style('white')
sns.set_context('talk', font_scale=0.8)
```

Loading the Dataset

In [22]:
```
dataset = pd.read_csv('dataset.csv')
dataset.head()
```

Out[22]:

	EmployeeNo	Division	Qualification	Gender	Channel_of_Recruitment	Trainings_Attended	Year_of_birth	Last_performance_score	Year_of_recruitment	Targets_met	Previous_Award	Training_score_average	State_Of_Origin	Foreign_schooled	Marital_Status	Past_Disciplina
0	YAK/S/00001	Commercial Sales and Marketing	MSc, MBA and PhD	Female	Direct Internal process	2	1986	12.5	2011	1	0	41	ANAMBRA	No	Married	
1	YAK/S/00002	Customer Support and Field Operations	First Degree or HND	Male	Agency and others	2	1991	12.5	2015	0	0	52	ANAMBRA	Yes	Married	
2	YAK/S/00003	Commercial Sales and Marketing	First Degree or HND	Male	Direct Internal process	2	1987	7.5	2012	0	0	42	KATSINA	Yes	Married	
3	YAK/S/00004	Commercial Sales and Marketing	First Degree or HND	Male	Agency and others	3	1982	2.5	2009	0	0	42	NIGER	Yes	Single	
4	YAK/S/00006	Information and Strategy	First Degree or HND	Male	Direct Internal process	3	1990	7.5	2012	0	0	77	AKWA IBOM	Yes	Married	

Data Description and Exploratory Visualisations

> There, I will provide data visualizations that summarizes or extracts relevant characteristics of features in our dataset. Let's look at each column in detail, get a better understanding of the dataset, and group them together when appropriate.

In [23]:
```
# Dataset columns
dataset.columns
```

Out[23]:
```
Index(['EmployeeNo', 'Division', 'Qualification', 'Gender',
       'Channel_of_Recruitment', 'Trainings_Attended', 'Year_of_birth',
       'Last_performance_score', 'Year_of_recruitment', 'Targets_met',
       'Previous_Award', 'Training_score_average', 'State_Of_Origin',
       'Foreign_schooled', 'Marital_Status', 'Past_Disciplinary_Action',
       'Previous_IntraDepartmental_Movement', 'No_of_previous_employers',
       'Promoted_or_Not'],
      dtype='object')
```

In [24]:
```
#data size
dataset.shape
```

Out[24]:
```
(38312, 19)
```

In [25]:
```
# Dataset header
dataset.head()
```

Out[25]:

	EmployeeNo	Division	Qualification	Gender	Channel_of_Recruitment	Trainings_Attended	Year_of_birth	Last_performance_score	Year_of_recruitment	Targets_met	Previous_Award	Training_score_average	State_Of_Origin	Foreign_schooled	Marital_Status	Past_Disciplina
0	YAK/S/00001	Commercial Sales and Marketing	MSc, MBA and PhD	Female	Direct Internal process	2	1986	12.5	2011	1	0	41	ANAMBRA	No	Married	
1	YAK/S/00002	Customer Support and Field Operations	First Degree or HND	Male	Agency and others	2	1991	12.5	2015	0	0	52	ANAMBRA	Yes	Married	
2	YAK/S/00003	Commercial Sales and Marketing	First Degree or HND	Male	Direct Internal process	2	1987	7.5	2012	0	0	42	KATSINA	Yes	Married	
3	YAK/S/00004	Commercial Sales and Marketing	First Degree or HND	Male	Agency and others	3	1982	2.5	2009	0	0	42	NIGER	Yes	Single	
4	YAK/S/00006	Information and Strategy	First Degree or HND	Male	Direct Internal process	3	1990	7.5	2012	0	0	77	AKWA IBOM	Yes	Married	

The dataset contains several numerical and categorical columns providing various information on employee's personal and employment details, as well as performance.

Checking for missing values

In [26]:
```
#Summing the missing values in the data
dataset.isnull().sum()
```

Out[26]:
```
EmployeeNo                              0
Division                                0
Qualification                        1679
Gender                                  0
