Employee Promotion Analysis

In [1]:

```
%load_ext nb_black
```

In [2]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [3]:

```
data = pd.read_csv("employee_promotion.csv")
```

In [4]:

```
data.head()
```

Out[4]:

	employee_id	department	region	education	gender	recruitment_channel	no_of_trainings
0	65438	Sales & Marketing	region_7	Master's & above	f	sourcing	1
1	65141	Operations	region_22	Bachelor's	m	other	1
2	7513	Sales & Marketing	region_19	Bachelor's	m	sourcing	1
3	2542	Sales & Marketing	region_23	Bachelor's	m	other	2
4	48945	Technology	region_26	Bachelor's	m	other	1

In [5]:

```
data.info()
```

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

In [6]:

```
features = data.iloc[:, :-1]
target = data.iloc[:, -1:]
```

In [7]:

```
features.head()
```

Out[7]:

	employee_id	department	region	education	gender	recruitment_channel	no_of_trainings
0	65438	Sales & Marketing	region_7	Master's & above	f	sourcing	1
1	65141	Operations	region_22	Bachelor's	m	other	1
2	7513	Sales & Marketing	region_19	Bachelor's	m	sourcing	1
3	2542	Sales & Marketing	region_23	Bachelor's	m	other	2
4	48945	Technology	region_26	Bachelor's	m	other	1

In [8]:

```
target.head()
```

Out[8]:

	is_promoted
0	0
1	0
2	0
3	0
4	0

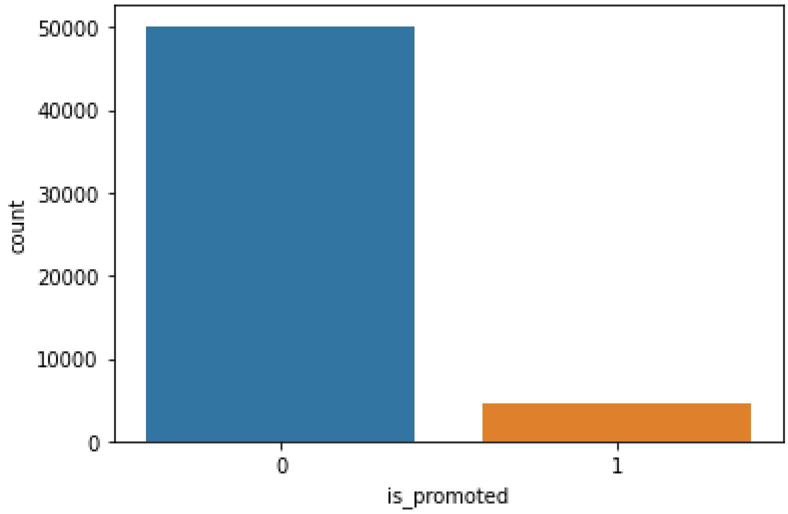
Categorical Columns Analysis

In [9]:

```
sns.countplot(x="is_promoted", data=data)
```

Out[9]:

```
<AxesSubplot:xlabel='is_promoted', ylabel='count'>
```



Observation:

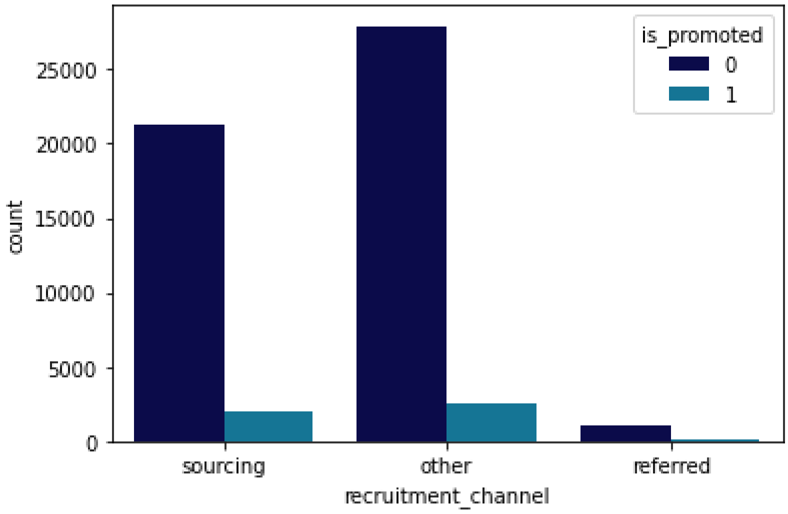
- We have very less no of employees who has promoted.

