5조 Kaggle 발표

changingjob - 이직 여부 예측

박유진 윤주연 정성윤 최예은

Contents

01. 데이터 소개

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

```python
data = pd.read_csv('changingjob_train.csv')
```

```python
data.head()
```

	Unnamed: 0	Unnamed: 0.1	city	city_development_Index	gender	relevent_experience	enrolled_university	education_level	major_discipline	experience	compa
0	0	0	city_103	0.920	Male	Has relevent experience	no_enrollment	Graduate	STEM	30	
1	1	1	city_40	0.776	Male	No relevent experience	no_enrollment	Graduate	STEM	15	
2	2	2	city_21	0.624	Other	No relevent experience	Full time course	Graduate	STEM	5	
3	3	3	city_162	0.767	Male	Has relevent experience	no_enrollment	Masters	STEM	30	
4	4	4	city_176	0.764	Other	Has relevent experience	Part time course	Graduate	STEM	11	

```python
data = data.iloc[:,2:]
```

1. 필요한 패키지 import

2. 'changingjob_train.csv' 데이터 불러오기

3. data 속성 확인
- shape:

18126 rows × 13 columns
- 속성

: city, city_development_Index, gender, relevent_experience, enrolled_university, education_level, major_discipline, experience, company_size, company_type, last_new_job, training hours
- target

: 이직 여부 → 이직 Yes: 1, 이직 No: 0

target을 제외한 부분 → data

```python
data['target'].value_counts()

#0: 이직 X / 1: 이직
```

```
0    13639
1     4487
Name: target, dtype: int64
```

* target 분포
0은 13639개,
1은 4487개
→ 0이 1보다 3배 더 많음.

02. 결측치 처리 및 속성별 EDA

- 결측치 확인

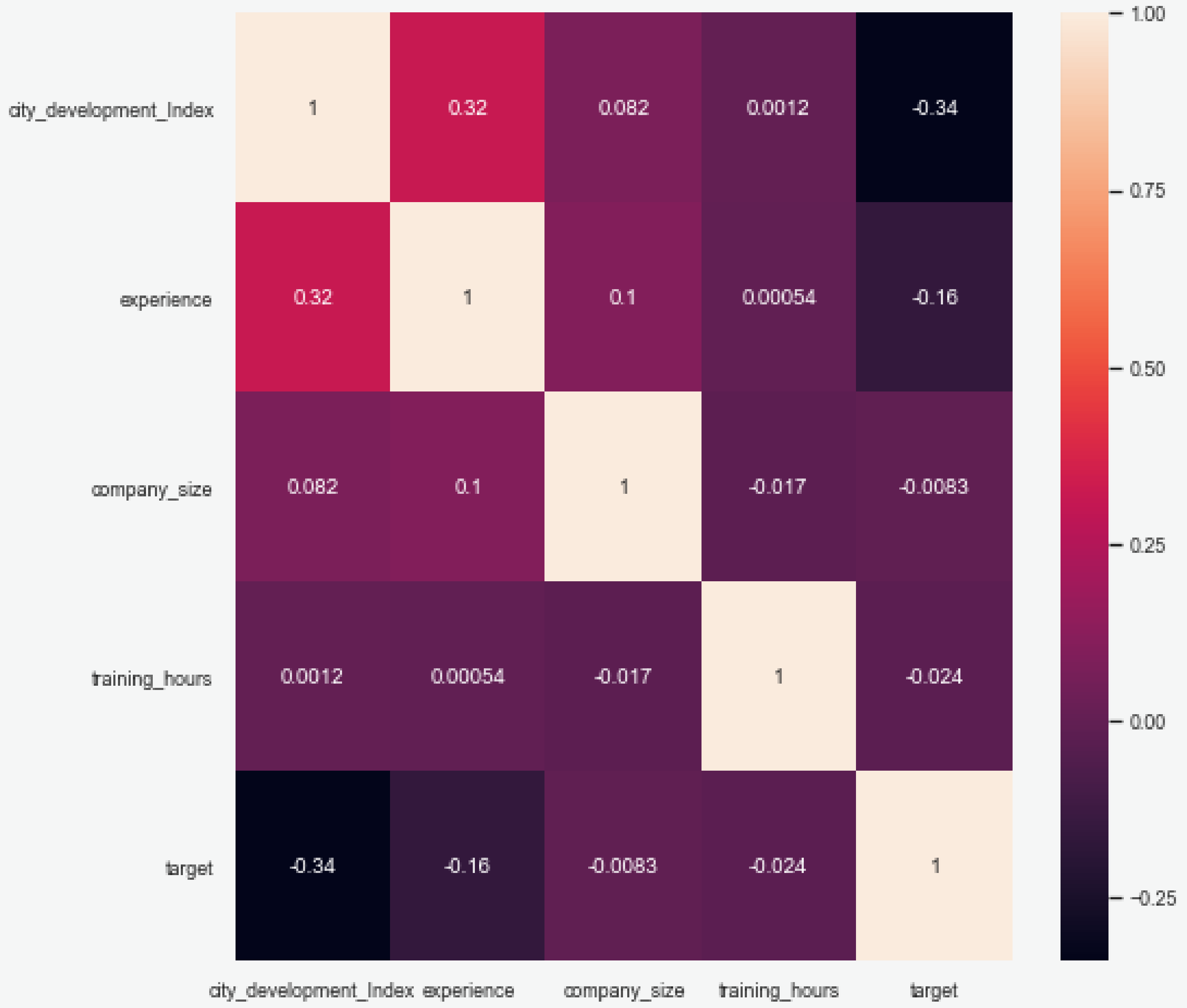
```
data.isnull().sum()
```

```
city                       0
city_development_Index     0
gender                     0
relevent_experience        0
enrolled_university        0
education_level            0
major_discipline        2572
experience                 0
company_size            5497
company_type               0
last_new_job               0
training_hours             0
target                     0
dtype: int64
```

→ major_discipline에 결측치가 2572개, company_size에 결측치가 5497개가 존재함을 확인할 수 있음.

- 상관관계 분석

```
plt.figure(figsize=(8,8))
sns.set(font_scale=0.8)
sns.heatmap(data.corr(), annot=True, cbar=True)
plt.show()

#target열과 상관 계수가 높은 피처 city_development_Index열(-0.34)
#city_development와 experience 상관계수는 0.32로 양의 상관관계가 있다.
```



02. 결측치 처리 및 속성별 EDA

- **city**

```
#1. city

len(data['city'].unique())
#unique 값 너무 많으므로 drop, 중요한 지표라고 생각되지 않음
```

```
123
```

```
data.drop(['city'], axis=1, inplace=True)
```

→ ‘city’속성에 너무 많은 unique한 값(123개) 존재하여 이직 여부를 예측하는 데 중요한 지표로 생각되지 않아 삭제하였다.