Channel_of_Recruitment                  0
Trainings_Attended                      0
Year_of_birth                           0
Last_performance_score                  0
Year_of_recruitment                     0
Targets_met                             0
Previous_Award                          0
Training_score_average                  0
State_Of_Origin                         0
Foreign_schooled                        0
Marital_Status                          0
Past_Disciplinary_Action                0
Previous_IntraDepartmental_Movement     0
No_of_previous_employers                0
Promoted_or_Not                         0
dtype: int64
```

The data provided has 1679 missing values in the Qualification .

In [27]:
```
# let's see the different qualifications we have
dataset.Qualification.value_counts()
```

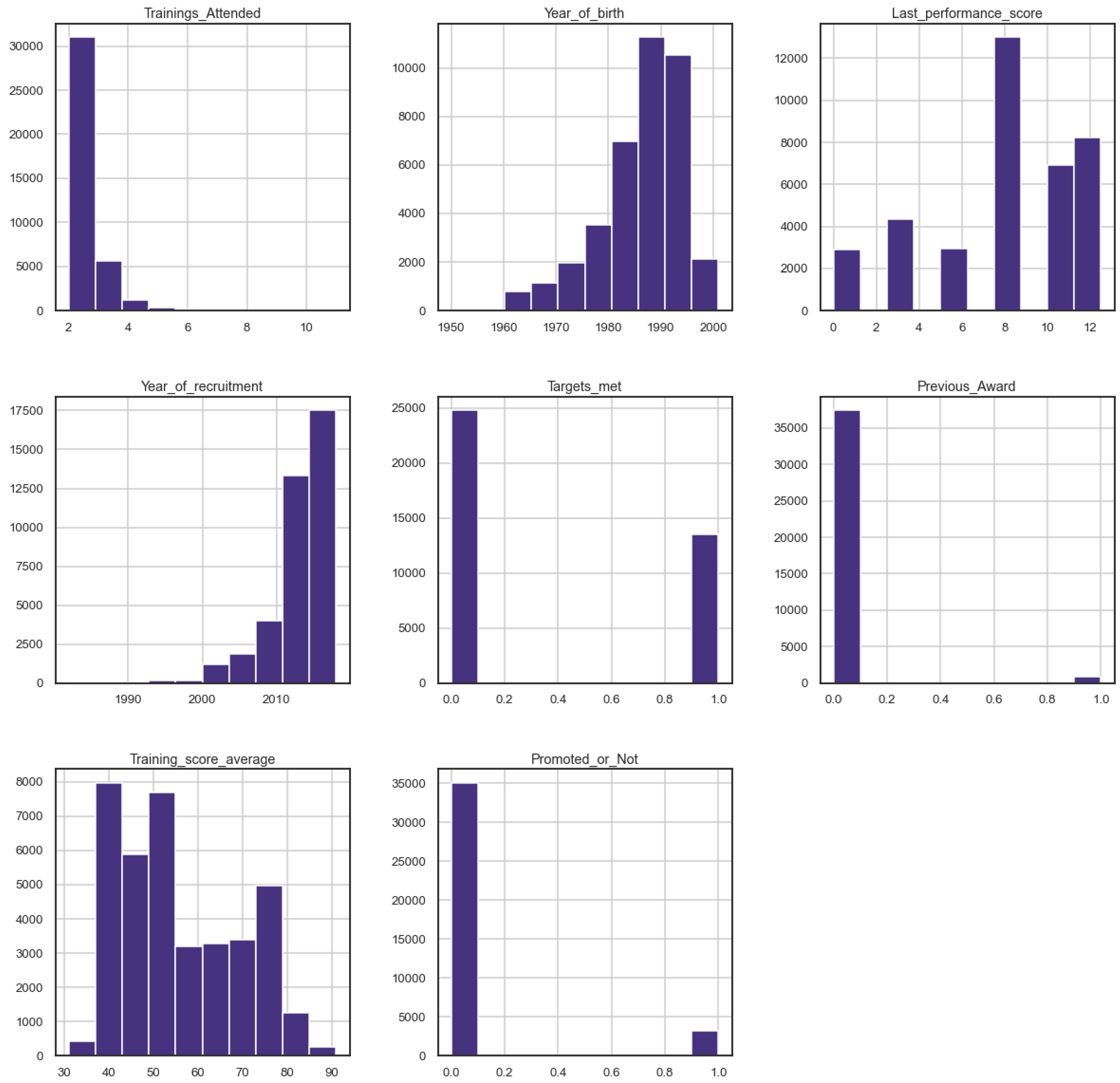
Out[27]:
```
First Degree or HND         25578
MSc, MBA and PhD            10469
Non-University Education      586
Name: Qualification, dtype: int64
```

In [28]:
```
# Getting the summary statistics of the data
dataset.describe()
```

Out[28]:

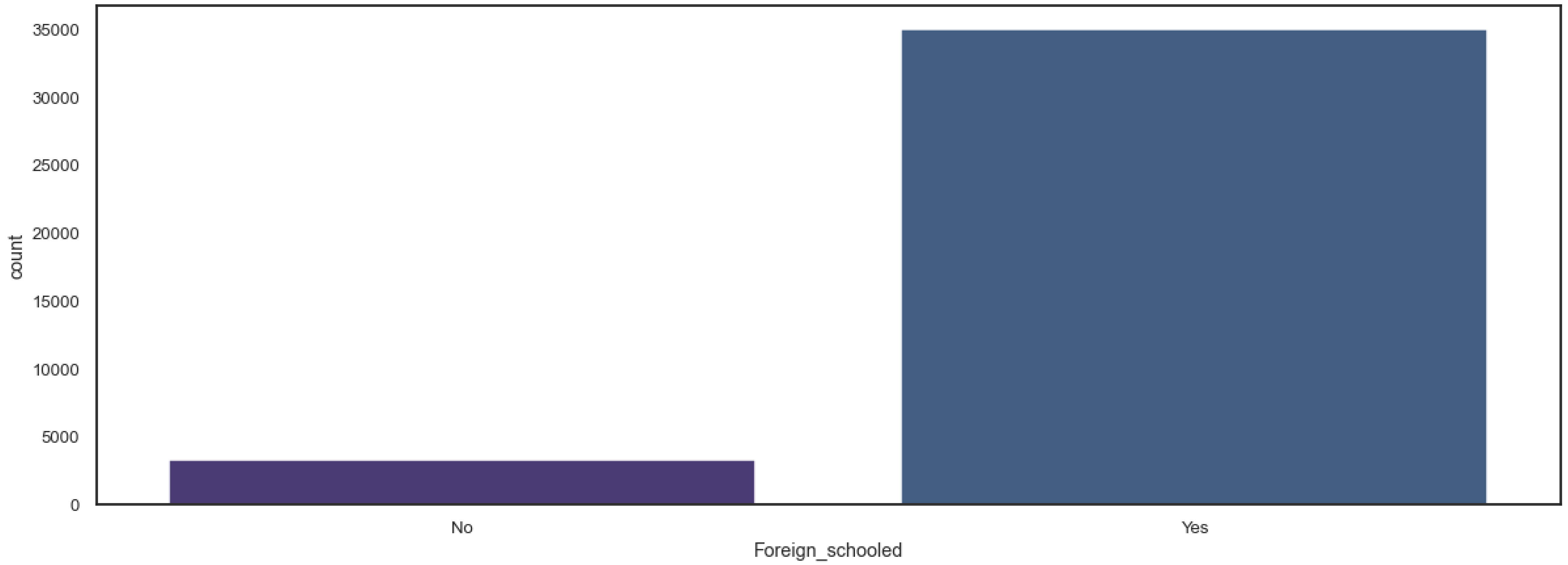
	Trainings_Attended	Year_of_birth	Last_performance_score	Year_of_recruitment	Targets_met	Previous_Award	Training_score_average	Promoted_or_Not
count	38312.000000	38312.000000	38312.000000	38312.000000	38312.000000	38312.000000	38312.000000	38312.000000
mean	2.253680	1986.209334	7.698959	2013.139695	0.352996	0.023152	55.366465	0.084595
std	0.609443	7.646047	3.744135	4.261451	0.477908	0.150388	13.362741	0.278282
min	2.000000	1950.000000	0.000000	1982.000000	0.000000	0.000000	31.000000	0.000000
25%	2.000000	1982.000000	5.000000	2012.000000	0.000000	0.000000	43.000000	0.000000
50%	2.000000	1988.000000	7.500000	2014.000000	0.000000	0.000000	52.000000	0.000000
75%	2.000000	1992.000000	10.000000	2016.000000	1.000000	0.000000	68.000000	0.000000
max	11.000000	2001.000000	12.500000	2018.000000	1.000000	1.000000	91.000000	1.000000

In [30]:
```
dataset.hist(figsize=(20,20))
plt.show()
```



From the above visualization, we can understand that it is only 'Training_score_average' column that is capable of determining whether an employee would be promoted or not, so we note that down and take some time to visualize the non-numeric variables

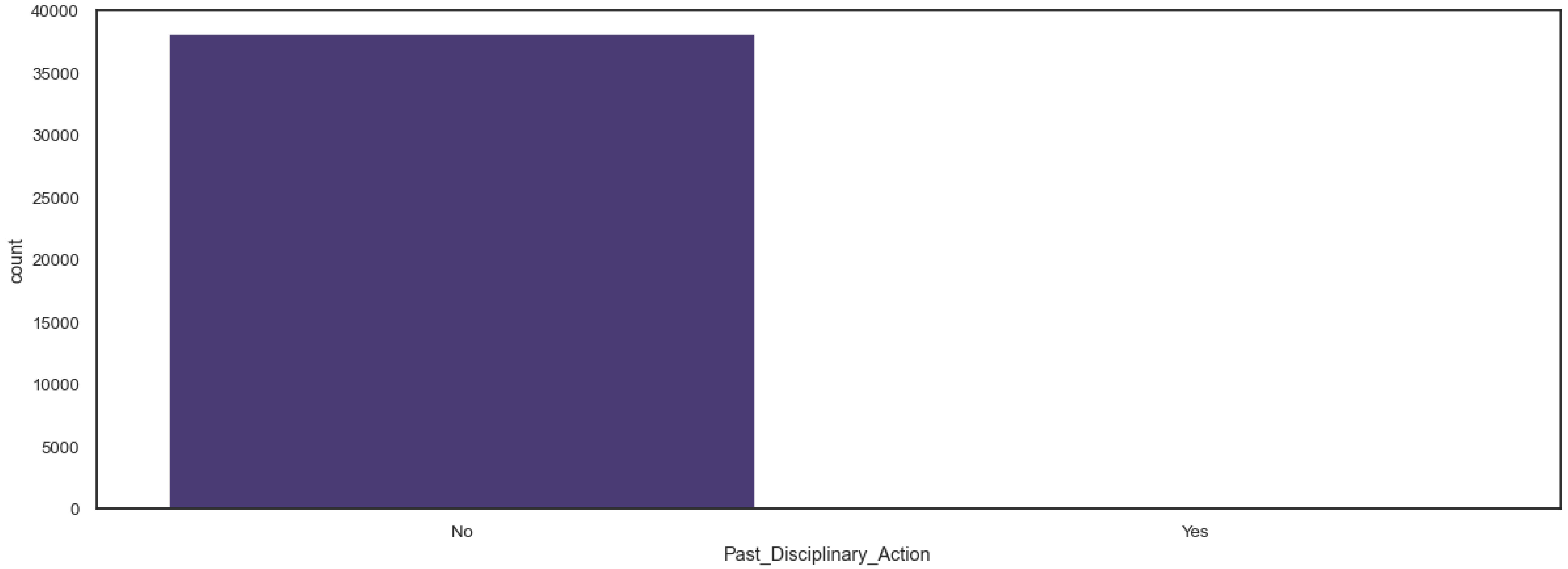
In [35]:
```
sns.countplot('Foreign_schooled',data = dataset)
plt.show()
```



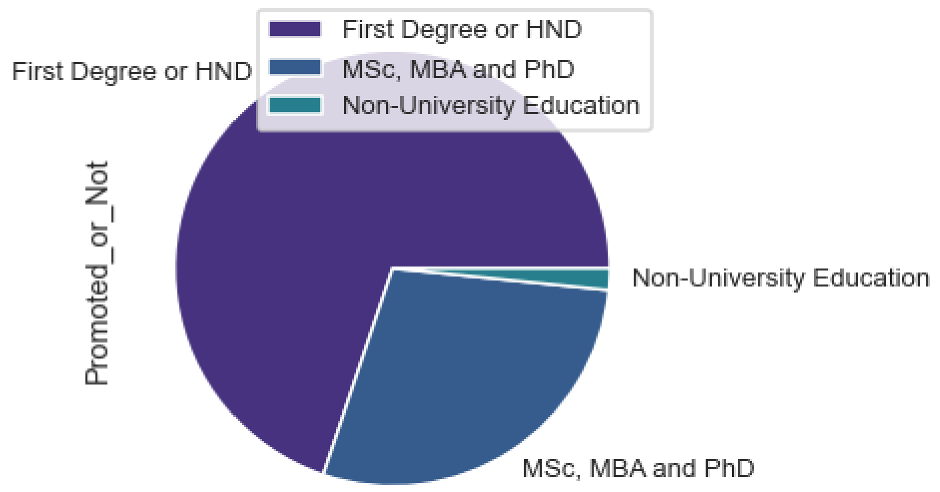
In [36]:
```
data.Foreign_schooled.value_counts()
```

Out[36]:
```
Yes    34995
No      3317
Name: Foreign_schooled, dtype: int64
```

In [38]:
```
sns.countplot('Past_Disciplinary_Action',data=dataset)
plt.show()
```



In [39]:
```
# Creating a pie chart to count employee by Qualification
df_qualification = dataset.groupby(['Qualification']).count()[['Promoted_or_Not']]
df_qualification.head()
df_qualification.plot.pie(y='Promoted_or_Not', figsize=(5, 5))
plt.legend(loc = 0)
plt.show()
```



We can see some interesting things about some of the non-numeric variables, but for us to be able to perform any analysis on those variables without sentiments, we have to encode them into integers

In [40]:
```
print("Percentage of Promoted Employees is {:.1f}% and non-promoted employees is: {:.1f}%".format(
    dataset[dataset['Promoted_or_Not'] == 1].shape[0] / dataset.shape[0]*100,
    dataset[dataset['Promoted_or_Not'] == 0].shape[0] / dataset.shape[0]*100))
```