In [10]:

```
sns.countplot(x="recruitment_channel", data=data, hue="is_promoted", pale
```

Out[10]:

```
<AxesSubplot:xlabel='recruitment_channel', ylabel='count'>
```



Observation

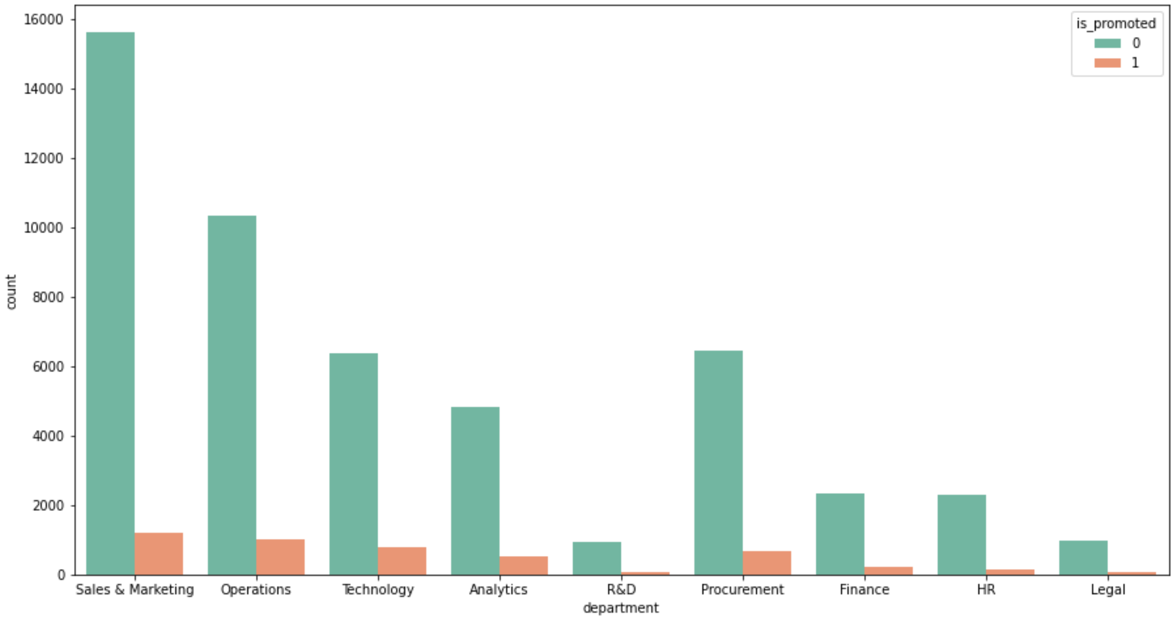
- As you can see referred categories have not that much values so it is not useful.

In [11]:

```
plt.figure(figsize=(15, 8))
sns.countplot(x="department", data=data, hue="is_promoted", palette="Set2
```

Out[11]:

```
<AxesSubplot:xlabel='department', ylabel='count'>
```



Observation:

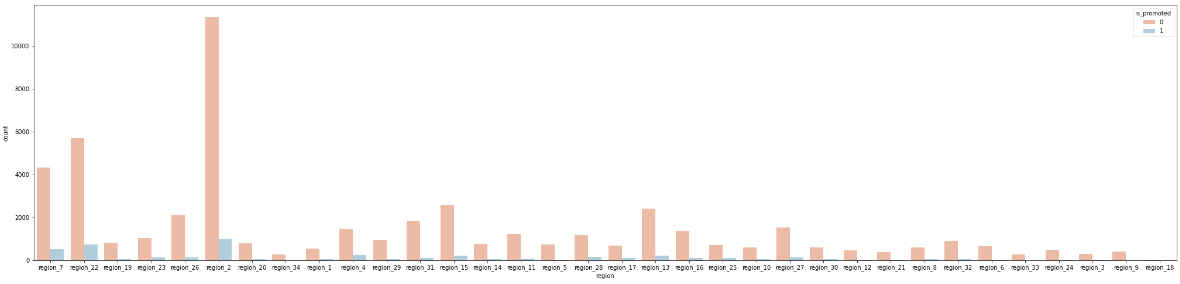
- Highest No of Emplyoees is in sales and marketing department.
- Analytics department employee has high chance they might get prmomoted.

In [12]:

```
plt.figure(figsize=(35, 8))
sns.countplot(x="region", data=data, hue="is_promoted", palette="RdBu")
```

Out[12]:

```
<AxesSubplot:xlabel='region', ylabel='count'>
```



Observation:

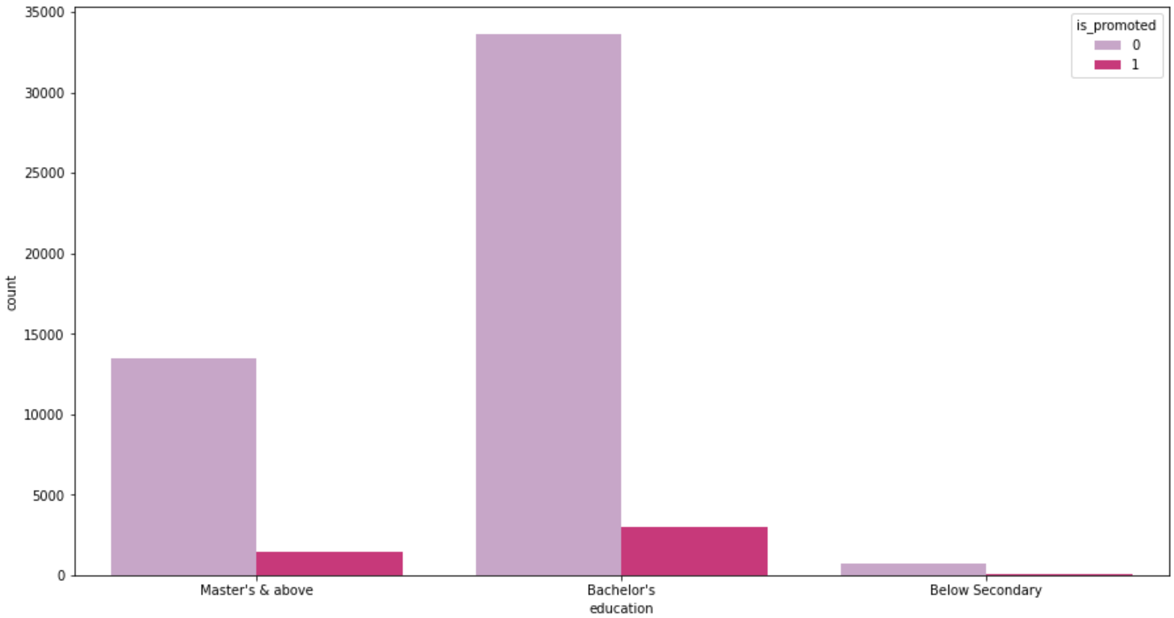
- Most of employees coming from region_7,22 and 2 compare to others.
- Region_2 has highest number of employees.