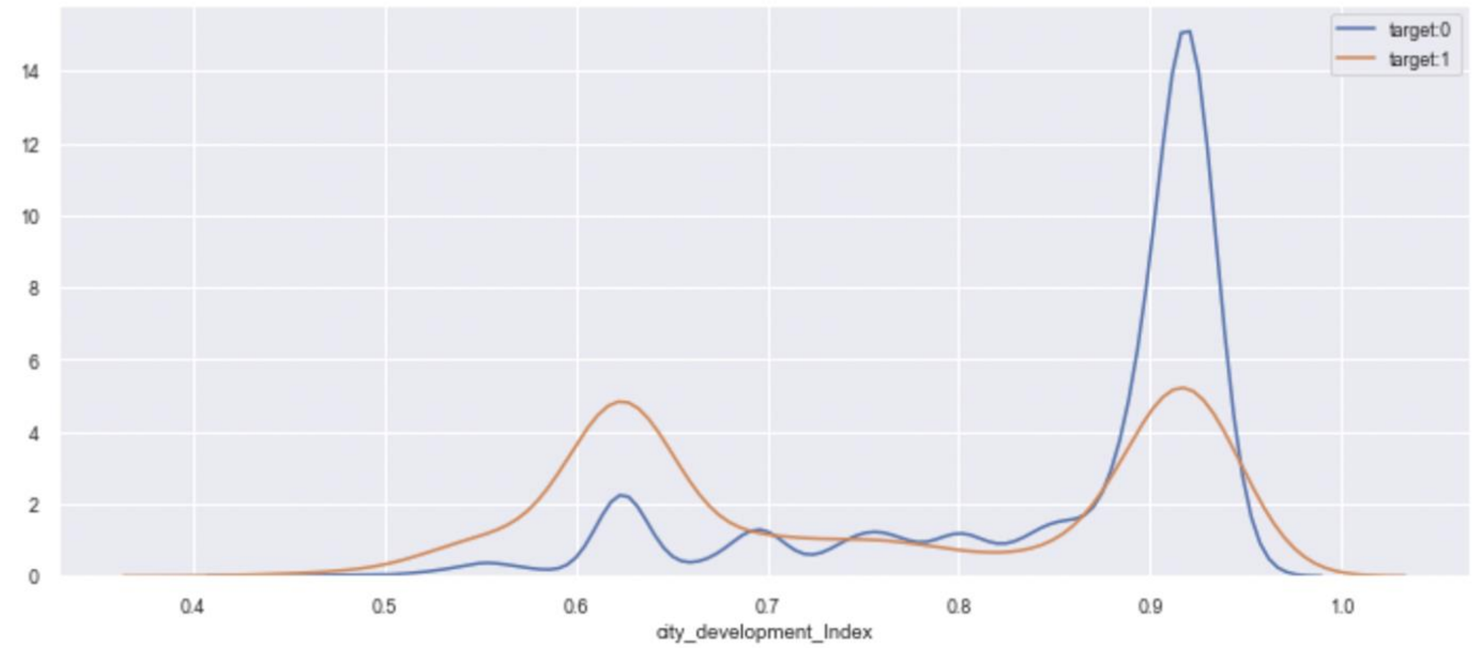
- **city_development_Index**

```
#2. city_development_Index

data['city_development_Index'].describe()
```

```
count    18126.000000
mean         0.829833
std          0.122993
min          0.448000
25%          0.743000
50%          0.910000
75%          0.920000
max          0.949000
Name: city_development_Index, dtype: float64
```

→ 속성 ‘city_development_Index’는 도시 발달 정도를 0~1의 지표로 나타낸 값.

```
plt.figure(figsize=(12,5))
sns.distplot(data[data.target==0]['city_development_Index'], hist=False, label='target:0')
sns.distplot(data[data.target==1]['city_development_Index'], hist=False, label='target:1')
plt.show()
#선진국일수록 job덜 바꿈
```



이직을 하는 건수는 city_development_Index가 0.6과 0.9일 때 눈에 띄게 증가함을 확인할 수 있다.

02. 결측치 처리 및 속성별 EDA

- **gender**

```
#3. Gender - LabelEncoding 필요

data['gender'].unique()
```

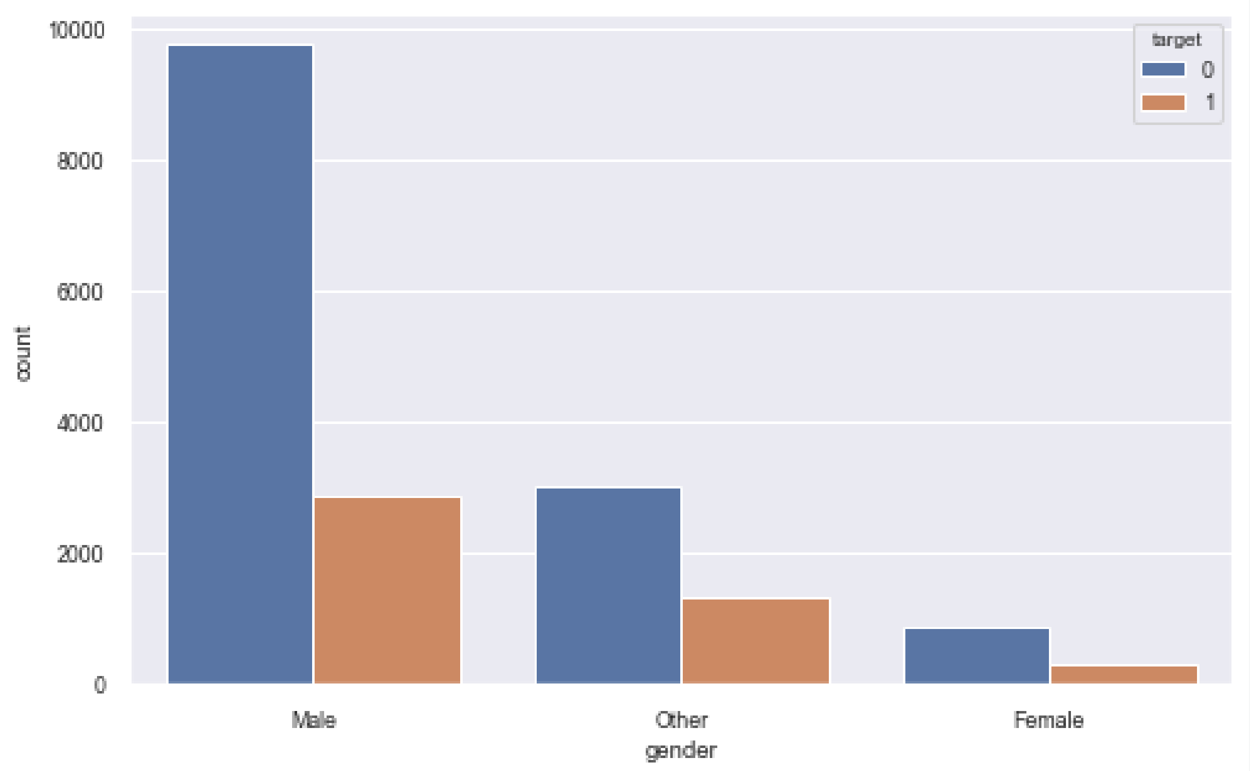
```
array(['Male', 'Other', 'Female'], dtype=object)
```

```
data['gender'].value_counts()
```

```
Male      12594
Other      4352
Female     1180
Name: gender, dtype: int64
```

gender에는 Male, Female, Ohter이 unique한 값으로 나타난다.

```
plt.figure(figsize=(8,5))
sns.countplot(x='gender', data=data, hue='target')

#other(기타) -> Male이 Female보다 많으므로 Male로 변환
```




```
data['gender'] = data['gender'].map({'Other':'Male', 'Male':'Male', 'Female':'Female'})
```

gender가 ‘Other’인 것을 최빈값 ‘Male’로 변환하였다.