```
Percentage of Promoted Employees is 8.5% and non-promoted employees is: 91.5%
```

In [42]:
```
dataset.head()
```

Out[42]:

oyeeNo	Division	Qualification	Gender	Channel_of_Recruitment	Trainings_Attended	Year_of_birth	Last_performance_score	Year_of_recruitment	Targets_met	Previous_Award	Training_score_average	State_Of_Origin	Foreign_schooled	Marital_Status	Past_Disciplinary_Action
S/00001	Commercial Sales and Marketing	MSc, MBA and PhD	Female	Direct Internal process	2	1986	12.5	2011	1	0	41	ANAMBRA	No	Married	No
S/00002	Customer Support and Field Operations	First Degree or HND	Male	Agency and others	2	1991	12.5	2015	0	0	52	ANAMBRA	Yes	Married	No
S/00003	Commercial Sales and Marketing	First Degree or HND	Male	Direct Internal process	2	1987	7.5	2012	0	0	42	KATSINA	Yes	Married	No
S/00004	Commercial Sales and Marketing	First Degree or HND	Male	Agency and others	3	1982	2.5	2009	0	0	42	NIGER	Yes	Single	No
S/00006	Information and Strategy	First Degree or HND	Male	Direct Internal process	3	1990	7.5	2012	0	0	77	AKWA IBOM	Yes	Married	No

As shown on the chart above, we see this is an imbalanced class problem. Indeed, the percentage of unpromoted Employees in our dataset is 91.5% and the percentage of promoted is: 8.5%

Encoding the non-numeric variables

In [45]:
```
# Encoading the categorical variables
from sklearn import preprocessing
#creating label encoder
le = preprocessing.LabelEncoder()
```

In [46]:
```
#converting string lables into numbers
dataset['Marital_Status']=le.fit_transform(dataset['Foreign_schooled'])