In [13]:

```
plt.figure(figsize=(15, 8))
sns.countplot(x="education", data=data, hue="is_promoted", palette="PuRd"
```

Out[13]:

```
<AxesSubplot:xlabel='education', ylabel='count'>
```



Observation:

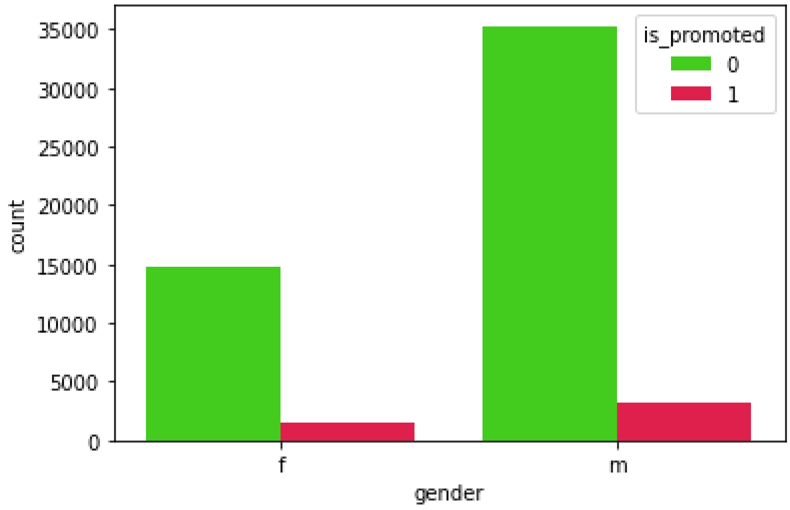
- We can remove below secondary education employee because it will not affected the final model.

In [14]:

```
sns.countplot(x="gender", data=data, hue="is_promoted", palette="prism")
```

Out[14]:

```
<AxesSubplot:xlabel='gender', ylabel='count'>
```



Ratio Male and Female Promotion

In [15]:

```
def promot_gender_finder(gender, is_promoted):
    return len(
        data.loc[(data["gender"] == gender) & (data["is_promoted"] == is_prom
    )


female_promoted = promot_gender_finder("f", 1)
female_not_promoted = promot_gender_finder("f", 0)

male_promoted = promot_gender_finder("m", 1)
male_not_promoted = promot_gender_finder("m", 0)
```

In [16]:

```
promot_ratio_female = female_promoted / (female_not_promoted + female_pr
promot_ratio_male = male_promoted / (male_promoted + male_not_promoted)
```

In [17]:

```
promot_ratio_male * 100, promot_ratio_female * 100
```

Out[17]:

```
(8.315149625935161, 8.993379107405591)
```

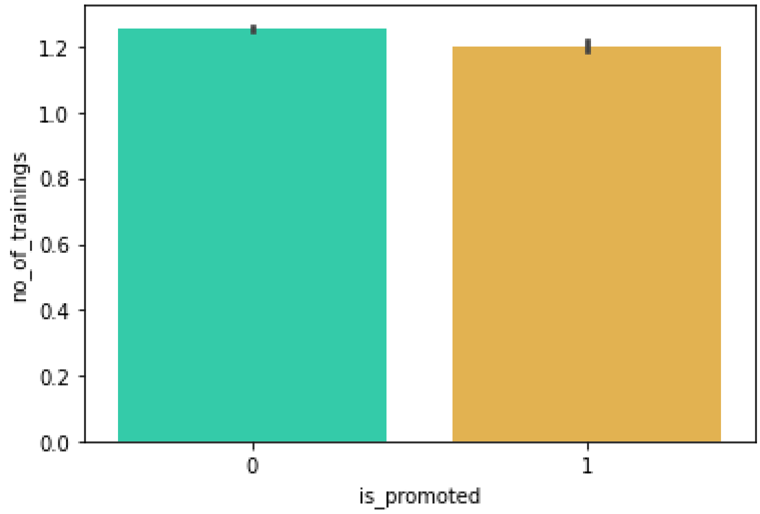
Numerical Columns Analysis

In [18]:

```
sns.barplot(x="is_promoted", y="no_of_trainings", data=data, palette="turbo
```

