HR Analytics: Job Change of Data Scientists

Note:

多數特稱為類別,且部分為特徵有高比例為唯一值

特徵:

enrollee_id:唯一ID city:所在城市 city_ development _index:城市發展指數 (連續) gender:性別 relevent_experience:相關經驗 enrolled_university:大學課程類型 education_level:教育程度 major_discipline:畢業學科 experience:工作經驗年數 company_size:當前公司員工數 company_type:當前雇主類型 last_new_job:上份工作與當前工作的年數差異 training_hours:培訓時數 (連續) target: 0 不尋找新工作, 1 尋找工作

定義問題: 了解特徵與 '學員願意到新公司上班而進行培訓' 之間的關係,意即具有何者特徵的學員,較有可能是為了找到新工作

In [16]:

```
from sklearn.feature selection import RFECV
from sklearn.pipeline import Pipeline
from imblearn.under sampling import RandomUnderSampler
from sklearn.pipeline import Pipeline
import numpy as np
from xgboost import XGBRegressor
from sklearn.model_selection import train_test_split, RandomizedSearchCV, cross_val_score
from sklearn import metrics
from sklearn.metrics import mean_squared_error, f1_score, mean_absolute_error
from sklearn import model selection
from sklearn import feature_selection
from xgboost import XGBClassifier
from sklearn import svm, tree, linear_model, neighbors, naive_bayes, ensemble, discrimina
from sklearn.preprocessing import LabelEncoder, OneHotEncoder, QuantileTransformer, Stand
from sklearn.compose import ColumnTransformer
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
train = pd.read_csv('aug_train.csv')
train.info()
```

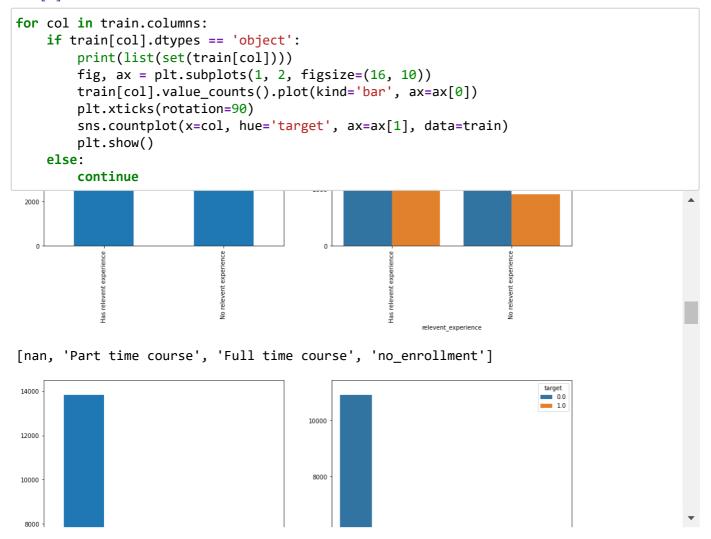
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 19158 entries, 0 to 19157
Data columns (total 14 columns):

#	Column	Non-Null Count	Dtype
0	enrollee_id	19158 non-null	int64
1	city	19158 non-null	object
2	<pre>city_development_index</pre>	19158 non-null	float64
3	gender	14650 non-null	object
4	relevent_experience	19158 non-null	object
5	enrolled_university	18772 non-null	object
6	education_level	18698 non-null	object
7	major_discipline	16345 non-null	object
8	experience	19093 non-null	object
9	company_size	13220 non-null	object
10	company_type	13018 non-null	object
11	last_new_job	18735 non-null	object
12	training_hours	19158 non-null	int64
13	target	19158 non-null	float64

dtypes: float64(2), int64(2), object(10)

memory usage: 2.0+ MB

In [2]:



city: 過度集中·'city_21'較容易找新工作

experience: 大於20較多 (間隔5?) ['10', '17', nan, '14', '11', '18', '16', '4', '1', '<1', '9', '15', '12', '5', '2', '>20', '8', '7', '3', '6', '20', '13', '19']

company_size: 較分散 (小公司跳槽大公司?) ['100-500', '10/49', '1000-4999', nan, '<10', '5000-9999', '50-99', '10000+', '500-999']

education_level: Graduate較多,且較容易找新工作 ['High School', 'Masters', 'Phd', nan, 'Graduate', 'Primary School']

major_discipline: 過度集中STEM · 且較容易找新工作 ['Humanities', nan, 'Other', 'Arts', 'Business Degree', 'No Major', 'STEM']

company_type: 過度集中Pvt Ltd ['Pvt Ltd', 'NGO', 'Early Stage Startup', nan, 'Public Sector', 'Funded Startup', 'Other']

last new job: 1年較多, never較容易找新工作 ['1', '2', nan, '3', '4', '>4', 'never']

gender: 多為男性·男女在target部分較無差異 ['Other', 'Male', nan, 'Female']

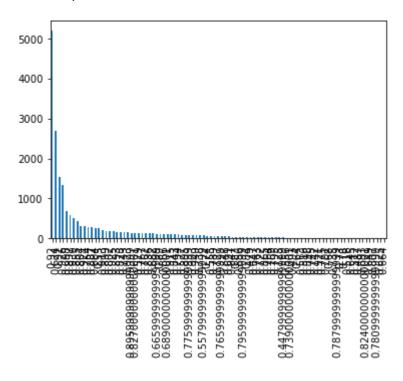
relevent_experience: 多具有相關經驗,且較不容易找新工作 ['Has relevent experience', 'No relevent experience']

In [3]:

```
train['city_development_index'].value_counts().plot(kind='bar')
# city_development_index: 和 city 分布相似
```

Out[3]:

<AxesSubplot:>

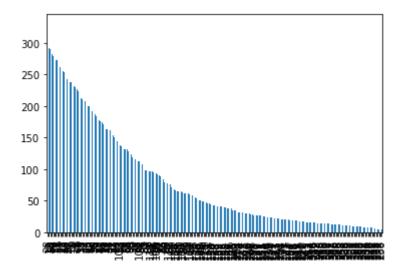


In [4]:

```
train['training_hours'].value_counts().plot(kind='bar')
# training_hours: 較分散(跟城市有關?)
```

Out[4]:

<AxesSubplot:>

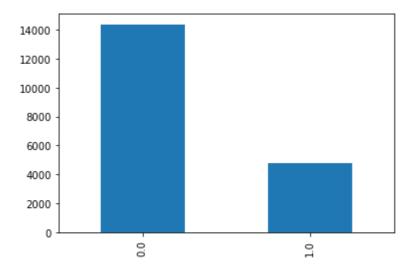


In [5]:

```
train['target'].value_counts().plot(kind='bar')
# target: 0約為1的3倍(不尋找工作? 找不到工作?)
```

Out[5]:

<AxesSubplot:>



In [6]:

```
train.columns[train.isnull().any().values == True]
```

Out[6]:

In [7]:

```
pd.crosstab(train[col].fillna('missing'),train['target'].fillna('missing'), normalize=Tru
```

Out[7]:

target	0.0	1.0	All
target			
0.0	0.750652	0.000000	0.750652
1.0	0.000000	0.249348	0.249348
All	0.750652	0.249348	1.000000

In [8]:

A11

```
correlation by : gender
       0.0
                              A11
target
                     1.0
gender
Female 0.062253 0.022253 0.084505
Male 0.696860 0.205597 0.902457
Other 0.009625 0.003413 0.013038
      0.768737 0.231263 1.000000
All
_____
correlation by : relevent_experience
target
                                     1.0
                                              A11
relevent experience
Has relevent experience 0.565351 0.154557 0.719908
No relevent experience 0.185301 0.094791 0.280092
                       0.750652 0.249348 1.000000
A11
------
correlation by : enrolled_university
                                1.0
                                          All
target
                        0.0
enrolled university
Full time course 0.123908 0.076231 0.200139
Part time course
                   0.047731 0.016088 0.063818
no_enrollment 0.580439 0.155604 0.736043
All
                   0.752078 0.247922 1.000000
correlation by : education_level
target
                    0.0
                            1.0
                                       A11
education_level
Graduate 0.446732 0.173548 0.620280
High School 0.086801 0.021072 0.107872
High School
Masters
              0.183228 0.050005 0.233234
               0.019039 0.003102 0.022141
Phd
Primary School 0.014280 0.002193 0.016472
All
    0.750080 0.249920 1.000000
-----
correlation by : major_discipline
                     0.0
                                        A11
target
                              1.0
major discipline
Arts
                0.012236 0.003243 0.015479
Business Degree 0.014745 0.005262 0.020006
                0.032303 0.008626 0.040930
Humanities
                0.010278 0.003365 0.013643
No Major
Other
                0.017069 0.006240 0.023310
STEM
                0.654696 0.231936 0.886632
                0.741328 0.258672 1.000000
All
correlation by : company_size
target
                 0.0
                           1.0
                                    A11
company_size
10/49
           0.085250 0.026021 0.111271
             0.163086 0.031392 0.194478
100-500
1000-4999
            0.085325 0.015129 0.100454
            0.123601 0.029123 0.152723
10000+
             0.191982 0.041225 0.233207
50-99
500-999
             0.054841 0.011498 0.066339
5000-9999
             0.034871 0.007716 0.042587
<10
             0.081997 0.016944 0.098941
```

0.820953 0.179047 1.000000

correlation by : company_type					
target	0.0	1.0	All		
company_type					
Early Stage Startup	0.035413	0.010908	0.046320		
Funded Startup	0.066139	0.010754	0.076894		
NGO	0.032570	0.007451	0.040022		
Other	0.007067	0.002228	0.009295		
Public Sector	0.057228	0.016132	0.073360		
Pvt Ltd	0.617760	0.136350	0.754110		
All	0.816178	0.183822	1.000000		

correlation by : last_new_job						
target	0.0	1.0	All			
<pre>last_new_job</pre>	last_new_job					
1	0.315719	0.113424	0.429143			
2	0.117427	0.037363	0.154790			
3	0.042327	0.012330	0.054657			
4	0.042754	0.012170	0.054924			
>4	0.143582	0.032026	0.175607			
never	0.091433	0.039445	0.130878			
All	0.753243	0.246757	1.000000			

In [9]:

```
# 資料清理
# 具有順序的編號
clean_nums = {
    'enrolled_university': {'Full time course': 3, 'Part time course': 2, 'no_enrollment'
    'relevent_experience': {'Has relevent experience': 1, 'No relevent experience': 0},
    'education_level': {'Masters': 4, 'Phd': 5, 'High School': 2, 'Primary School': 1,
    'company_size': {'<10': 0, '10/49': 1, '50-99': 2, '100-500': 3, '500-999': 4, '1000-
    'last_new_job': {'>4': 5, 'never': 0},
    'experience': {'>20': '25', '<1': '0'}
}
train = train.replace(clean nums)
# 將city 編碼
label = LabelEncoder()
train['city'] = label.fit transform(train['city'])
# major discipline 與 company type 删除
train = train.drop(['major_discipline', 'company_type'], axis=1)
# NA 處理
# print(train['gender'].unique())
train['gender'] = train['gender'].fillna('Other')
# 假設NA代表在職中,且無經驗,教育程度為未受過教育,因此為@
train[['last_new_job', 'experience', 'education_level']] = train[[
    'last_new_job', 'experience', 'education_level']].fillna(0)
# 假設NA代表輟學,因此同屬於'no enrollment'
train['enrolled_university'] = train['enrolled_university'].fillna(1)
# company_size 則依據 'education_level' 進行插補
train['company_size'] = train['company_size'].fillna(train.groupby(
    'education level')['company size'].transform('mean').round())
# gender 用 one-hot,照字母順序處理列名稱
onehot = OneHotEncoder()
train[['Female', 'Male', 'Other']] = onehot.fit_transform(
   train[['gender']]).toarray()
# training hours 和 experience 分為5個級距
train['training_hours_cut'] = pd.qcut(
   train['training_hours'], 5, labels=[1, 2, 3, 4, 5])
train['experience_cut'] = pd.qcut(
   train['experience'].astype(int), 5, labels=[1, 2, 3, 4, 5])
for col in train.columns:
   if col not in ['gender', 'city_development_index']:
       train[col] = train[col].astype('int64')
train.head(5)
```

Out[9]:

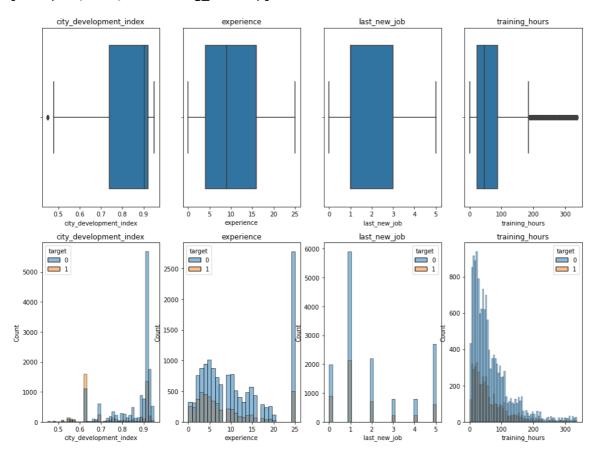
	enrollee_id	city	city_development_index	gender	relevent_experience	enrolled_university
0	8949	5	0.920	Male	1	1
1	29725	77	0.776	Male	0	1
2	11561	64	0.624	Other	0	3
3	33241	14	0.789	Other	0	1
4	666	50	0.767	Male	1	1
4						>

In [10]:

```
fig, ax = plt.subplots(2, 4, figsize=(16, 12))
sns.boxplot(x='city_development_index', hue='target', data=train,
              ax=ax[0, 0]).set(title='city_development_index')
sns.boxplot(x='experience', hue='target', data=train,
              ax=ax[0, 1]).set(title='experience')
sns.boxplot(x='last_new_job', hue='target', data=train,
              ax=ax[0, 2]).set(title='last_new_job')
sns.boxplot(x='training_hours', hue='target', data=train,
              ax=ax[0, 3]).set(title='training_hours')
sns.histplot(x='city_development_index', hue='target', data=train,
             ax=ax[1, 0]).set(title='city_development_index')
sns.histplot(x='experience', hue='target', data=train,
             ax=ax[1, 1]).set(title='experience')
sns.histplot(x='last_new_job', hue='target', data=train,
             ax=ax[1, 2]).set(title='last_new_job')
sns.histplot(x='training_hours', hue='target', data=train,
             ax=ax[1, 3]).set(title='training_hours')
```

Out[10]:

[Text(0.5, 1.0, 'training_hours')]



In [11]:

```
y_re = train[['target']]
x_test = train.drop('target', axis=1)
# 將資料標準化
num_col = ['experience', 'company_size', 'last_new_job', 'training_hours_cut',
           'experience_cut', 'education_level', 'enrolled_university']
skew_col = ['city_development_index', 'training_hours']
norm num = Pipeline(
    steps=[
        ('scaler', StandardScaler())
)
skew_num = Pipeline(
    steps=[
        ('Quantile', QuantileTransformer(output_distribution='normal')),
        ('scaler', StandardScaler())
preprocess = ColumnTransformer(
    Γ
        ('norm', norm_num, num_col),
        ('skew', skew_num, skew_col)
    ]
)
X = preprocess.fit_transform(x_test)
xtest = pd.DataFrame(X, columns=num_col +
                     skew_col).join(x_test.drop(num_col+skew_col, axis=1))
x_re = xtest[['city_development_index', 'relevent_experience', 'enrolled_university', 'ed
               'experience', 'company_size', 'last_new_job', 'training hours',
              'Female', 'Male', 'Other']]
```

In [12]:

```
# Undersampling
undersampler = RandomUnderSampler(random_state=42)
x, y = RandomUnderSampler(random_state=42).fit_resample(x_re, y_re)

x_train, x_test, y_train, y_test = train_test_split(
    x, y, test_size=0.2, random_state=432)
```

In [17]:

```
model = \lceil
    # Ensemble Methods
    ensemble.AdaBoostClassifier(),
    ensemble.BaggingClassifier(),
    ensemble.ExtraTreesClassifier(),
    ensemble.GradientBoostingClassifier(),
    ensemble.RandomForestClassifier(),
    # GLM
    linear model.SGDClassifier(),
    # Navies Bayes
    naive_bayes.BernoulliNB(),
    naive_bayes.GaussianNB(),
    # Nearest Neighbor
    neighbors.KNeighborsClassifier(),
    # SVM
    svm.SVC(probability=True),
    svm.LinearSVC(),
    # Trees
    tree.DecisionTreeClassifier(),
    tree.ExtraTreeClassifier(),
    # Discriminant Analysis
    discriminant analysis.LinearDiscriminantAnalysis(),
    discriminant_analysis.QuadraticDiscriminantAnalysis(),
    # xqboost
    XGBClassifier()
]
model_result_org = pd.DataFrame(
    columns=['model', 'parameters', 'cv_accuracy', 'mae', 'mse', 'f1'])
row index = 0
for ml in model:
    print(ml.__class__.__name__)
    ml.fit(x_train, y_train)
    y_pred = ml.predict(x_test)
    model_result_org.loc[row_index, 'model'] = ml.__class__.__name__
    model_result_org.loc[row_index, 'parameters'] = str(ml.get_params())
model_result_org.loc[row_index, 'mae'] = mean_absolute_error(y_test, y_pred)
    model_result_org.loc[row_index, 'mse'] = mean_squared_error(y_test, y_pred)
    model_result_org.loc[row_index, 'f1'] = f1_score(y_test, y_pred)
    model_result_org.loc[row_index, 'cv_accuracy'] = cross_val_score(
        ml, x_train, y_train, cv=10, scoring='accuracy').mean()
    row_index += 1
model result org
# 第一次試做 : f1 score最好為 GaussianNB 之 0.513875
# 第二次試做 : f1_score最好為 GradientBoosting 為 0.751387 (部分資料標準化 + 欠採樣 + Quant
# 第三次試做 : f1 score最好為 GradientBoosting (加入cross val做確認)
```

```
{ DODISITAD . FAISE,
2
            ExtraTreesClassifier
                                                            'ccp alpha': 0.0,
                                               'class ...
                                       {'ccp alpha': 0.0,
3
       GradientBoostingClassifier
                                              'criterion':
                                                            0.746044
                                                                        0.25798
                                                                                   0.25798 0.751387
                                       'friedman_mse'...
                                       {'bootstrap': True,
                                        'ccp_alpha': 0.0,
4
         RandomForestClassifier
                                                            0.718697 0.271586 0.271586
                                                                                             0.73371
                                             'class_w...
                                        {'alpha': 0.0001,
                  SGDClassifier
                                                              0.65537  0.374673  0.374673  0.676018
5
                                        'average': False,
                                           'class_wei...
                                   {'alpha': 1.0, 'binarize':
                    BernoulliNB
6
                                                            0.619126 0.379906 0.379906 0.630346
                                      0.0, 'class_prior':...
                                         {'priors': None,
7
                   GaussianNB
                                                            0.652624 0.349555 0.349555
                                                                                             0.65567
                                  'var smoothing' 1e-09)
```

In [18]:

```
# Hyper-Parameters
model = ensemble.GradientBoostingClassifier()
model.fit(x_train, y_train)
result_cv = cross_val_score(model, x_train, y_train,
                            cv=10, scoring='accuracy').mean()
param = {'n estimators': [40, 50, 60], 'learning rate':[0.5, 0.1, 0.05], 'max features':
new_model = GridSearchCV(model, param, cv=10, scoring='accuracy')
new model.fit(x train, y train)
print(result_cv)
print(new_model.score(x_train, y_train))
print(new model.best params )
DataConversionwarning: A column-vector y was passed when a lo array was
expected. Please change the shape of y to (n_samples, ), for example usi
ng ravel().
  y = column_or_1d(y, warn=True)
C:\Users\jerry\anaconda3\lib\site-packages\sklearn\ensemble\ gb.py:494:
DataConversionWarning: A column-vector y was passed when a 1d array was
expected. Please change the shape of y to (n_samples, ), for example usi
ng ravel().
  y = column_or_1d(y, warn=True)
C:\Users\jerry\anaconda3\lib\site-packages\sklearn\ensemble\_gb.py:494:
DataConversionWarning: A column-vector y was passed when a 1d array was
expected. Please change the shape of y to (n samples, ), for example usi
ng ravel().
  y = column_or_1d(y, warn=True)
C:\Users\jerry\anaconda3\lib\site-packages\sklearn\ensemble\ gb.py:494:
DataConversionWarning: A column-vector y was passed when a 1d array was
expected. Please change the shape of y to (n_samples, ), for example usi
ng ravel().
  y = column_or_1d(y, warn=True)
C:\Users\jerry\anaconda3\lib\site-packages\sklearn\ensemble\_gb.py:494:
```

In [19]:

```
# feature selection
model = ensemble.GradientBoostingClassifier()
model rfecv = RFECV(estimator=model, step=1, cv=10)
model_rfecv.fit(x_train, y_train)
column_rfe = x_train.columns.values[model_rfecv.get_support()]
result_cv = cross_val_score(model, x_train[column_rfe], y_train,
                            cv=10, scoring='accuracy').mean()
param = {'n_estimators': [40, 50, 60], 'learning_rate': [
    0.5, 0.1, 0.05], 'max_features': ['sqrt', 'log2', 8, None], 'max_depth': [3, 6, 9]}
new_model = GridSearchCV(model, param, cv=10, scoring='accuracy')
new_model.fit(x_train[column_rfe], y_train)
print(result cv)
print(column rfe)
print(new_model.score(x_train[column_rfe], y_train))
print(new_model.best_params_)
DataConversionwarning: A column-vector y was passed when a ld array was
expected. Please change the shape of y to (n_samples, ), for example usi
ng ravel().
  y = column or 1d(y, warn=True)
C:\Users\jerry\anaconda3\lib\site-packages\sklearn\ensemble\_gb.py:494:
DataConversionWarning: A column-vector y was passed when a 1d array was
expected. Please change the shape of y to (n_samples, ), for example usi
ng ravel().
  y = column_or_1d(y, warn=True)
C:\Users\jerry\anaconda3\lib\site-packages\sklearn\ensemble\_gb.py:494:
DataConversionWarning: A column-vector y was passed when a 1d array was
expected. Please change the shape of y to (n_samples, ), for example usi
ng ravel().
  y = column_or_1d(y, warn=True)
C:\Users\jerry\anaconda3\lib\site-packages\sklearn\ensemble\ gb.py:494:
DataConversionWarning: A column-vector y was passed when a 1d array was
expected. Please change the shape of y to (n_samples, ), for example usi
ng ravel().
  y = column_or_1d(y, warn=True)
C:\Users\jerry\anaconda3\lib\site-packages\sklearn\ensemble\_gb.py:494:
```

['city_development_index' 'relevent_experience' 'enrolled_university' 'education_level' 'experience' 'company_size' 'last_new_job' 'training_hours' 'Male'] {'learning_rate': 0.1, 'max_depth': 3, 'max_features': None, 'n_estimators': 50}

In [22]:

```
test = pd.read csv('aug test.csv')
test = test.replace(clean_nums)
test['city'] = label.fit_transform(test['city'])
test = test.drop(['major_discipline', 'company_type'], axis=1)
test['gender'] = test['gender'].fillna('Other')
test[['last_new_job', 'experience', 'education_level']] = test[[
     'last_new_job', 'experience', 'education_level']].fillna(0)
test['enrolled_university'] = test['enrolled_university'].fillna(1)
test['company size'] = test['company size'].fillna(test.groupby(
    'education_level')['company_size'].transform('mean').round())
test[['Female', 'Male', 'Other']] = onehot.fit_transform(
    test[['gender']]).toarray()
test['training_hours_cut'] = pd.qcut(
    test['training_hours'], 5, labels=[1, 2, 3, 4, 5])
test['experience_cut'] = pd.qcut(
    test['experience'].astype(int), 5, labels=[1, 2, 3, 4, 5])
for col in test.columns:
    if col not in ['gender', 'city_development_index']:
        test[col] = test[col].astype('int64')
X = preprocess.fit transform(test)
xtest = pd.DataFrame(X, columns=num col +
                     skew_col).join(test.drop(num_col+skew_col, axis=1))
column_new = ['city_development_index', 'relevent_experience', 'enrolled_university',
              'education_level', 'experience', 'company_size', 'last_new_job', 'training
x_re = xtest[column_new]
model = ensemble.GradientBoostingClassifier(
    n_estimators=50, learning_rate=0.1, max_depth=3)
model.fit(x_train[column_new], y_train)
test["target"] = model.predict(x re)
test.info()
```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2129 entries, 0 to 2128
Data columns (total 17 columns):

#	Column	Non-Null Count	Dtype
0	enrollee_id	2129 non-null	int64
1	city	2129 non-null	int64
2	<pre>city_development_index</pre>	2129 non-null	float64
3	gender	2129 non-null	object
4	relevent_experience	2129 non-null	int64
5	enrolled_university	2129 non-null	int64
6	education_level	2129 non-null	int64
7	experience	2129 non-null	int64
8	company_size	2129 non-null	int64
9	last_new_job	2129 non-null	int64
10	training_hours	2129 non-null	int64
11	Female	2129 non-null	int64
12	Male	2129 non-null	int64
13	Other	2129 non-null	int64
14	training_hours_cut	2129 non-null	int64
15	experience_cut	2129 non-null	int64
16	target	2129 non-null	int64

dtypes: float64(1), int64(15), object(1)

memory usage: 282.9+ KB

C:\Users\jerry\anaconda3\lib\site-packages\sklearn\ensemble_gb.py:494: Da taConversionWarning: A column-vector y was passed when a 1d array was expe cted. Please change the shape of y to (n_samples,), for example using rav el().

y = column_or_1d(y, warn=True)