dataset['Foreign_schooled']=le.fit_transform(dataset['Foreign_schooled'])

dataset['Past_Disciplinary_Action']=le.fit_transform(dataset['Past_Disciplinary_Action'])

dataset['Previous_IntraDepartmental_Movement']=le.fit_transform(dataset['Previous_IntraDepartmental_Movement'])

dataset['No_of_previous_employers']=le.fit_transform(dataset['No_of_previous_employers'])

dataset['Division']=le.fit_transform(dataset['Division'])

dataset['Gender']=le.fit_transform(dataset['Gender'])

dataset['Channel_of_Recruitment']=le.fit_transform(dataset['Channel_of_Recruitment'])

dataset['State_Of_Origin']=le.fit_transform(dataset['State_Of_Origin'])
```

In [47]:
```
dataset.head()
```

Out[47]:

	EmployeeNo	Division	Qualification	Gender	Channel_of_Recruitment	Trainings_Attended	Year_of_birth	Last_performance_score	Year_of_recruitment	Targets_met	Previous_Award	Training_score_average	State_Of_Origin	Foreign_schooled	Marital_Status	Past_Disciplinary_
0	YAK/S/00001	1	MSc, MBA and PhD	0	1	2	1986	12.5	2011	1	0	41	3	0	0	
1	YAK/S/00002	2	First Degree or HND	1	0	2	1991	12.5	2015	0	0	52	3	1	1	
2	YAK/S/00003	1	First Degree or HND	1	1	2	1987	7.5	2012	0	0	42	20	1	1	
3	YAK/S/00004	1	First Degree or HND	1	0	3	1982	2.5	2009	0	0	42	26	1	1	
4	YAK/S/00006	4	First Degree or HND	1	1	3	1990	7.5	2012	0	0	77	2	1	1	

In [48]:
```
dataset.drop('Qualification', axis=1, inplace=True)
```

In [49]:
```
dataset.head()
```

Out[49]:

ender	Channel_of_Recruitment	Trainings_Attended	Year_of_birth	Last_performance_score	Year_of_recruitment	Targets_met	Previous_Award	Training_score_average	State_Of_Origin	Foreign_schooled	Marital_Status	Past_Disciplinary_Action	Previous_IntraDepartmental_Movemen
0	1	2	1986	12.5	2011	1	0	41	3	0	0	0	
1	0	2	1991	12.5	2015	0	0	52	3	1	1	0	
1	1	2	1987	7.5	2012	0	0	42	20	1	1	0	
1	0	3	1982	2.5	2009	0	0	42	26	1	1	0	
1	1	3	1990	7.5	2012	0	0	77	2	1	1	0	

Correlation

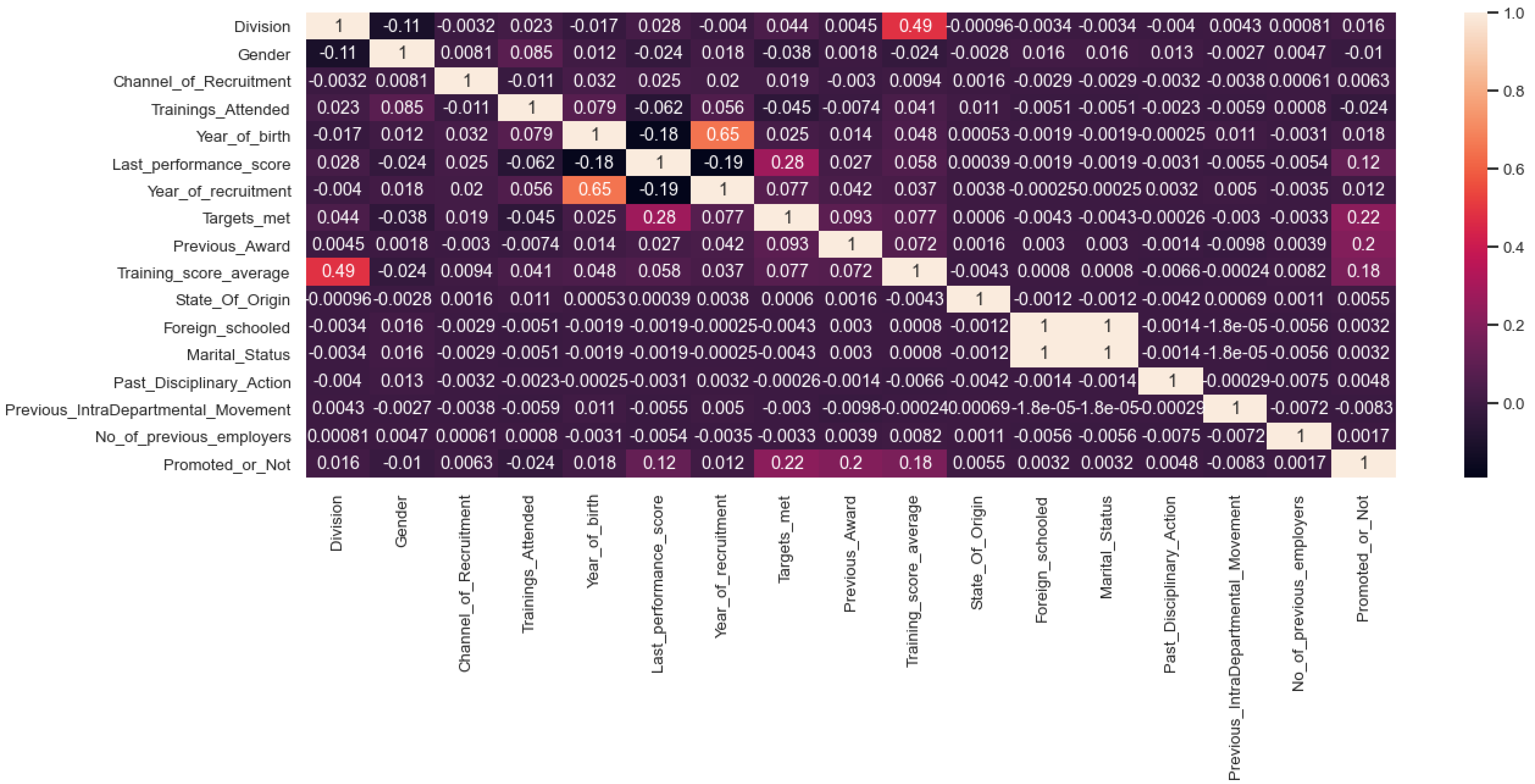
Let's take a look at some of most significant correlations. It is worth remembering that correlation coefficients only measure linear correlations.

In [50]:
```
dataset.corr()
```

Out[50]:

	Division	Gender	Channel_of_Recruitment	Trainings_Attended	Year_of_birth	Last_performance_score	Year_of_recruitment	Targets_met	Previous_Award	Training_score_average	State_Of_Origin	Foreign_schooled	Marital_Status	Past_D
Division	1.000000	-0.107572	-0.003205	0.022635	-0.016845	0.027623	-0.004005	0.043780	0.004503	0.487098	-0.000955	-0.003430	-0.003430	
Gender	-0.107572	1.000000	0.008076	0.084906	0.012095	-0.023586	0.017644	-0.038382	0.001773	-0.024311	-0.002833	0.016073	0.016073	