02. 결측치 처리 및 속성별 EDA

- **relevent_experience**

```
#4. relevent_experience - LabelEncoding 필요

data['relevent_experience'].unique()
```

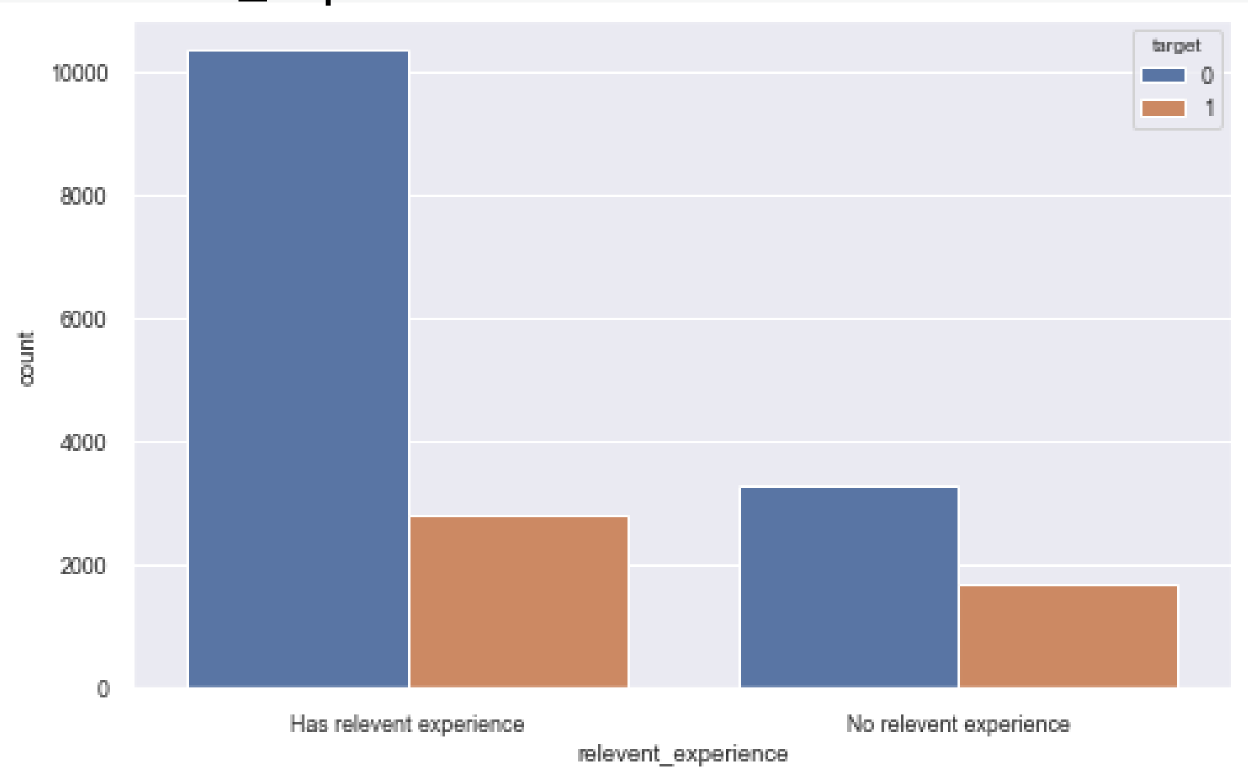
```
array(['Has relevent experience', 'No relevent experience'], dtype=object)
```

```
plt.figure(figsize=(8,5))
sns.countplot(x='relevent_experience', data=data, hue='target')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x2b58029edd8>
```

→ 'relevent experience'가 있거나 없거나로 나타난다.

'relevent_experience' 분포 확인



- **enrolled_university**

```
#5. enrolled_university - LabelEncoding 필요

data['enrolled_university'].unique()
```

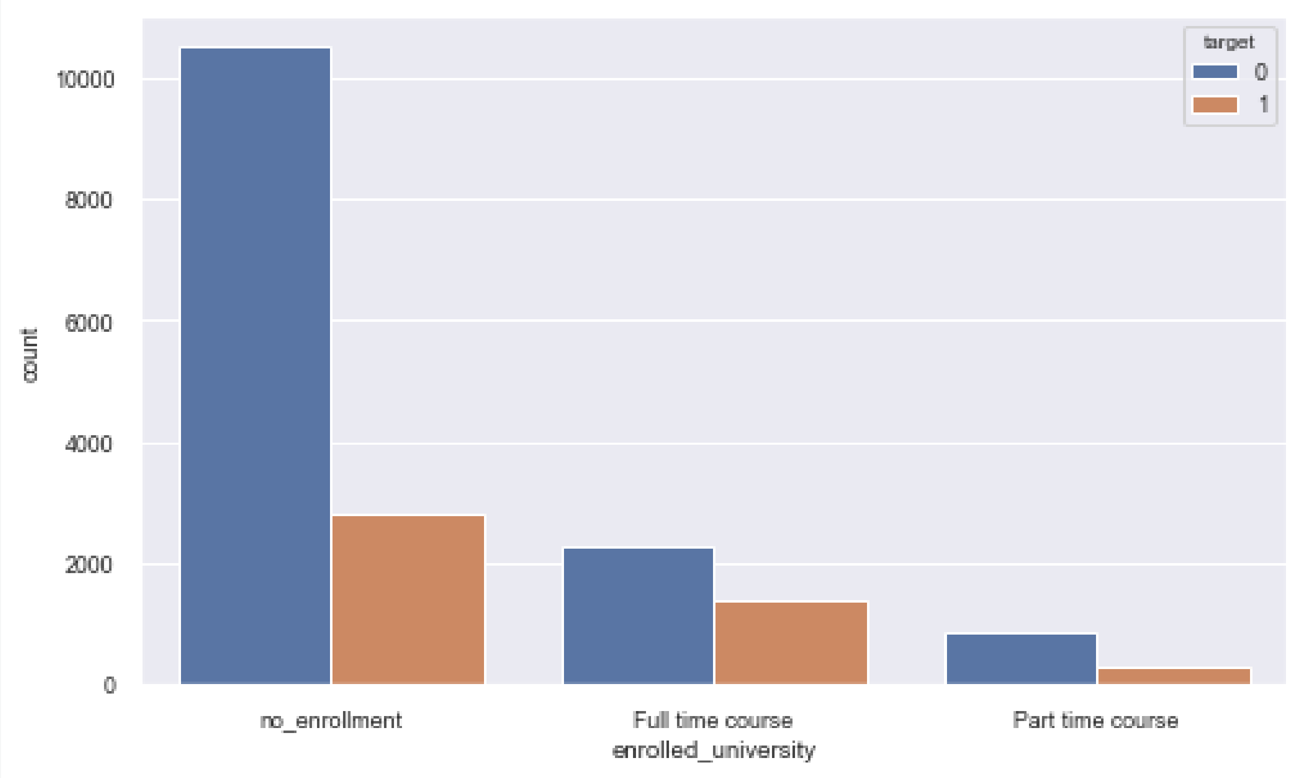
```
array(['no_enrollment', 'Full time course', 'Part time course'],
      dtype=object)
```

```
plt.figure(figsize=(8,5))
sns.countplot(x='enrolled_university', data=data, hue='target')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x2b5802f8eb8>
```

→ enrolled_university'는 'no enrollment', 'Full time course', 'Part time course' 세 가지 값을 가진다.