Out[18]:

```
<AxesSubplot:xlabel='is_promoted', ylabel='no_of_trainings'>
```



Observation:

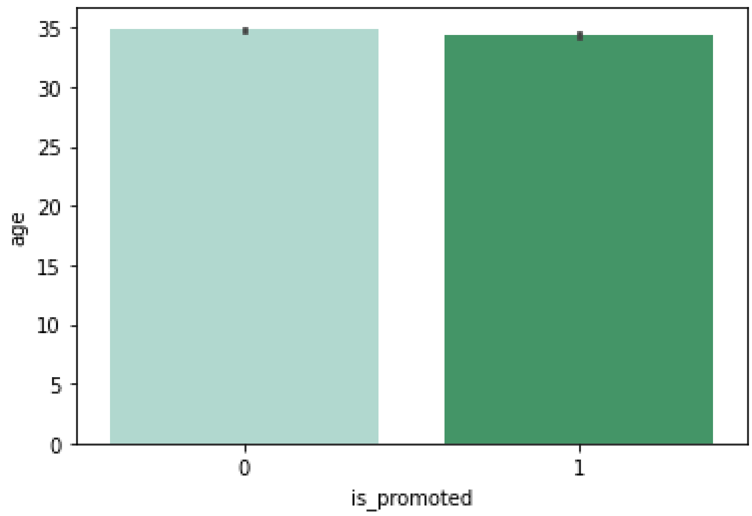
- No Of Trainings feature will not much affect the promotion of employee.

In [19]:

```
sns.barplot(x="is_promoted", y="age", data=data, palette="BuGn")
```

Out[19]:

```
<AxesSubplot:xlabel='is_promoted', ylabel='age'>
```



Observation:

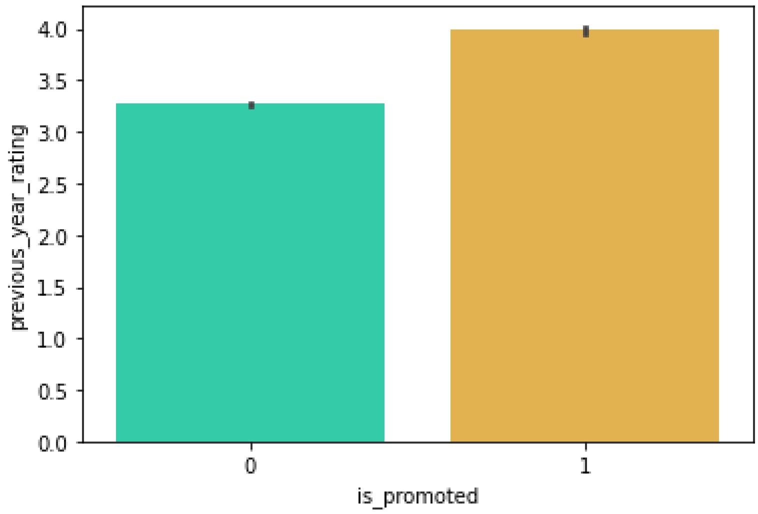
- Age Feature Doesn't affect Employee Promotion.

In [20]:

```
sns.barplot(x="is_promoted", y="previous_year_rating", data=data, palette='
```

Out[20]:

```
<AxesSubplot:xlabel='is_promoted', ylabel='previous_year_rating'>
```



Observation:

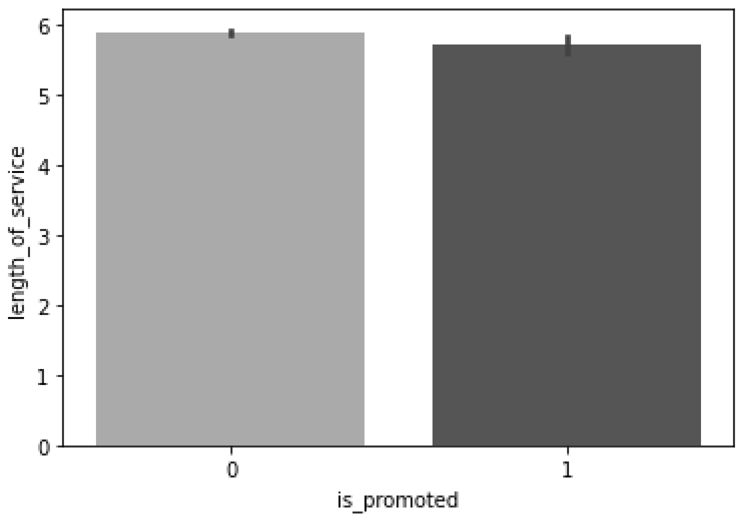
- Previous Year Rating is an Important feature for employee promotion.