Channel_of_Recruitment	-0.003205	0.008076	1.000000	-0.011279	0.031744	0.025190	0.019725	0.019151	-0.003005	0.009362	0.001632	-0.002931	-0.002931	
Trainings_Attended	0.022635	0.084906	-0.011279	1.000000	0.078710	-0.062042	0.056215	-0.044789	-0.007409	0.041065	0.010643	-0.005108	-0.005108	
Year_of_birth	-0.016845	0.012095	0.031744	0.078710	1.000000	-0.175572	0.654666	0.025337	0.013627	0.048390	0.000531	-0.001877	-0.001877	
Last_performance_score	0.027623	-0.023586	0.025190	-0.062042	-0.175572	1.000000	-0.190333	0.276350	0.026587	0.057836	0.000386	-0.001923	-0.001923	
Year_of_recruitment	-0.004005	0.017644	0.019725	0.056215	0.654666	-0.190333	1.000000	0.076910	0.041995	0.037477	0.003785	-0.000253	-0.000253	
Targets_met	0.043780	-0.038382	0.019151	-0.044789	0.025337	0.276350	0.076910	1.000000	0.092934	0.077201	0.000604	-0.004294	-0.004294	
Previous_Award	0.004503	0.001773	-0.003005	-0.007409	0.013627	0.026587	0.041995	0.092934	1.000000	0.072360	0.001590	0.002960	0.002960	
Training_score_average	0.487098	-0.024311	0.009362	0.041065	0.048390	0.057836	0.037477	0.077201	0.072360	1.000000	-0.004252	0.000796	0.000796	
State_Of_Origin	-0.000955	-0.002833	0.001632	0.010643	0.000531	0.000386	0.003785	0.000604	0.001590	-0.004252	1.000000	-0.001243	-0.001243	
Foreign_schooled	-0.003430	0.016073	-0.002931	-0.005108	-0.001877	-0.001923	-0.000253	-0.004294	0.002960	0.000796	-0.001243	1.000000	1.000000	
Marital_Status	-0.003430	0.016073	-0.002931	-0.005108	-0.001877	-0.001923	-0.000253	-0.004294	0.002960	0.000796	-0.001243	1.000000	1.000000	
Past_Disciplinary_Action	-0.004048	0.012799	-0.003240	-0.002260	-0.000251	-0.003065	0.003217	-0.000264	-0.001374	-0.006620	-0.004244	-0.001373	-0.001373	
Previous_IntraDepartmental_Movement	0.004342	-0.002715	-0.003799	-0.005871	0.011412	-0.005478	0.004988	-0.002965	-0.009762	-0.000237	0.000689	-0.000018	-0.000018	
No_of_previous_employers	0.000813	0.004717	0.000612	0.000796	-0.003117	-0.005428	-0.003550	-0.003308	0.003887	0.008194	0.001101	-0.005570	-0.005570	
Promoted_or_Not	0.015582	-0.010437	0.006324	-0.024345	0.017991	0.119690	0.012287	0.224518	0.201434	0.178448	0.005488	0.003202	0.003202	

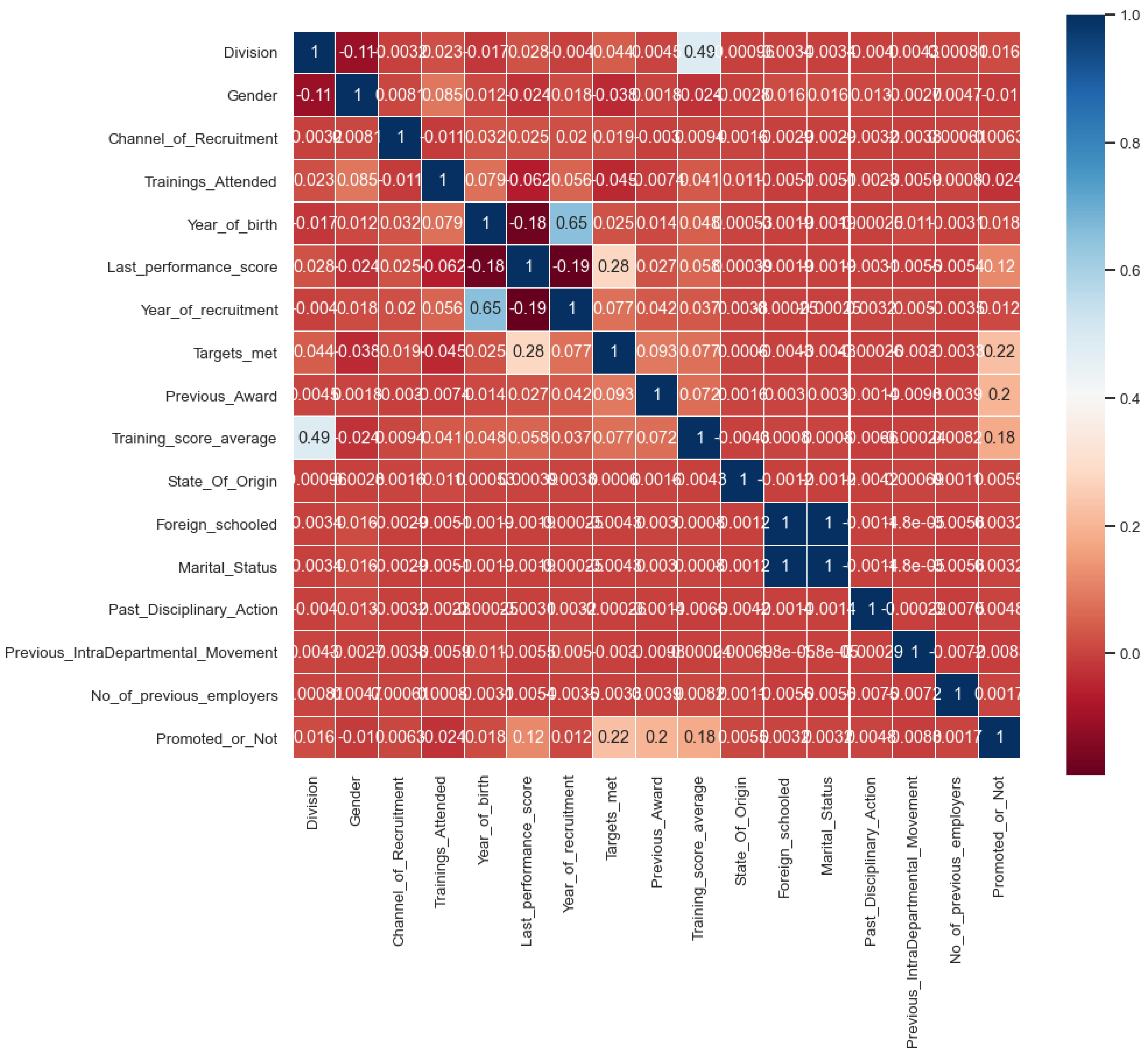
In [51]:
```
sns.heatmap(dataset.corr(), annot=True)
plt.show()
```



In [58]:

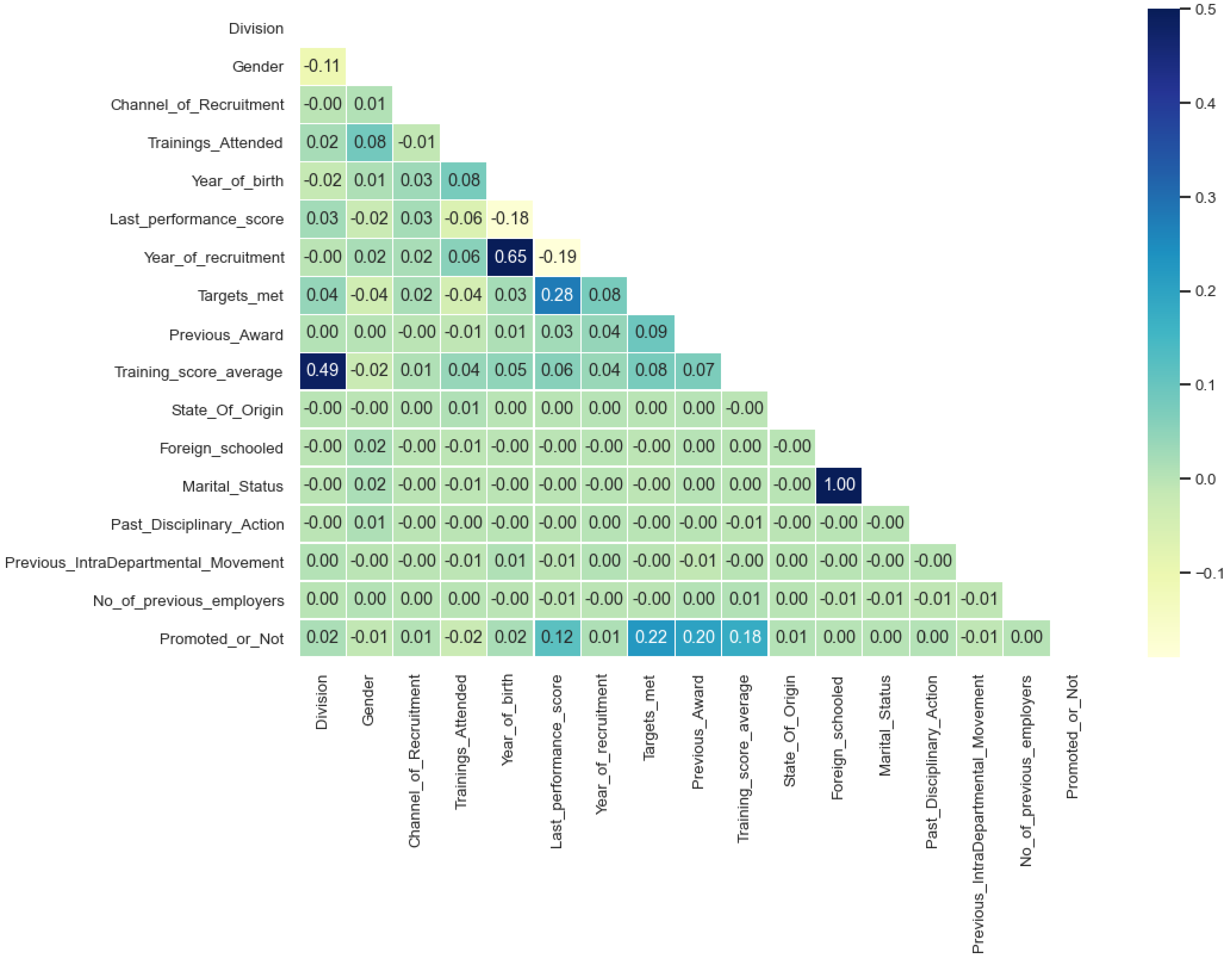
```
colormap = plt.cm.RdBu
plt.figure(figsize=(14,12))
plt.title('Pearson Correlation of Features', y=1.05, size=15)
sns.heatmap(dataset.corr(),linewidths=0.1,vmax=1.0,
            square=True, cmap=colormap, linecolor='white', annot=True)
plt.show()
```

Pearson Correlation of Features



In [54]:

```
# Calculate correlations
corr = dataset.corr()
mask = np.zeros_like(corr)
mask[np.triu_indices_from(mask)] = True
# Heatmap
plt.figure(figsize=(15, 10))
sns.heatmap(corr,
            vmax=.5,
            mask=mask,
             annot=True, fmt='.2f',
            linewidths=.2, cmap="YlGnBu")
plt.show()
```



As shown above, many of the variables are positively correlated to the column 'Promoted_or_Not'

In [59]:
```
# Find correlations with the target and sort
correlations = dataset.corr()['Promoted_or_Not'].sort_values()
print('Most Positive Correlations: \n', correlations.tail(5))
print('\nMost Negative Correlations: \n', correlations.head(5))
```

```
Most Positive Correlations:
 Last_performance_score    0.119690
Training_score_average    0.178448
Previous_Award            0.201434
Targets_met               0.224518
Promoted_or_Not           1.000000
Name: Promoted_or_Not, dtype: float64

Most Negative Correlations:
 Trainings_Attended                    -0.024345
Gender                               -0.010437
Previous_IntraDepartmental_Movement   -0.008289
No_of_previous_employers               0.001690
Foreign_schooled                       0.003202
Name: Promoted_or_Not, dtype: float64
```

EDA Concluding Remarks

Let's summarise the findings from this EDA:

> - The dataset only feature one missing or erroneous data values, with all features in their correct data type.

- The strongest positive correlations with the target features are: **Last_performance_score**, **Training_score_average**, **Previous_Award**, **Targets_met**.
- The strongest negative correlations with the target features are: **Trainings_Attended**, **Gender**, **Previous_IntraDepartmental_Movement**, **No_of_previous_employers *, and *Foreign_schooled** .
- The dataset is **imbalanced** with the majoriy of observations describing unpromoted employees.
- Several features (ie columns) are redundant for our analysis, namely: Qualification, EmployeeID, Year, and Gender.

Other observations include:

-

Feature Selection

In [61]:
```
dataset.columns
```

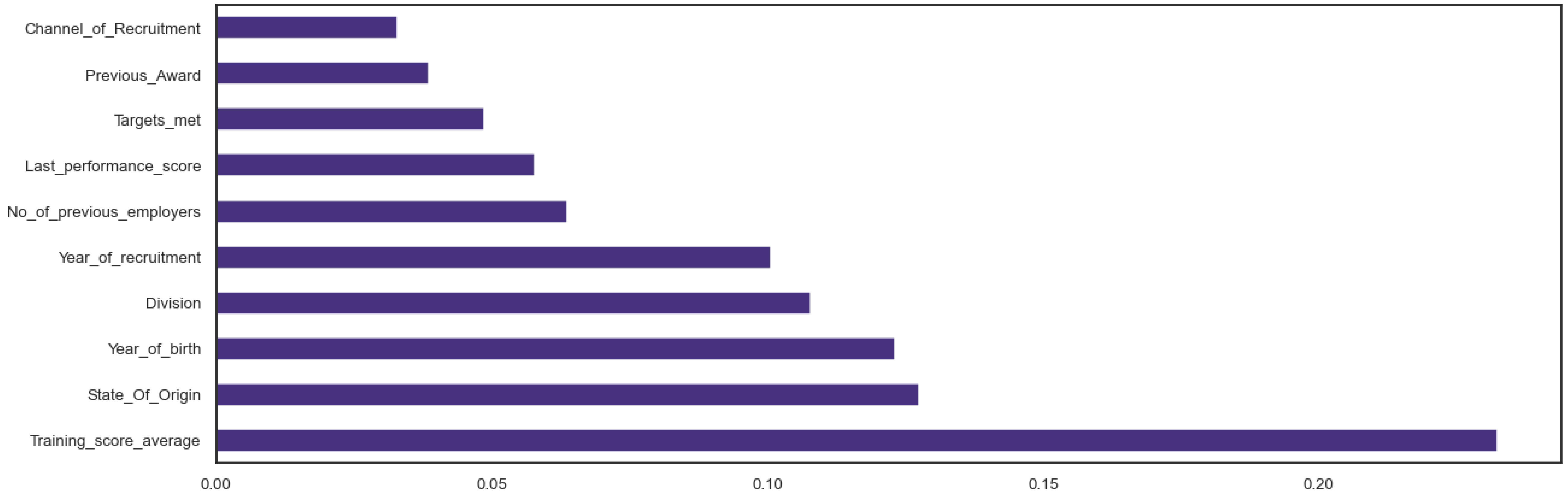
Out[61]:
```
Index(['EmployeeNo', 'Division', 'Gender', 'Channel_of_Recruitment',
       'Trainings_Attended', 'Year_of_birth', 'Last_performance_score',
       'Year_of_recruitment', 'Targets_met', 'Previous_Award',
       'Training_score_average', 'State_Of_Origin', 'Foreign_schooled',
       'Marital_Status', 'Past_Disciplinary_Action',
       'Previous_IntraDepartmental_Movement', 'No_of_previous_employers',
       'Promoted_or_Not'],
      dtype='object')
```

In [62]:
```
features = dataset[['Division', 'Gender','Channel_of_Recruitment', 'Trainings_Attended', 'Year_of_birth',
       'Last_performance_score', 'Year_of_recruitment', 'Targets_met',
       'Previous_Award', 'Training_score_average', 'State_Of_Origin',
       'Foreign_schooled', 'Marital_Status', 'Past_Disciplinary_Action',
       'Previous_IntraDepartmental_Movement', 'No_of_previous_employers']]
target = dataset['Promoted_or_Not']
```

optional

In [64]:
```
from sklearn.ensemble import ExtraTreesClassifier
model = ExtraTreesClassifier()
model.fit(features,target)
print(model.feature_importances_)
feat_importance = pd.Series(model.feature_importances_,index=features.columns)
feat_importance.nlargest(10).plot(kind = 'barh')
plt.show()
```