'enrolled_university' 분포 확인



02. 결측치 처리 및 속성별 EDA

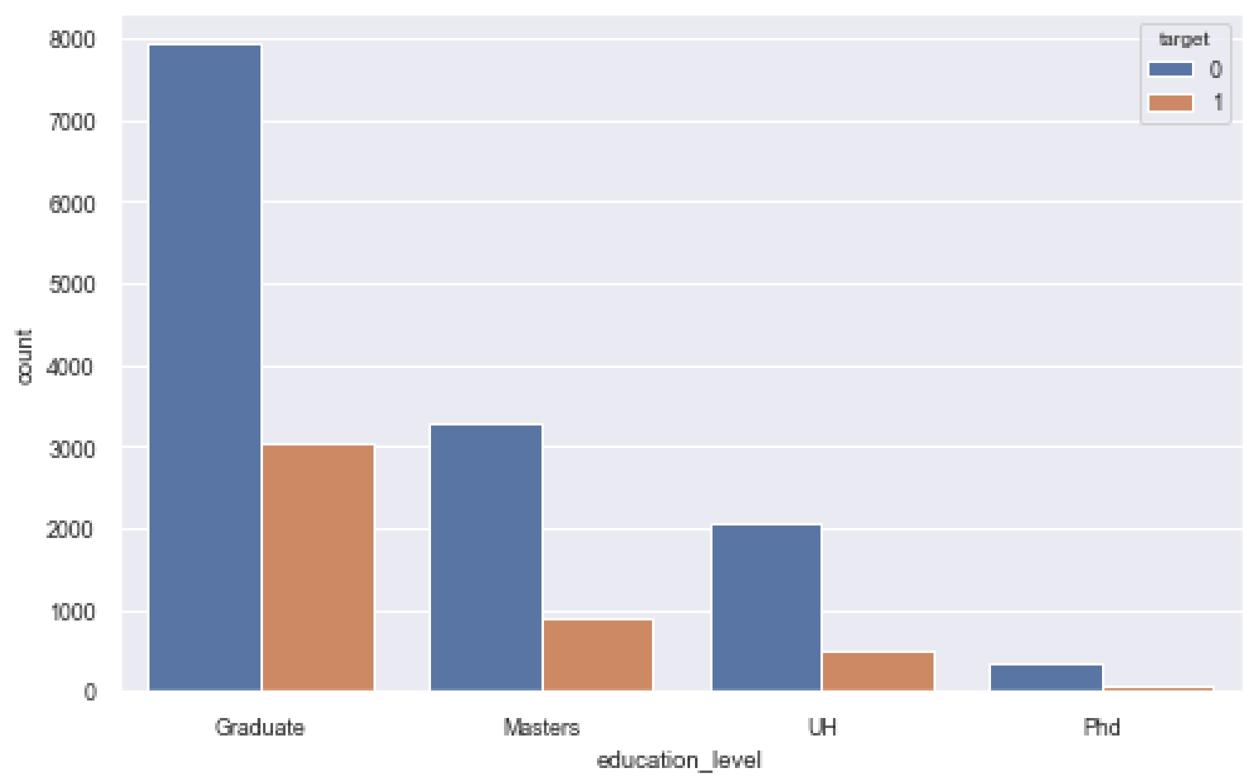
- **education_level**

```
#6. education_level - LabelEncoding

data['education_level'].value_counts()
```

```
Graduate     10962
Masters       4189
UH            2572
Phd            403
Name: education_level, dtype: int64
```

```
plt.figure(figsize=(8,5))
sns.countplot(x='education_level', data=data, hue='target')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x2b58075a9e8>
```



- **major_discipline**

```
#7. major_discipline - LabelEncoding 필요

data['major_discipline'].value_counts(dropna=False)
```

```
STEM                13980
NaN                  2572
Humanities            650
Other                 369
Business Degree       314
Arts                  241
Name: major_discipline, dtype: int64
```

```
data['major_discipline'].fillna('UH', inplace=True)

#결측값 개수가 education_level의 UH 개수와 같음
#전공 결측값 = 고졸을 의미한다는 것을 알 수 있다.
```

02. 결측치 처리 및 속성별 EDA

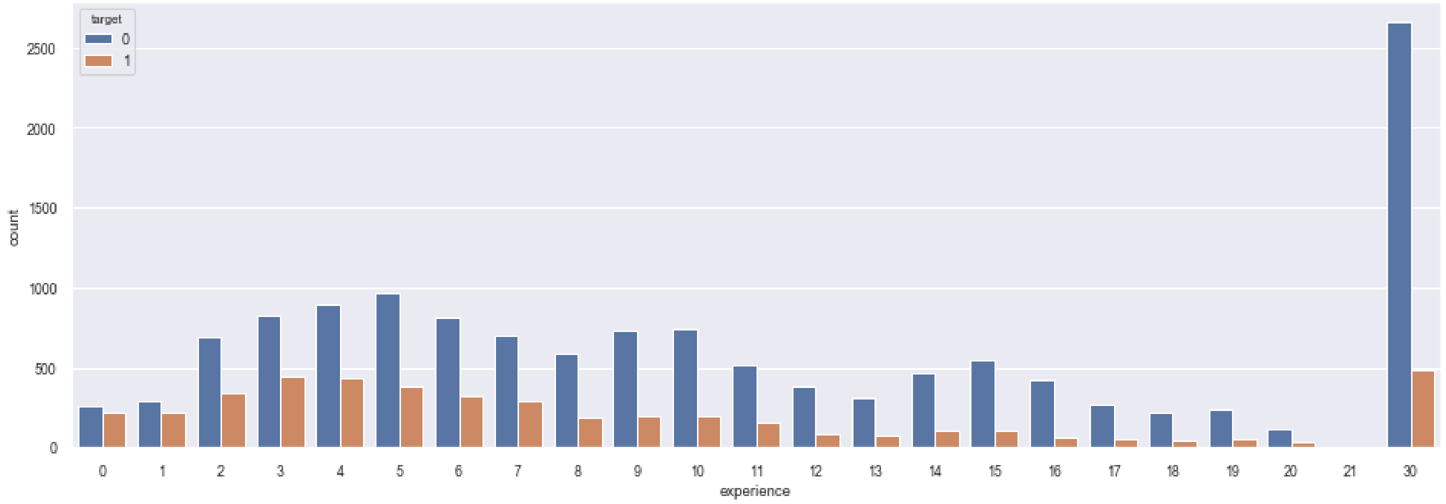
- **experience**

```
#8. experience

data['experience'].unique()
```

```
array([30, 15,  5, 11, 13,  7, 17,  2, 16,  1,  4, 10,  0, 14, 18, 19, 12,
        3,  6,  9,  8, 20, 21], dtype=int64)
```

```
plt.figure(figsize=(16, 5))
sns.countplot(x='experience',hue="target",data=data)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x2b5807524a8>
```