In [21]:

```
sns.barplot(x="is_promoted", y="length_of_service", data=data, palette="bir
```

Out[21]:

```
<AxesSubplot:xlabel='is_promoted', ylabel='length_of_service'>
```



Observation:

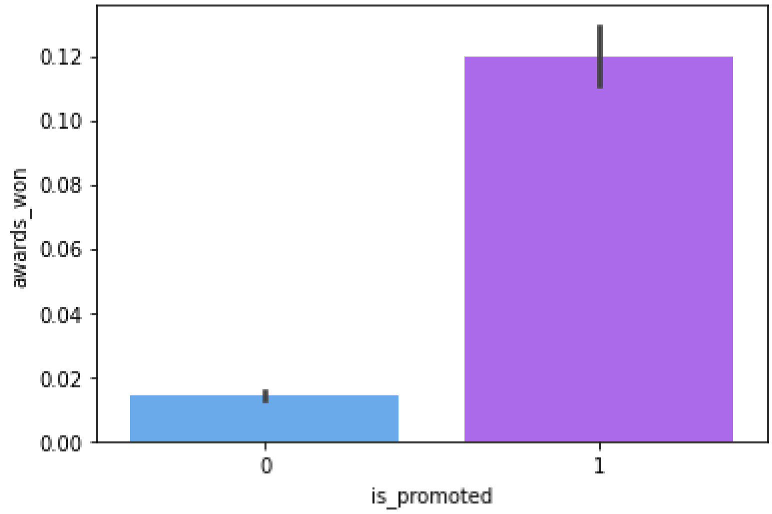
- Length of Service Feature Doesn't affect Employee Promotion.

In [22]:

```
sns.barplot(x="is_promoted", y="awards_won", data=data, palette="cool")
```

Out[22]:

```
<AxesSubplot:xlabel='is_promoted', ylabel='awards_won'>
```



Observation:

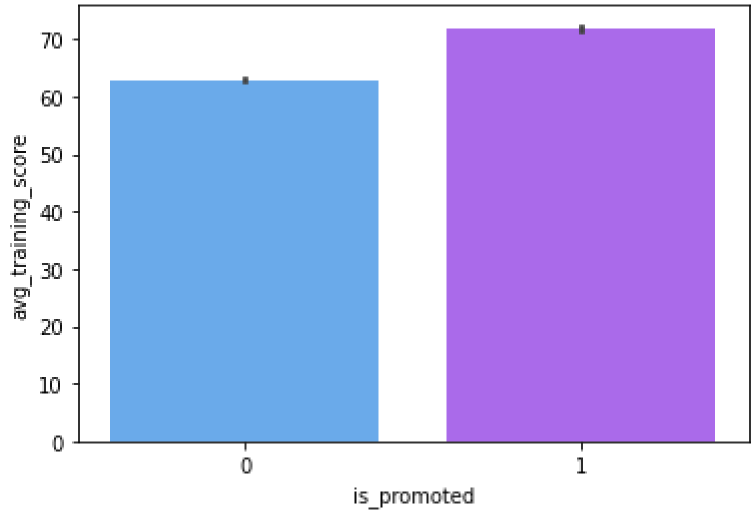
- Awards Won is an Important feature for employee promotion.

In [23]:

```
sns.barplot(x="is_promoted", y="avg_training_score", data=data, palette="co
```

Out[23]:

```
<AxesSubplot:xlabel='is_promoted', ylabel='avg_training_score'>
```



Observation:

- Average training score might be useful feature for employee promotion.

Final Notes From Data Visualization:-

- In Recruitment_channel feature we will convert referred category to other_recruitment_channel.
- No of trainings, Length of Service and age is not that much important feature.

Feature Selection

In [24]:

```
from sklearn.feature_selection import mutual_info_classif
from sklearn.preprocessing import LabelEncoder
from sklearn.impute import SimpleImputer
```

In [25]:

```
features.head()
```

Out[25]:

	employee_id	department	region	education	gender	recruitment_channel	no_of_trainings
0	65438	Sales & Marketing	region_7	Master's & above	f	sourcing	1
1	65141	Operations	region_22	Bachelor's	m	other	1
2	7513	Sales & Marketing	region_19	Bachelor's	m	sourcing	1
3	2542	Sales & Marketing	region_23	Bachelor's	m	other	2
4	48945	Technology	region_26	Bachelor's	m	other	1

In [26]:

```
features = features.iloc[:, 1:]
```

In [27]:

```
le = LabelEncoder()
columns = ["department", "region", "education", "gender", "recruitment_chan
encoded_features = features.copy()
for column_name in columns:
    encoded_features.loc[:, column_name] = le.fit_transform(
        encoded_features.loc[:, column_name]
    )
```

In [28]:

```
imputer = SimpleImputer()
encoded_features = imputer.fit_transform(encoded_features)
```

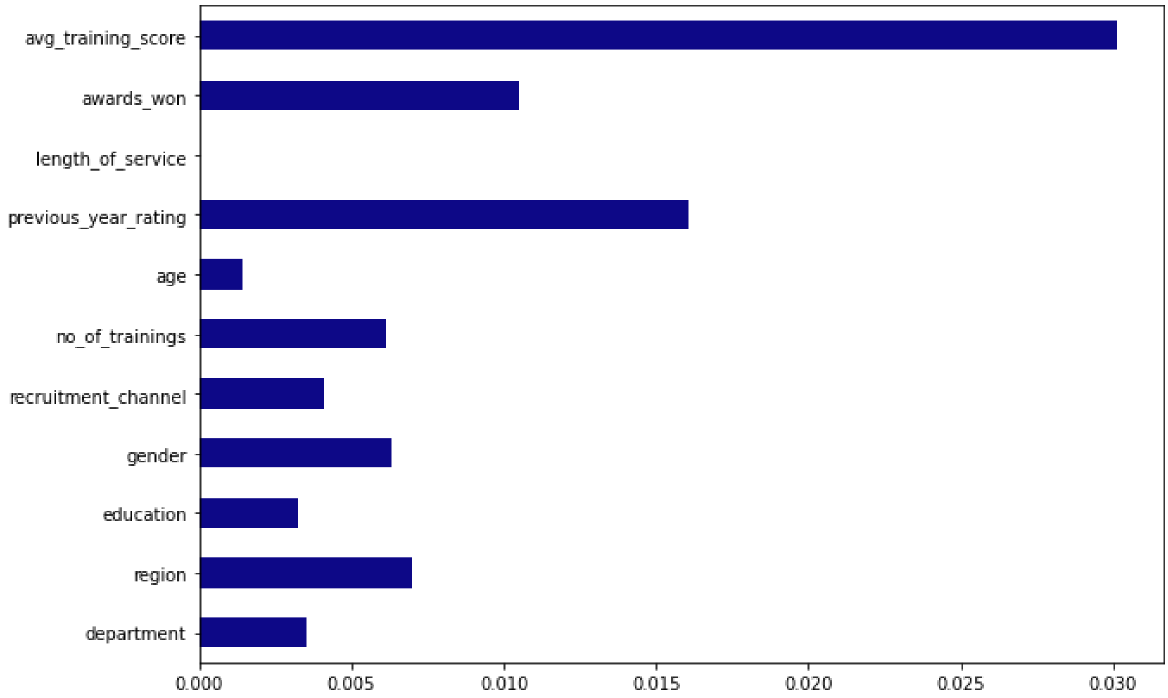
Information Gain

In [29]:

```
importances = mutual_info_classif(encoded_features, target.values.ravel())
```

In [30]:

```
feat_importance = pd.Series(importances, features.columns)
plt.figure(figsize=(10, 7))
feat_importance.plot(kind="barh", colormap="plasma")
plt.show()
```



Observation:

- We can remove age and length_of_service feature for now.

Chi-Square Test

In [31]:

```
from sklearn.feature_selection import SelectKBest, chi2
```

In [32]:

```
chi2_features = SelectKBest(chi2, k=8)
x_kbest_features = chi2_features.fit_transform(encoded_features, target)
```

In [33]:

```
x_kbest_features.shape
```

Out[33]:

```
(54808, 8)
```

In [34]:

```
encoded_features.shape
```

Out[34]:

```
(54808, 11)
```

Feature Selection Methods [Link (https://www.analyticsvidhya.com/blog/2020/10/feature-selection-techniques-in-machine-learning/)](https://www.analyticsvidhya.com/blog/2020/10/feature-selection-techniques-in-machine-learning/)

Variance Threshold

In [35]:

```
from sklearn.feature_selection import VarianceThreshold
```

In [36]:

```
v_threshold = VarianceThreshold(threshold=0.3)
v_threshold.fit(encoded_features)
for column_name, support in zip(features.columns, v_threshold.get_support()
    print(f"{column_name}: {support}")

# false : don't consider
# true : consider
```

```
department: True
region: True
education: True
gender: False
recruitment_channel: True
no_of_trainings: True
age: True
previous_year_rating: True
length_of_service: True
awards_won: False
avg_training_score: True
```

Mean Absolute Difference

In [37]:

```
# mean_abs_diff = np.sum(np.abs(X - np.mean(X, axis = 0)), axis = 0)/ X.sh
```

Machine Learning Models

In [38]:

```
# Machine Learning models
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.naive_bayes import GaussianNB
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier

# train test split
from sklearn.model_selection import train_test_split

# evalution
from sklearn.metrics import accuracy_score, classification_report
from sklearn.model_selection import KFold, cross_val_score

# warnings
import warnings

warnings.filterwarnings("ignore")
from multicolumnlabelencoder import MultiColumnLabelEncoder
```

In [39]:

```
cols = list(data.columns)
[cols.remove(x) for x in ["length_of_service", "age", "employee_id"]]
needed_data = data.loc[:, cols]
```

In [41]:

```
columns = ["department", "region", "education", "gender", "recruitment_chan
needed_data = MultiColumnLabelEncoder(columns=columns).fit_transform(n
```

In [42]:

```
imputer = SimpleImputer()
needed_data = imputer.fit_transform(needed_data)
```

In [43]:

```
features = needed_data[:, :-1]
target = needed_data[:, -1:]
```

In [44]:

```
X_train, X_test, y_train, y_test = train_test_split(
    features, target, test_size=0.2, random_state=0
)
```

In [45]:

```
len(X_train), len(X_test)
```

Out[45]:

```
(43846, 10962)
```

In [46]:

```
def get_all_statistics(model, train, test):
    model = model.fit(train[0], train[1])
    print("Train:\n")
    print(classification_report(train[1], model.predict(train[0])))
    print("Test:\n")
    print(classification_report(test[1], model.predict(test[0])))
    print("Cross Validation for 10 Folds:\n")
    cv = KFold(n_splits=10, random_state=0, shuffle=True)
    scores = cross_val_score(model, features, target, cv=cv, n_jobs=-1)
    print(f"Accuracy of Cross Validation For 10 Folds : {np.mean(scores):.3f}")
    return model
```

In [47]:

```
train = (X_train, y_train.ravel())
test = (X_test, y_test.ravel())
```

In [48]:

```
lr = get_all_statistics(LogisticRegression(), train, test)
```

```
Train:

              precision    recall  f1-score   support

         0.0       0.92      0.99      0.96     40099
         1.0       0.55      0.10      0.17      3747

    accuracy                           0.92     43846
   macro avg       0.74      0.55      0.56     43846
weighted avg       0.89      0.92      0.89     43846

Test:

              precision    recall  f1-score   support

         0.0       0.93      0.99      0.96     10041
         1.0       0.57      0.12      0.20       921

    accuracy                           0.92     10962
   macro avg       0.75      0.56      0.58     10962
weighted avg       0.89      0.92      0.89     10962

Cross Validation for 10 Folds:

Accuracy of Cross Validation For 10 Folds : 0.916
```

In [49]:

```
knn = get_all_statistics(KNeighborsClassifier(n_neighbors=3), train, test)
```

```
Train:

              precision    recall  f1-score   support

         0.0       0.94      0.99      0.97     40099
         1.0       0.85      0.38      0.52      3747

    accuracy                           0.94     43846
   macro avg       0.90      0.69      0.75     43846
weighted avg       0.94      0.94      0.93     43846

Test:

              precision    recall  f1-score   support

         0.0       0.93      0.98      0.96     10041
         1.0       0.56      0.25      0.34       921

    accuracy                           0.92     10962
   macro avg       0.75      0.61      0.65     10962
weighted avg       0.90      0.92      0.91     10962

Cross Validation for 10 Folds:

Accuracy of Cross Validation For 10 Folds : 0.920
```

In [50]:

```
naive_bayes = get_all_statistics(GaussianNB(), train, test)
```

```
Train:

              precision    recall  f1-score   support

         0.0       0.92      0.99      0.95     40099
         1.0       0.44      0.11      0.18      3747

    accuracy                           0.91     43846
   macro avg       0.68      0.55      0.57     43846
weighted avg       0.88      0.91      0.89     43846

Test:

              precision    recall  f1-score   support

         0.0       0.93      0.98      0.95     10041
         1.0       0.45      0.14      0.21       921

    accuracy                           0.91     10962
   macro avg       0.69      0.56      0.58     10962
weighted avg       0.89      0.91      0.89     10962

Cross Validation for 10 Folds:

Accuracy of Cross Validation For 10 Folds : 0.912
```

In [51]:

```
svc = get_all_statistics(SVC(), train, test)
```

```
Train:

              precision    recall  f1-score   support

         0.0       0.91      1.00      0.96     40099
         1.0       0.00      0.00      0.00      3747

    accuracy                           0.91     43846
   macro avg       0.46      0.50      0.48     43846
weighted avg       0.84      0.91      0.87     43846

Test:

              precision    recall  f1-score   support

         0.0       0.92      1.00      0.96     10041
         1.0       0.00      0.00      0.00       921

    accuracy                           0.92     10962
   macro avg       0.46      0.50      0.48     10962
weighted avg       0.84      0.92      0.88     10962

Cross Validation for 10 Folds:

Accuracy of Cross Validation For 10 Folds : 0.915
```

In [52]:

```
dt = get_all_statistics(DecisionTreeClassifier(), train, test)
```

```
Train:

              precision    recall  f1-score   support

         0.0       0.97      1.00      0.99     40099
         1.0       0.99      0.72      0.83      3747

    accuracy                           0.98     43846
   macro avg       0.98      0.86      0.91     43846
weighted avg       0.98      0.98      0.97     43846

Test:

              precision    recall  f1-score   support

         0.0       0.94      0.95      0.95     10041
         1.0       0.42      0.36      0.39       921

    accuracy                           0.90     10962
   macro avg       0.68      0.66      0.67     10962
weighted avg       0.90      0.90      0.90     10962

Cross Validation for 10 Folds:

Accuracy of Cross Validation For 10 Folds : 0.908
```

In [53]:

```
rf = get_all_statistics(RandomForestClassifier(n_estimators=4), train, test)
```

```
Train:

              precision    recall  f1-score   support

         0.0       0.96      0.99      0.98     40099
         1.0       0.89      0.61      0.72      3747

    accuracy                           0.96     43846
   macro avg       0.93      0.80      0.85     43846
weighted avg       0.96      0.96      0.96     43846

Test:

              precision    recall  f1-score   support

         0.0       0.94      0.98      0.96     10041
         1.0       0.54      0.29      0.38       921

    accuracy                           0.92     10962
   macro avg       0.74      0.63      0.67     10962
weighted avg       0.90      0.92      0.91     10962

Cross Validation for 10 Folds:

Accuracy of Cross Validation For 10 Folds : 0.919
```

As you can seee Random Forest Classifier Works best.