```
[0.10779381 0.01738946 0.03287144 0.0275274  0.12306725 0.05769836
 0.10067554 0.04849852 0.03850856 0.23230947 0.12757852 0.0047444
 0.00480172 0.00170974 0.01116717 0.06365865]
```



In [65]:
```
target = dataset['Promoted_or_Not']
features = dataset[['Training_score_average','Last_performance_score','Division']]
```

Splitting data into training and testing sets

Prior to implementating or applying any Machine Learning algorithms, we must decouple training and testing datasets from our master dataframe.

In [66]:
```
#Splitting the dataset
from sklearn.model_selection import train_test_split
```

In [67]:
```
features_train,features_test,target_train,target_test = train_test_split(features,target, test_size = 0.2, random_state = 0)
```

In [68]:
```
features_train
```

Out[68]:

	Training_score_average	Last_performance_score	Division
14599	52	12.5	6
4	77	7.5	4
28190	66	10.0	8
10683	69	7.5	3
10970	72	2.5	8
...	...	...	...
20757	63	2.5	8
32103	58	12.5	2
30403	44	0.0	1
21243	41	7.5	1
2732	79	12.5	4

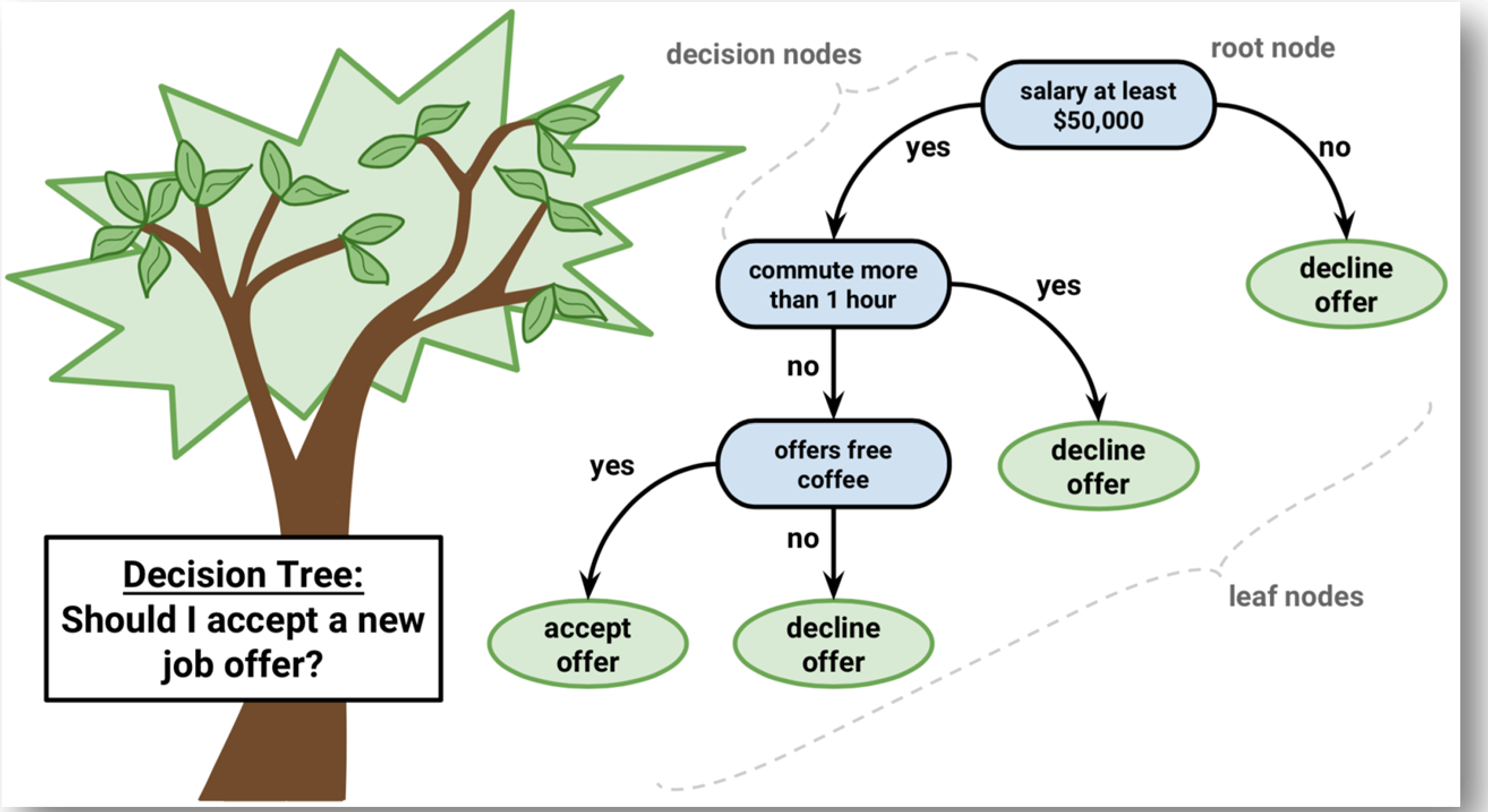
30649 rows × 3 columns

Building Machine Learning Models

We are going to be building different models with different machine learning algorithms, and them comparing them to see which one works best. We are going to be building our models with the following algorithms.

- Decision Trees Classifier
- Logistic Regression
- Random Forest Classifier
- Support Vector Machine
- Gradient Boosting Classifier

Decision tree algorithm is a type of non-linear classification model, where data points pass through a tree-like process in order to predict an output variable.



In [69]:
```
#Fitting the Decision tree classifier
from sklearn.tree import DecisionTreeClassifier
```

In [70]:
```
clasifier = DecisionTreeClassifier()
model = clasifier.fit(features_train, target_train)
```

In [79]:
```
DecisionTreeClassifier?
```

In [80]:
```
#Prediction
target_pred = model.predict(features_test)
```

In [81]:
```
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
```

In [82]:
```
accuracy_score(target_test,target_pred)
```

Out[82]:
```
0.9466266475270781
```

In [88]:
```
print(confusion_matrix(target_test,target_pred))
```

```
[[7000    7]
 [ 402  254]]
```

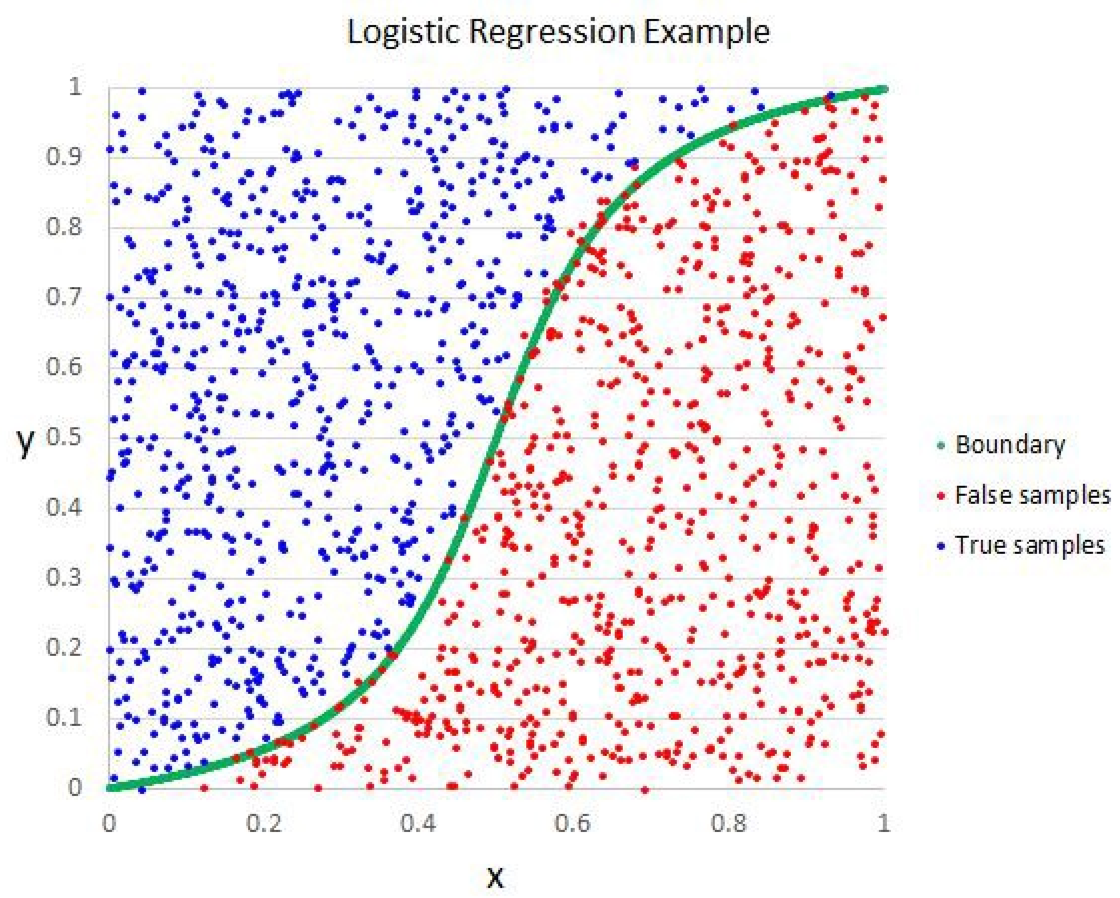
In [87]:
```
print(classification_report(target_test,target_pred))
```

```
              precision    recall  f1-score   support

           0       0.95      1.00      0.97      7007
           1       0.97      0.39      0.55       656

    accuracy                           0.95      7663
   macro avg       0.96      0.69      0.76      7663
weighted avg       0.95      0.95      0.94      7663
```

Logistic Regression is a Machine Learning classification algorithm that is used to predict the probability of a categorical dependent variable. Logistic Regression is classification algorithm that is not as sophisticated as the ensemble methods or boosted decision trees method discuss benchmark.



In [89]:
```
from sklearn.linear_model import LogisticRegression
clasifier = LogisticRegression()
model = clasifier.fit(features_train, target_train)
```

In [90]:
```
target_pred = model.predict(features_test)
accuracy_score(target_test, target_pred)
```

Out[90]:
```
0.9147853321153595
```

In [91]:
```
print(confusion_matrix(target_test,target_pred))
```

```
[[7007    0]
 [ 653    3]]
```

In [92]:
```
print(classification_report(target_test,target_pred))
```