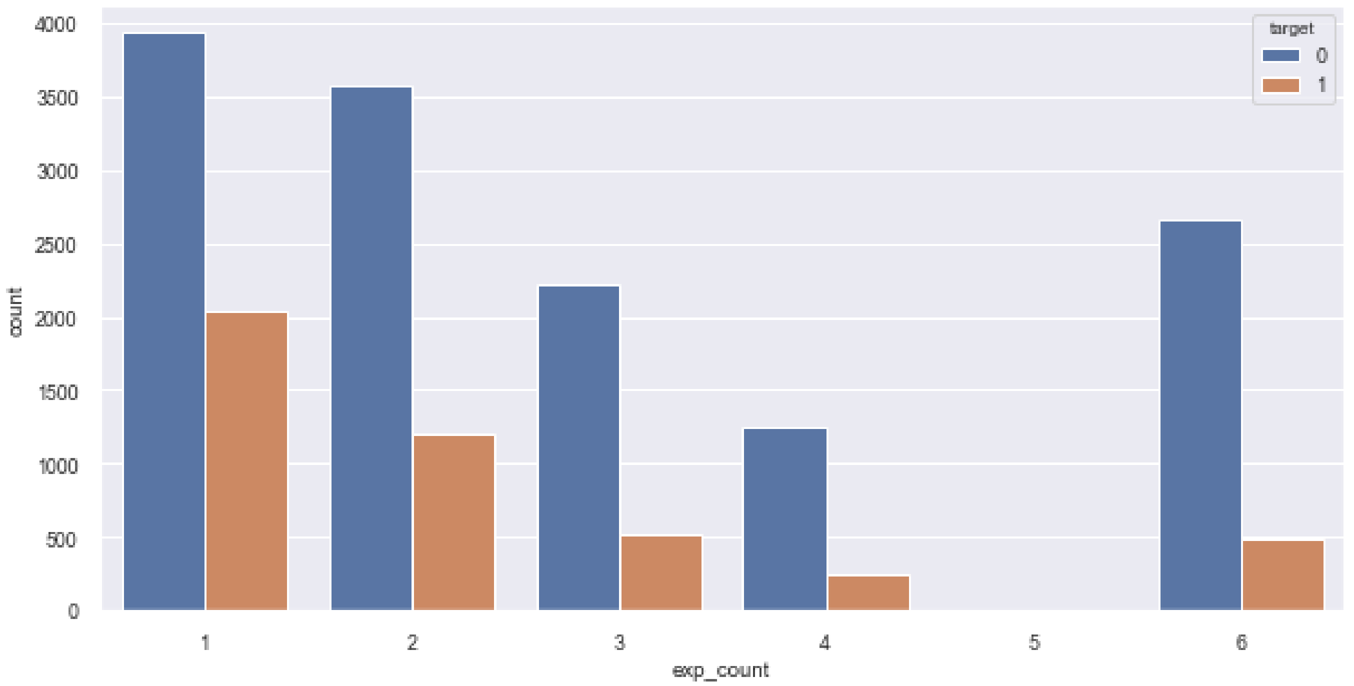
→ 너무 많은 unique한 값 존재

구간화

```
def year(x):
    if x['experience'] <= 5:
        return 1
    elif x['experience'] > 5  and x['experience'] <= 10:
        return 2
    elif x['experience'] > 10 and x['experience'] <= 15:
        return 3
    elif x['experience'] > 15 and x['experience'] <= 20:
        return 4
    elif x['experience'] > 20 and x['experience'] <= 25:
        return 5
    elif x['experience'] > 25 and x['experience'] <= 30:
        return 6

data['exp_count'] = data.apply(year, axis=1)
```

```
plt.figure(figsize=(10,5))
sns.countplot(x='exp_count', hue='target', data=data)

#경험기간이 길수록 이직률 줄어듦.
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x2b5808f0f28>
```




```
data['experience'] = data['exp_count']
data.drop(['exp_count'], axis=1, inplace=True)
```

02. 결측치 처리 및 속성별 EDA

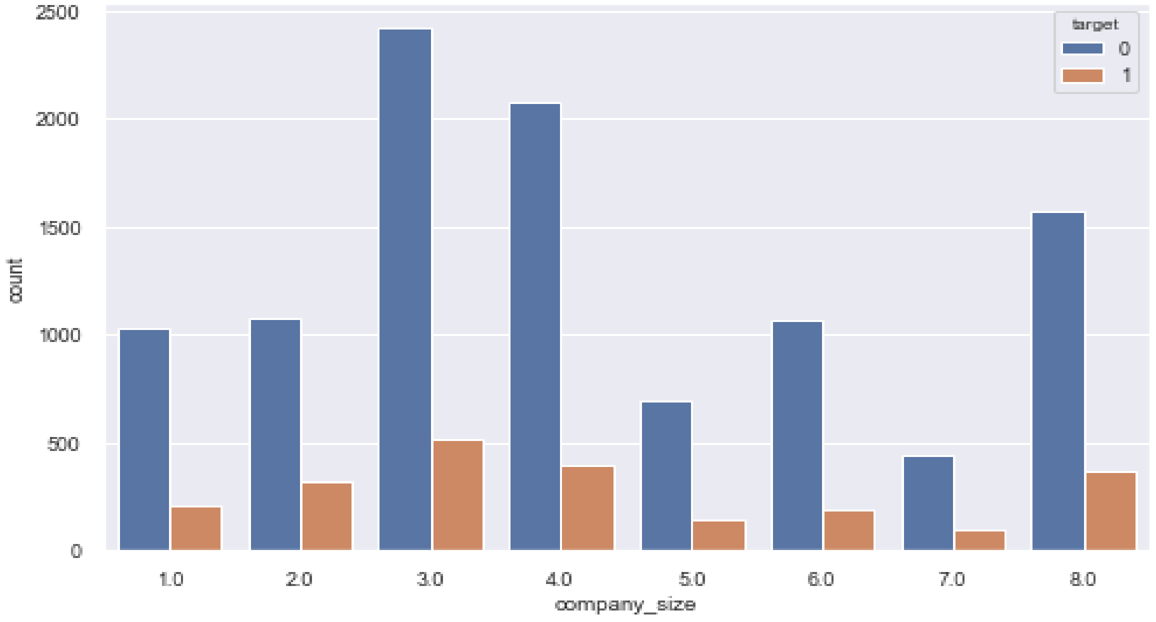
- **company_size**

```
# 9. company_size
data['company_size'].value_counts(dropna=False)
```

```
NaN     5497
3.0     2934
4.0     2465
8.0     1941
2.0     1405
6.0     1264
1.0     1245
5.0      837
7.0      538
Name: company_size, dtype: int64
```

```
plt.figure(figsize=(8,5))
sns.countplot(x='company_size', hue='target', data=data)

#결측값도 많고, 특징 보이지 않으므로 drop
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x2b5809615c0>
```



→ 일정한 패턴이 없음& 결측값 5497개로 많음 → 삭제

```
data.drop(['company_size'], axis=1, inplace=True)
```

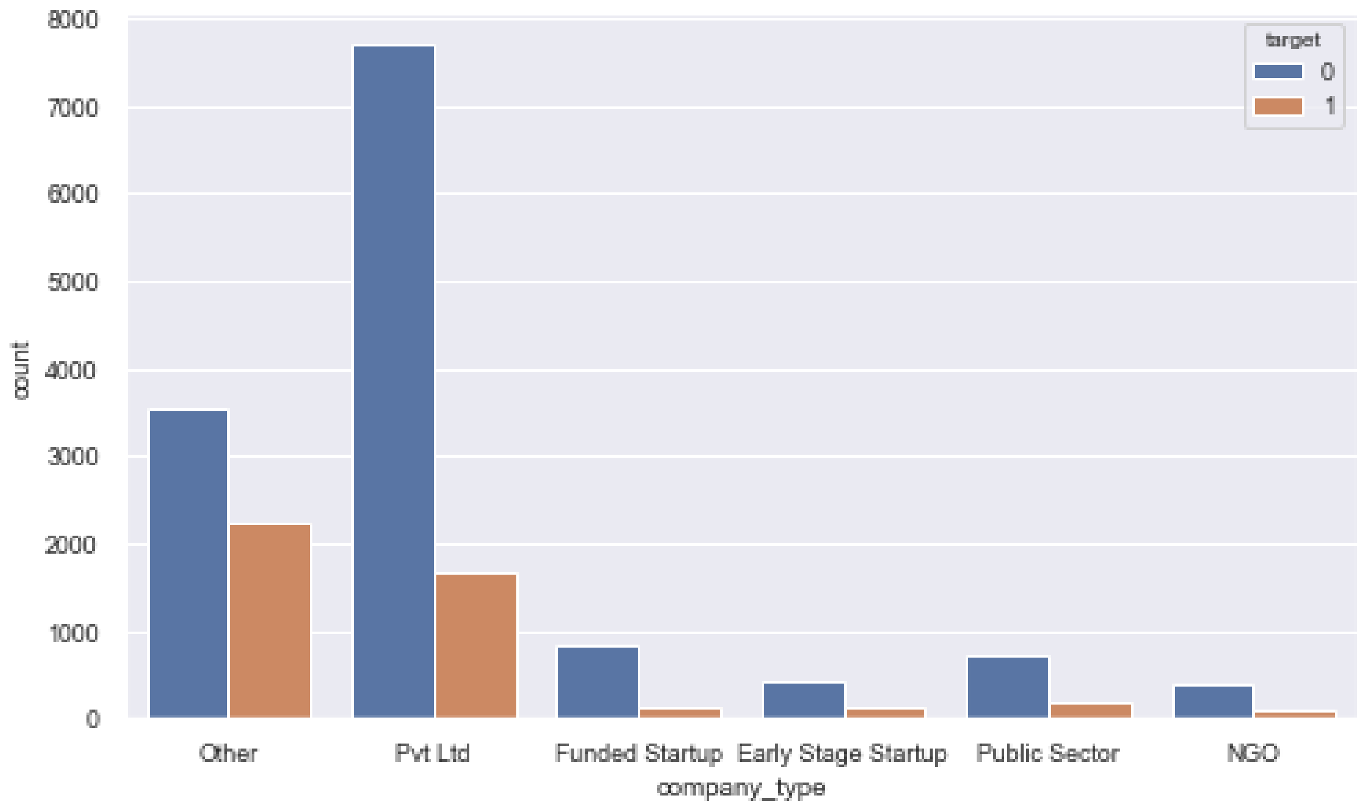
- **company_type**

```
#10. company_type - LabelEncoding 필요

data['company_type'].unique()
```

```
array(['Other', 'Pvt Ltd', 'Funded Startup', 'Early Stage Startup',
       'Public Sector', 'NGO'], dtype=object)
```

```
plt.figure(figsize=(8,5))
sns.countplot(x='company_type', hue='target', data=data)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x2b580958668>
```



02. 결측치 처리 및 속성별 EDA

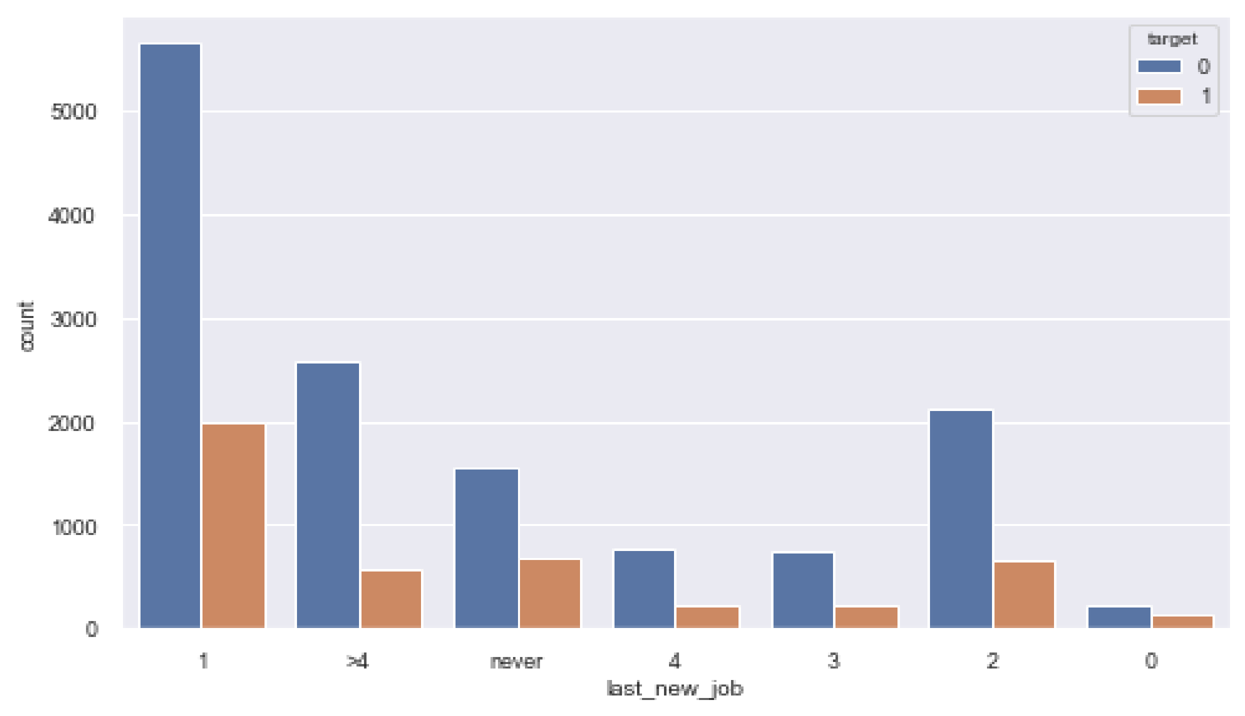
- **last_new_job**

```
#11. last_new_job - LabelEncoding 필요

data['last_new_job'].unique()
```

```
array(['1', '>4', 'never', '4', '3', '2', '0'], dtype=object)
```

```
plt.figure(figsize=(8,5))
sns.countplot(x='last_new_job', hue='target', data=data)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x2b580868940>
```



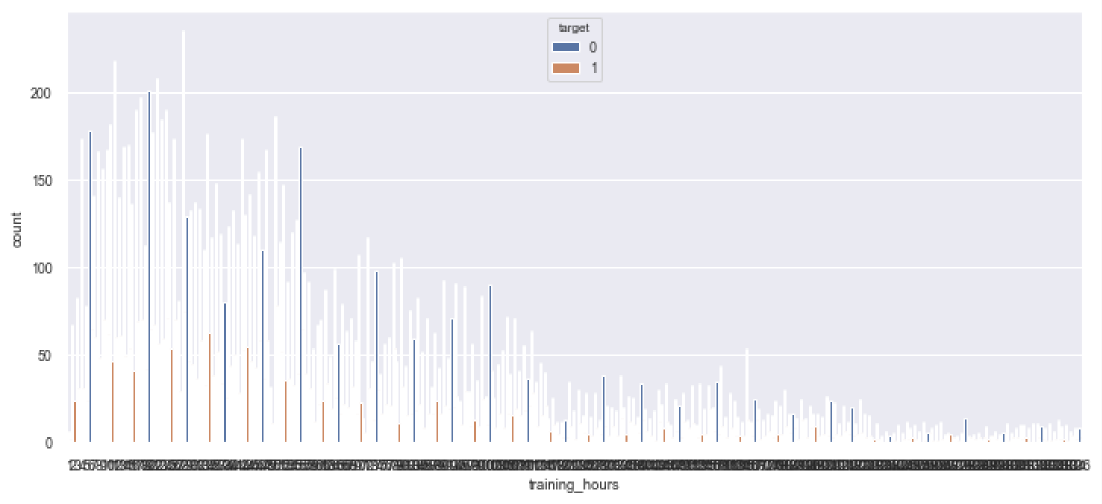
- **training_hours**

```
#12. training_hours

len(data['training_hours'].unique())
```

```
241
```

```
plt.figure(figsize=(12,5))
sns.countplot(x='training_hours', hue='target', data=data)

#training_hours가 적을수록 이직률 낮음
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x2b5806422e8>
```



03. 데이터 전처리

- **레이블 인코딩**

```
#레이블 인코딩

from sklearn.preprocessing import LabelEncoder

col_lb = ['gender','relevent_experience','enrolled_university','education_level','major_discipline',
          'company_type','last_new_job']

def encoding(li):
    for col in li:
        encoder = LabelEncoder()
        data[col] = encoder.fit_transform(data[col])
        print(col)
        for i, j in enumerate(encoder.classes_):
            print(j, '->', i)
        print('')

encoding(col_lb)
```

```
data.head()
```

	city_development_Index	gender	relevent_experience	enrolled_university	education_level	major_discipline	experience	company_type	last_new_job	training_hours	target
0	0.920	1	0	2	0	4	6	3	1	36	1
1	0.776	1	1	2	0	4	3	5	5	47	0
2	0.624	1	1	0	0	4	1	3	6	83	0
3	0.767	1	0	2	1	4	6	1	4	8	0
4	0.764	1	0	1	0	4	3	3	1	24	1

결과

```
gender
Female -> 0
Male -> 1

relevent_experience
Has relevent experience -> 0
No relevent experience -> 1

enrolled_university
Full time course -> 0
Part time course -> 1
no_enrollment -> 2

education_level
Graduate -> 0
Masters -> 1
Phd -> 2
UH -> 3

major_discipline
Arts -> 0
Business Degree -> 1
Humanities -> 2
Other -> 3
STEM -> 4
UH -> 5

company_type
Early Stage Startup -> 0
Funded Startup -> 1
NGO -> 2
Other -> 3
Public Sector -> 4
Pvt Ltd -> 5

last_new_job
0 -> 0
1 -> 1
2 -> 2
3 -> 3
4 -> 4
>4 -> 5
never -> 6
```

03. 데이터 전처리

- **Feature Scaling – MinMaxScaler**

```
#피처 스케일링

from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler()
data.loc[:,:'training_hours'] = scaler.fit_transform(data.loc[:,:'training_hours'])

data.head()
```

	city_development_Index	gender	relevent_experience	enrolled_university	education_level	major_discipline	experience	company_type	last_new_job	training_hours	target
0	0.942116	1.0	0.0	1.0	0.000000	0.8	1.0	0.6	0.166667	0.104478	1
1	0.654691	1.0	1.0	1.0	0.000000	0.8	0.4	1.0	0.833333	0.137313	0
2	0.351297	1.0	1.0	0.0	0.000000	0.8	0.0	0.6	1.000000	0.244776	0
3	0.636727	1.0	0.0	1.0	0.333333	0.8	1.0	0.2	0.666667	0.020896	0
4	0.630739	1.0	0.0	0.5	0.000000	0.8	0.4	0.6	0.166667	0.068657	1

- **traing set/test set 분리**

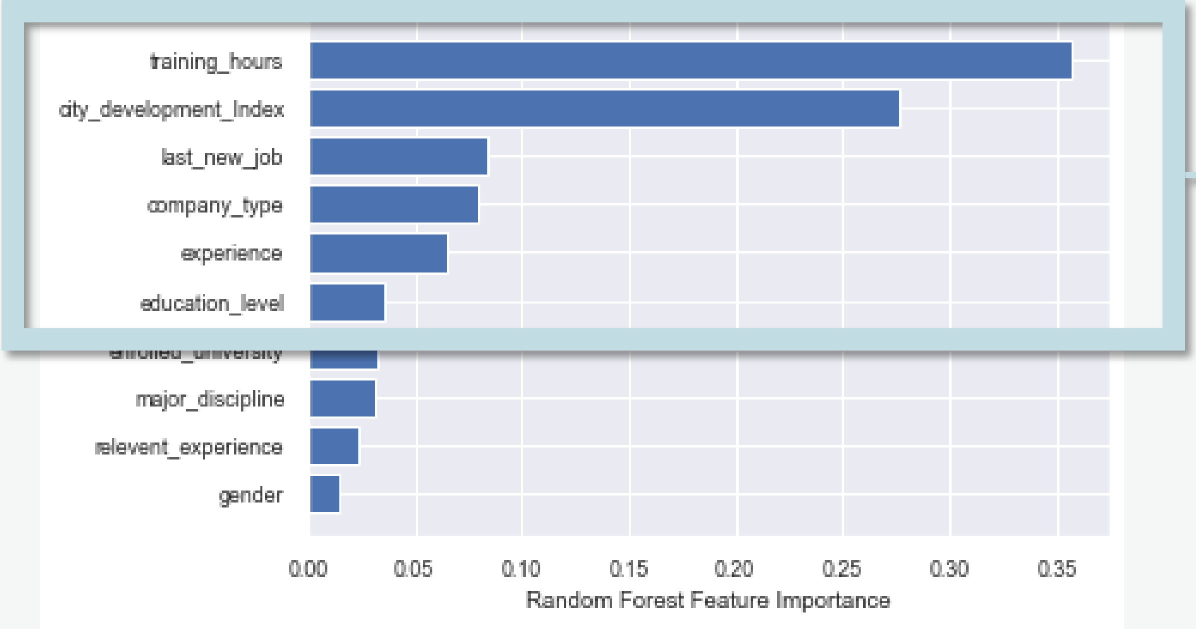
```
from sklearn.model_selection import train_test_split

X_data = data.iloc[:,:-1]
y_data = data.iloc[:,-1]

X_train, X_test, y_train, y_test = train_test_split(X_data, y_data, test_size = 0.3, random_state=42)
```

03. 데이터 전처리

- **유의미한 변수 추출 – RandomForestClassifier의 feature_importances 사용**

```
from sklearn.ensemble import RandomForestClassifier

rf = RandomForestClassifier(n_estimators=200, random_state=0)
rf.fit(X_train, y_train)
sorted_idx = rf.feature_importances_.argsort()
plt.barh(data.columns[sorted_idx], rf.feature_importances_[sorted_idx])
plt.xlabel("Random Forest Feature Importance")
```

```
Text(0.5, 0, 'Random Forest Feature Importance')
```



유의미한 변수로 Top6 추출
: training hours, city_development_Index, last_new_job, company_type, experience, education_level

```
X_train = X_train[['training_hours','city_development_Index','last_new_job',
                   'company_type','experience','education_level']]
X_test = X_test[['training_hours','city_development_Index','last_new_job',
                 'company_type','experience','education_level']]
```

04. 모델링

- 모델링 : KNN, SVM, Logistic Regression

```
#KNN

from sklearn import neighbors

knn = neighbors.KNeighborsClassifier()
knn.fit(X_train, y_train)
pred_knn = knn.predict(X_test)
```

```
#SVM

from sklearn.svm import SVC

svm_l = SVC(kernel='linear')
svm_l.fit(X_train, y_train)
pred_svm_l = svm_l.predict(X_test)

svm_r = SVC(kernel = 'rbf')
svm_r.fit(X_train, y_train)
pred_svm_r = svm_r.predict(X_test)
```

```
#Logistic Regression

from sklearn.linear_model import LogisticRegression

lr = LogisticRegression()
lr.fit(X_train, y_train)
pred_lr = lr.predict(X_test)
```

- 정확도 측정

```
#정확도 측정

from sklearn.metrics import accuracy_score

ac_knn = accuracy_score(y_test, pred_knn)
ac_svm_l = accuracy_score(y_test, pred_svm_l)
ac_svm_r = accuracy_score(y_test, pred_svm_r)
ac_lr = accuracy_score(y_test, pred_lr)

print(ac_knn, ac_svm_l, ac_svm_r, ac_lr)

#SVM(비선형)의 정확도 제일 높게 나오므로 SVM GridSearchCV 실행
```

```
0.7546892239794042 0.7583670467083486 0.779882309672738 0.7765722692166238
```

KNN	SVM-linear	SVM-rbf	Logistic Regression
0.7546892239794042	0.7583670467083486	0.779882309672738	0.7765722692166238

SVM Radial Bias Function Kernel 의
정확도가 제일 높게 나옴

GridSearchCV 실행

04. 모델링

```
#GridSearchCV

from sklearn.model_selection import GridSearchCV
```

```
#SVM(비선형) - GridSearch

param_grid = {'C': [10, 100, 150],
              'gamma': [0,1, 1, 2]}

grid_svm_r = GridSearchCV(svm_r, param_grid, cv=5, refit=True)
grid_svm_r.fit(X_train, y_train)
print(grid_svm_r.best_params_)
```

```
{'C': 150, 'gamma': 1}
```

```
grid_pred_svm = grid_svm_r.predict(X_test)
print(accuracy_score(y_test, grid_pred_svm))
```

```
0.78411180581096
```

train_data를 통한
SVM GridSearchCV 모델 학습

최종 정확도 = 0.784

05. Test data의 Target 예측

- **Train data에서 한 작업을 똑같이 진행함**

1. test data 확인 및 필요없는 열 삭제

```
test =  pd.read_csv('changingjob_testx.csv')
```

```
test.head()
```

	Unnamed: 0	Unnamed: 0.1	city	city_development_Index	gender	relevent_experience	enrolled_university	education_level	major_discipline	experience
0	0	18126	city_128	0.527	Other	Has relevent experience	no_enrollment	Graduate	STEM	4
1	1	18127	city_114	0.926	Other	Has relevent experience	no_enrollment	Graduate	STEM	16
2	2	18128	city_114	0.926	Male	Has relevent experience	no_enrollment	Graduate	STEM	12
3	3	18129	city_67	0.855	Male	Has relevent experience	no_enrollment	Graduate	STEM	0
4	4	18130	city_100	0.887	Male	Has relevent experience	no_enrollment	Graduate	STEM	2

```
test = test.iloc[:,2:]
```

05. Test data의 Target 예측

2. 데이터 전처리 진행 - drop하거나, 새로운 값을 넣어준 속성만 진행

```
test.drop(['city'], axis=1, inplace=True)
test['gender'] = test['gender'].map({'Other':'Male', 'Male':'Male', 'Female':'Female'})
test['major_discipline'].fillna('UH', inplace=True)
test['exp_count'] = test.apply(year, axis=1)
test['experience'] = test['exp_count']
test.drop(['exp_count'], axis=1, inplace=True)
test.drop(['company_size'], axis=1, inplace=True)
```

3. 레이블 인코딩

```
#레이블 인코딩

col_lb = ['gender','relevent_experience','enrolled_university','education_level',
          'major_discipline','company_type','last_new_job']

def encoding(li):
    for col in li:
        encoder = LabelEncoder()
        test[col] = encoder.fit_transform(test[col])

encoding(col_lb)
```

05. Test data의 Target 예측

4. 피처 스케일링

```
#피처 스케일링

test.loc[:,:'training_hours'] = scaler.transform(test.loc[:,:'training_hours'])

test.head()
```

	city_development_Index	gender	relevent_experience	enrolled_university	education_level	major_discipline	experience	company_type	last_new_job	training_hours
0	0.157685	1.0	0.0	1.0	0.0	0.8	0.0	1.0	0.666667	0.104478
1	0.954092	1.0	0.0	1.0	0.0	0.8	0.6	1.0	0.833333	0.020896
2	0.954092	1.0	0.0	1.0	0.0	0.8	0.4	1.0	0.666667	0.101493
3	0.812375	1.0	0.0	1.0	0.0	0.8	0.0	0.6	0.166667	0.119403
4	0.876248	1.0	0.0	1.0	0.0	0.8	0.0	1.0	0.333333	0.047761

5. Target 값 예측 진행 및 정확도 측정

```
test = test[['training_hours','city_development_Index','last_new_job',
             'company_type','experience','education_level']]
```

```
y_test_pred = grid_svm_r.predict(test)
```

```
y_pred = pd.DataFrame(y_test_pred)
y_pred.columns =['target']
y_pred['index'] = y_pred.index
y_pred = y_pred[['index', 'target']]

y_pred.to_csv("kaggle.csv", header=True, index=False)
```

0.78750

kaggle score

감사합니다