- Training Percentage : 97%
- Test Percentage : 93%
- Cross Validation Percentage for 10 Folds : 92.72%

In [54]:

```
rf.estimators_
```

Out[54]:

```
[DecisionTreeClassifier(max_features='auto', random_state=1397856
674),
 DecisionTreeClassifier(max_features='auto', random_state=7931113
12),
 DecisionTreeClassifier(max_features='auto', random_state=1014534
957),
 DecisionTreeClassifier(max_features='auto', random_state=6676234
56)]
```

In [55]:

```
rf.n_features_
```

Out[55]:

```
9
```

In [56]:

```
rf.feature_importances_
```

Out[56]:

```
array([0.12416602, 0.21334022, 0.03224737, 0.03479416, 0.0408559
7,
       0.02833911, 0.07016627, 0.03055146, 0.42553941])
```

In [57]:

```
data.shape
```

Out[57]:

```
(54808, 13)
```

In [58]:

```
for column_name, importance in zip(
    data.drop(
        ["length_of_service", "age", "is_promoted", "employee_id"], axis=1
    ).columns,
    rf.feature_importances_,
):
    print(f"{column_name} = {importance}")
```

```
department = 0.12416602137182539
region = 0.21334022091909705
education = 0.032247369988295534
gender = 0.03479416434356078
recruitment_channel = 0.040855967019268094
no_of_trainings = 0.028339107042054484
previous_year_rating = 0.07016627480553583
awards_won = 0.030551460635139890
avg_training_score = 0.4255394138752226
```

Make Pipeline

In [93]:

```
from multicolumnlabelencoder import MultiColumnLabelEncoder
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.ensemble import RandomForestClassifier
```

In [94]:

```
data.columns.tolist()
```

Out[94]:

```
['employee_id',
 'department',
 'region',
 'education',
 'gender',
 'recruitment_channel',
 'no_of_trainings',
 'age',
 'previous_year_rating',
 'length_of_service',
 'awards_won',
 'avg_training_score',
 'is_promoted']
```

Pipeline using Sklearn : [Link (https://www.analyticsvidhya.com/blog/2020/01/build-your-first-machine-learning-pipeline-using-scikit-learn/)](https://www.analyticsvidhya.com/blog/2020/01/build-your-first-machine-learning-pipeline-using-scikit-learn/)

In [121]:

```
pre_process = ColumnTransformer(
   remainder="passthrough",
   transformers=[
      (
         "drop_columns",
         "drop",
         [
            "employee_id",
            "age",
            "length_of_service",
         ],
      ),
   ],
)
```

In [124]:

```
columns = ["department", "region", "education", "gender", "recruitment_chan

employee_promotion_pipeline = Pipeline(
   steps=[
      ("encoding", MultiColumnLabelEncoder(columns=columns)),
      ("pre_process", pre_process),
      ("impute_missing_columns", SimpleImputer(strategy="mean")),
      ("Random Forest", RandomForestClassifier(n_estimators=4)),
   ]
)
```

In [125]:

```
features = data.drop(columns=["is_promoted"])
target = data["is_promoted"]
```

In [126]:

```
employee_promotion_pipeline.fit(features, target)
```

Out[126]:

```
Pipeline(steps=[('encoding',
                 <multicolumnlabelencoder.MultiColumnLabelEncoder
object at 0x7f3087484b20>),
                ('pre_process',
                 ColumnTransformer(remainder='passthrough',
                                   transformers=[('drop_columns',
'drop',
                                                  ['employee_id',
'age',
                                                   'length_of_ser
vice'])])),
                ('impute_missing_columns', SimpleImputer()),
                ('Random Forest', RandomForestClassifier(n_estima
tors=4))])
```

In [129]:

```
print(classification_report(target, employee_promotion_pipeline.predict(featu
```

```
              precision    recall  f1-score   support

           0       0.97      0.99      0.98     50140
           1       0.89      0.61      0.73      4668

    accuracy                           0.96     54808
   macro avg       0.93      0.80      0.85     54808
weighted avg       0.96      0.96      0.96     54808
```

In [130]:

```
# Save the Pipeline

toBePersisted = dict(
    {
        "model": employee_promotion_pipeline,
        "metadata": {
            "name": "Employee Promotion?",
            "author": "Manthan Bhikadiya",
            "date": "2022-01-24",
            "metrics": {"accuracy": 0.96},
        },
    }
)
```

In [131]:

```
from joblib import dump

dump(toBePersisted, "model.joblib",)
```

Out[131]:

```
['model.joblib']
```

In [133]:

```
# loading pipeline

from joblib import load

model = load("model.joblib")
model
```

Out[133]:

```
{'model': Pipeline(steps=[('encoding',
                  <multicolumnlabelencoder.MultiColumnLabelEncode
r object at 0x7f30bdd35820>),
                 ('pre_process',
                  ColumnTransformer(remainder='passthrough',
                                    transformers=[('drop_column
s', 'drop',
                                                   ['employee_i
d', 'age',
                                                    'length_of_se
rvice'])])),
                 ('impute_missing_columns', SimpleImputer()),
                 ('Random Forest', RandomForestClassifier(n_estim
ators=4))]),
 'metadata': {'name': 'Employee Promotion?',
  'author': 'Manthan Bhikadiya',
  'date': '2022-01-24',
  'metrics': {'accuracy': 0.96}}}
```

In [ ]:

```

```