```
              precision    recall  f1-score   support

           0       0.91      1.00      0.96      7007
           1       1.00      0.00      0.01       656

    accuracy                           0.91      7663
   macro avg       0.96      0.50      0.48      7663
weighted avg       0.92      0.91      0.87      7663
```

Random Forest is a popular and versatile machine learning method that is capable of solving both regression and classification. Random Forest is a brand of Ensemble learning, as it relies on an ensemble of decision trees. It aggregates Classification (or Regression) Trees. A decisi
that can be used to classify an observation in a dataset.

Random Forest fits a number of decision tree classifiers on various **sub-samples of the dataset** and use **averaging** to improve the predictive accuracy and control over-fitting. Random Forest can handle a large number of features, and is helpful for estimating which of your variables
modeled.

In [97]:
```
from sklearn.ensemble import RandomForestClassifier
clasifier = RandomForestClassifier(n_estimators=200, )
model = clasifier.fit(features_train, target_train)
```

In [98]:
```
target_pred = model.predict(features_test)
accuracy_score(target_test,target_pred)
```

Out[98]: 0.9462351559441472

In [99]:
```
print(confusion_matrix(target_test,target_pred))
```

```
[[7001    6]
 [ 406  250]]
```

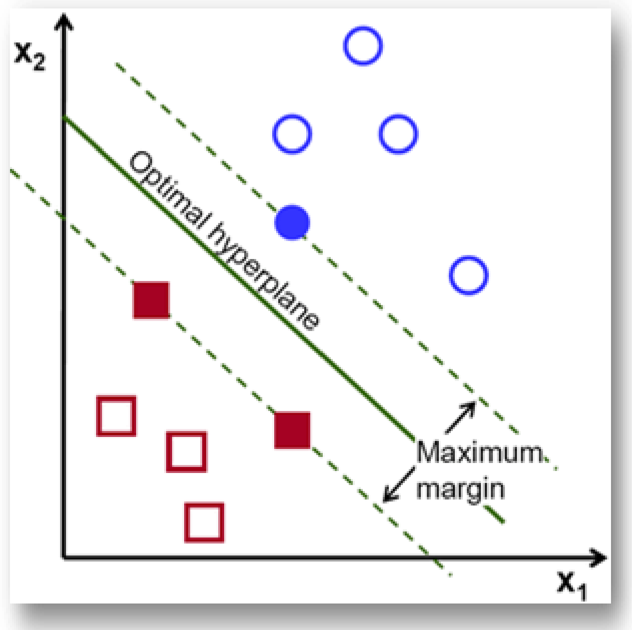
In [100]:
```
print(classification_report(target_test,target_pred))
```

```
              precision    recall  f1-score   support

           0       0.95      1.00      0.97      7007
           1       0.98      0.38      0.55       656

    accuracy                           0.95      7663
   macro avg       0.96      0.69      0.76      7663
weighted avg       0.95      0.95      0.94      7663
```

The **support vector machine** is arguably one of the most popular and powerful classification algorithm today, the primary idea behind support vector machine is to find a hyperplane in an N-dimensional space(N — the number of features) that distinctly classifies the data points.



In [107]:
```
from sklearn.svm import SVC
clasifier = SVC(kernel='poly', random_state=0)
model = clasifier.fit(features_train, target_train)
```

In [108]:
```
target_pred = model.predict(features_test)
accuracy_score(target_test,target_pred)
```

Out[108]:
```
0.9143938405324286
```

In [109]:
```
print(confusion_matrix(target_test,target_pred))
```

```
[[7007    0]
 [ 656    0]]
```

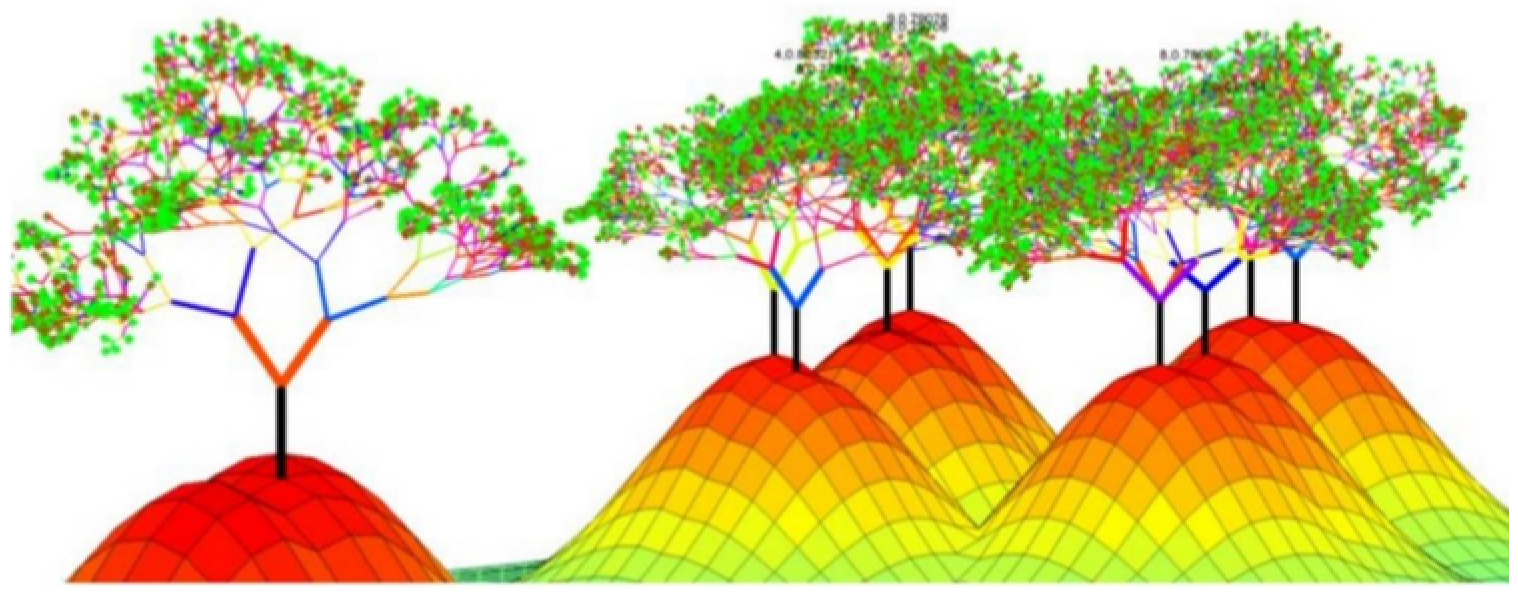
In [110]:
```
print(classification_report(target_test,target_pred))
```

```
              precision    recall  f1-score   support

           0       0.91      1.00      0.96      7007
           1       0.00      0.00      0.00       656

    accuracy                           0.91      7663
   macro avg       0.46      0.50      0.48      7663
weighted avg       0.84      0.91      0.87      7663
```

Gradient Boosting algorithm



In [111]:
```
from sklearn.ensemble import GradientBoostingClassifier
clasifier = GradientBoostingClassifier()
model = clasifier.fit(features_train, target_train)
```

In [112]:
```
target_pred = model.predict(features_test)
accuracy_score(target_test,target_pred)
```

Out[112]:
```
0.9459741615555266
```

In [113]:
```
print(confusion_matrix(target_test,target_pred))
```

```
[[7001    6]
 [ 408  248]]
```

In [114]:
```
print(classification_report(target_test,target_pred))
```

```
              precision    recall  f1-score   support

           0       0.94      1.00      0.97      7007
           1       0.98      0.38      0.55       656

    accuracy                           0.95      7663
   macro avg       0.96      0.69      0.76      7663
weighted avg       0.95      0.95      0.93      7663
```

Concluding Remarks

Based on our analysis so far, we can present YAKUB TRADING GROUP our model which is capable of predicting the employees in the company that is likely to be promoted with over 94% accuracy based on the following variables. Training_score_average, Last_performance_score, your Hackathon

In [ ]: