1 Data Science Career Change Likelihood

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Data Science Career Change Likelihood

1.1 Overview

Client: RADS - Recruiting Awesome Data Scientists Incorporation. Data Scientist recruiting firm looking for potential future Data Scientists.

Data, Methodology, and Analysis:

Data source: HR Analytics https://www.kaggle.com/arashnic/hr-analytics-job-change-of-data-scientists (https://www.kaggle.com/arashnic/hr-analytics-job-change-of-data-scientists)

Context: the data is from a company that is active in Big Data and Data Science and ran a training program with the intention to hire data scientists among people who successfully passed courses they conducted.

This dataset includes current credentials, demographics, experience, education, which will help us build models for RADs about candidates that are likely to be looking for a job change.

Models:

1. Logistic Regression Classifier
2. Decision Tree Classifier
3. Random Forest Classifier
4. Gradient Booster Classifier

2 Data Exploration, Cleansing, Visualization, and Preparation

Data Exploration
Explore HR Analytics data

Data Cleansing
Check for duplicates; drop NaN (missing) values and unnecessary columns; continuously clean data as necessary

Data Visualization
Use visualizations to explore the data and determine how to further refine the dataset in order to prepare for modeling

Data Preparation
Prepare the data for modeling

2.1 Data Exploration and Cleansing

Import data and all packages needed for data exploration and modeling

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns

from sklearn.model_selection import train_test_split
from sklearn.impute import SimpleImputer
import sklearn.preprocessing as preprocessing
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import OneHotEncoder, StandardScaler, MinMaxScal
from sklearn.metrics import classification_report, accuracy_score
from sklearn import tree
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
from sklearn import svm, datasets
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import KFold
from sklearn.metrics import confusion_matrix
from sklearn.metrics import plot_confusion_matrix
from sklearn.metrics import ConfusionMatrixDisplay
from sklearn.feature_selection import RFE

import pydotplus
from sklearn.tree import export_graphviz, plot_tree
from pydotplus import graph_from_dot_data
from IPython.display import Image
#from dtreeviz.trees import *

import os
import warnings
```

executed in 1.28s, finished 07:59:47 2022-01-10

In [2]:
```
# Import data

df = pd.read_csv('aug_train.csv',index_col=0)
```

executed in 35ms, finished 07:59:48 2022-01-10

In [3]:
```
# View dataframe

df
```

executed in 21ms, finished 07:59:48 2022-01-10

Out[3]:

	city	city_development_index	gender	relevent_experience	enrolled_university	educa
enrollee_id						
8949	city_103	0.920	Male	Has relevent experience	no_enrollment	
29725	city_40	0.776	Male	No relevent experience	no_enrollment	
11561	city_21	0.624	NaN	No relevent experience	Full time course	
33241	city_115	0.789	NaN	No relevent experience	NaN	
666	city_162	0.767	Male	Has relevent experience	no_enrollment	
...	...	...	...	...	...	
7386	city_173	0.878	Male	No relevent experience	no_enrollment	
31398	city_103	0.920	Male	Has relevent experience	no_enrollment	
24576	city_103	0.920	Male	Has relevent experience	no_enrollment	
5756	city_65	0.802	Male	Has relevent experience	no_enrollment	Hi
23834	city_67	0.855	NaN	No relevent experience	no_enrollment	Prima

19158 rows × 13 columns

In [4]:
```
# Explore columns and values

df.info()
```
executed in 14ms, finished 07:59:48 2022-01-10

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 19158 entries, 8949 to 23834
Data columns (total 13 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   city                    19158 non-null  object 
 1   city_development_index  19158 non-null  float64
 2   gender                  14650 non-null  object 
 3   relevent_experience     19158 non-null  object 
 4   enrolled_university     18772 non-null  object 
 5   education_level         18698 non-null  object 
 6   major_discipline        16345 non-null  object 
 7   experience              19093 non-null  object 
 8   company_size            13220 non-null  object 
 9   company_type            13018 non-null  object 
 10  last_new_job            18735 non-null  object 
 11  training_hours          19158 non-null  int64  
 12  target                  19158 non-null  float64
dtypes: float64(2), int64(1), object(10)
memory usage: 2.0+ MB
```

2.1.1 Feature Description Definitions

Features

enrollee_id: Unique ID for candidate

city: City code

city_development_index: Development index of the city (scaled)

gender: Gender of candidate

relevant_experience: Relevant experience of candidate

enrolled_university: Type of University course enrolled if any

education_level: Education level of candidate

major_discipline: Education major discipline of candidate

experience: Candidate total experience in years

company_size: Number of employees in current employer's company

company_type: Type of current employer

lastnewjob: Difference in years between previous job and current job

training_hours: Data science course training hours completed target: 0 – Not looking for job change, 1 – Looking for a job change

In [5]:
```
# Check for duplicates

df.duplicated().sum()
```
executed in 15ms, finished 07:59:48 2022-01-10

Out[5]:
```
49
```

In [6]:
```
# Drop duplicates

df = df.drop_duplicates()
```
executed in 17ms, finished 07:59:48 2022-01-10

In [7]:
```
# Check there are no duplicates remaining

df.duplicated().sum()
```
executed in 16ms, finished 07:59:48 2022-01-10

Out[7]:
```
0
```

In [8]:
```
# Check sum of Missing (NaN) values

df.isna().sum()
```
executed in 10ms, finished 07:59:48 2022-01-10

Out[8]:
```
city                         0
city_development_index       0
gender                    4508
relevent_experience          0
enrolled_university        386
education_level            460
major_discipline          2809
experience                  65
company_size              5920
company_type              6122
last_new_job               423
training_hours               0
target                       0
dtype: int64
```

In [9]:
```
# Create formula to observe percentages of the values missing

df_missing = df.isna().sum()
df_missing/len(df)
```
executed in 12ms, finished 07:59:48 2022-01-10

Out[9]:
```
city                      0.000000
city_development_index    0.000000
gender                    0.235910
relevent_experience       0.000000
enrolled_university       0.020200
education_level           0.024072
major_discipline          0.146999
experience                0.003402
company_size              0.309802
company_type              0.320373
last_new_job              0.022136
training_hours            0.000000
target                    0.000000
dtype: float64
```

In [10]:
```
# Check data types

df.info()
```
executed in 13ms, finished 07:59:48 2022-01-10

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 19109 entries, 8949 to 23834
Data columns (total 13 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   city                    19109 non-null  object 
 1   city_development_index  19109 non-null  float64
 2   gender                  14601 non-null  object 
 3   relevent_experience     19109 non-null  object 
 4   enrolled_university     18723 non-null  object 
 5   education_level         18649 non-null  object 
 6   major_discipline        16300 non-null  object 
 7   experience              19044 non-null  object 
 8   company_size            13189 non-null  object 
 9   company_type            12987 non-null  object 
 10  last_new_job            18686 non-null  object 
 11  training_hours          19109 non-null  int64  
 12  target                  19109 non-null  float64
dtypes: float64(2), int64(1), object(10)
memory usage: 2.0+ MB
```

In [11]:
```
# Drop 65 NaN values in 'experience'

df = df.dropna(subset=['experience'])
```
executed in 7ms, finished 07:59:48 2022-01-10

In [12]:
```
# Check there are no NaN values remaining for 'experience'

df.isna().sum()
```
executed in 10ms, finished 07:59:48 2022-01-10

Out[12]:
```
city                         0
city_development_index       0
gender                    4459
relevent_experience          0
enrolled_university        381
education_level            450
major_discipline          2792
experience                   0
company_size              5897
company_type              6086
last_new_job               399
training_hours               0
target                       0
dtype: int64
```

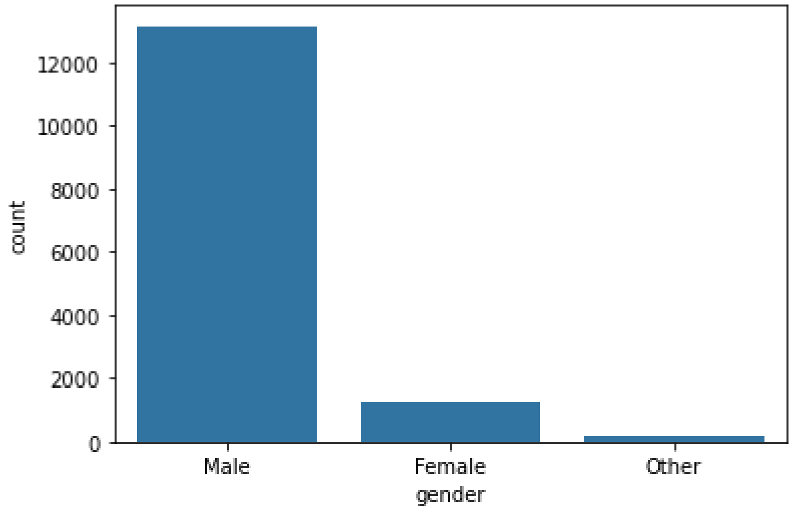
In [13]:
```
# Explore the value counts of each feature

for col in df.columns:
    print(df[col].value_counts())
```
executed in 29ms, finished 07:59:48 2022-01-10

```
city_103    4300
city_21     2680
city_16     1527
city_114    1334
city_160     842
            ...
city_121       3
city_111       3
city_129       3
city_171       1
city_140       1
Name: city, Length: 123, dtype: int64
0.920    5142
0.624    2680
0.910    1527
0.926    1334
0.698     676
         ...
0.649       4
```

2.2 Data Visualization

In [14]:
```
sns.countplot(x='gender',data=df, color='tab:blue')
```
executed in 105ms, finished 07:59:48 2022-01-10

Out[14]:
```
<AxesSubplot:xlabel='gender', ylabel='count'>
```

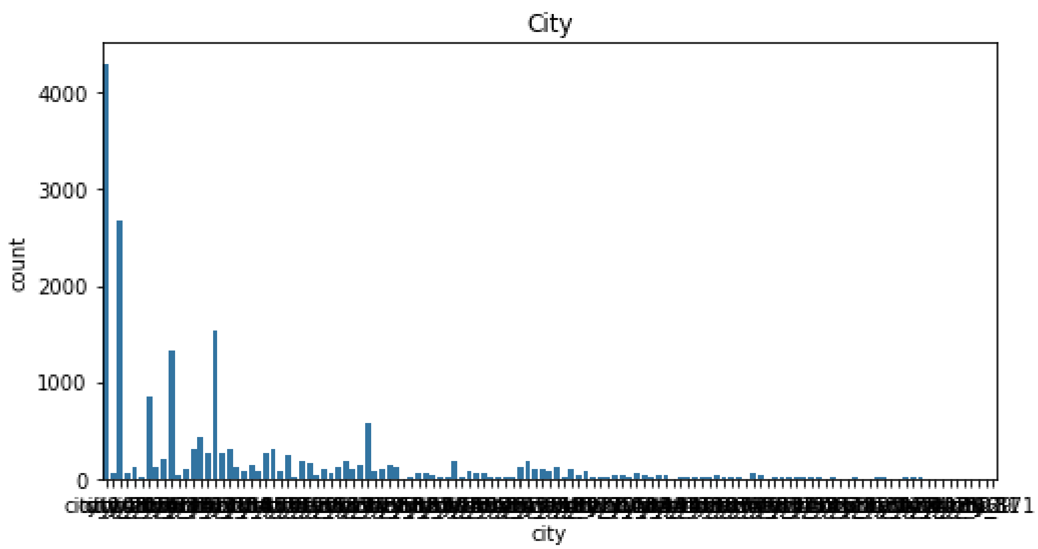


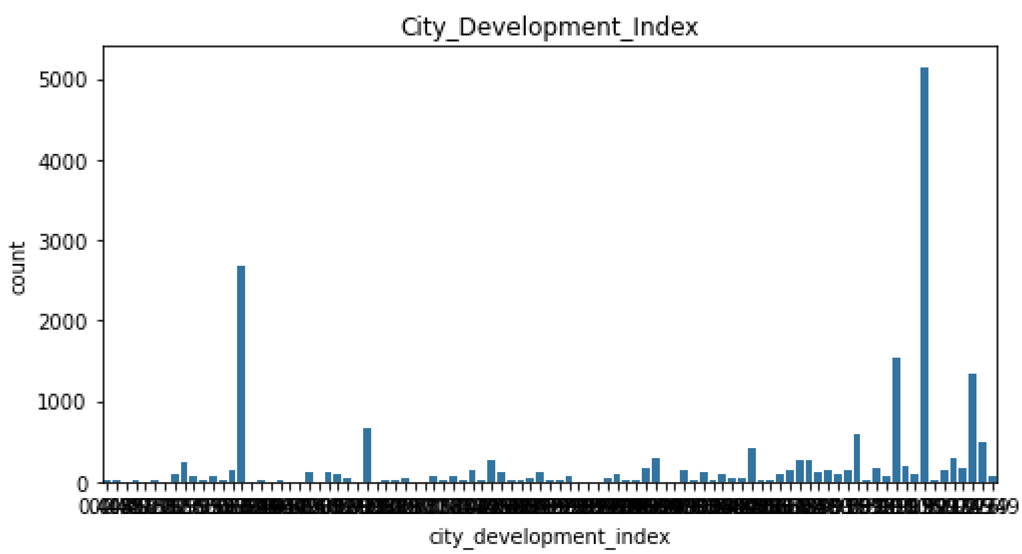
In [15]:
```
df['gender'].value_counts()
```
executed in 5ms, finished 07:59:48 2022-01-10

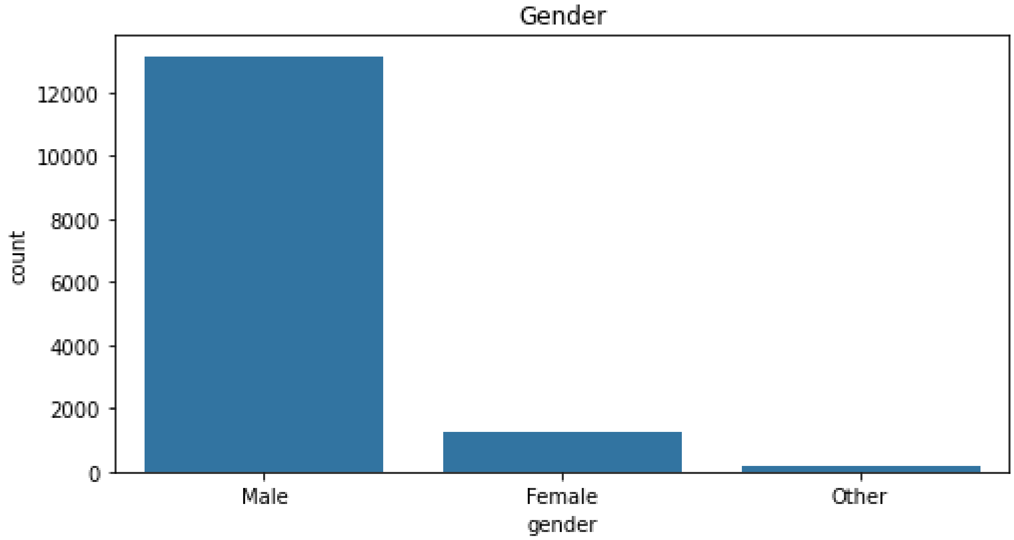
Out[15]:
```
Male      13161
Female     1236
Other       188
Name: gender, dtype: int64
```

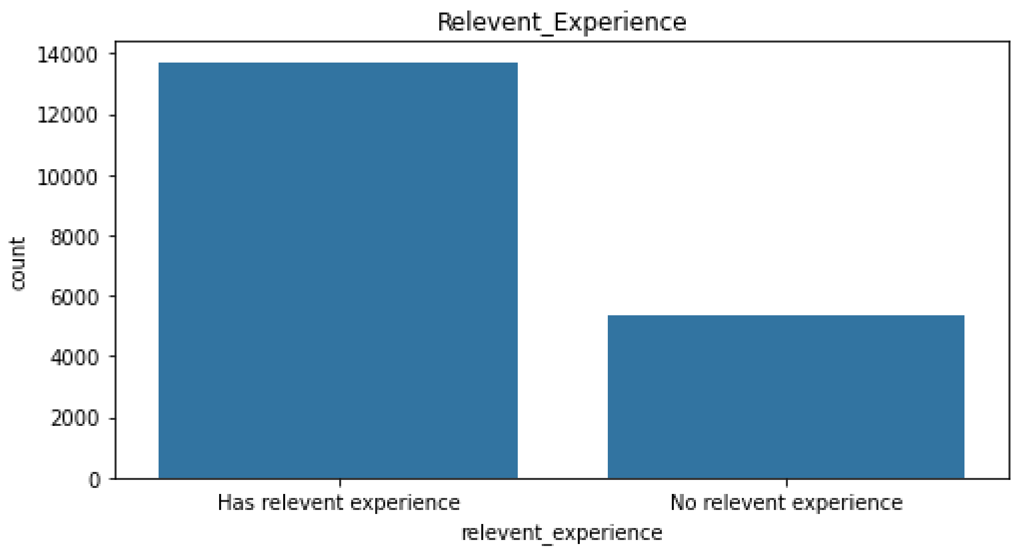
In [16]:
```
for col in df.columns:
    fig,ax=plt.subplots(figsize=(8,4))
    if col!='training_hours':
        sns.countplot(x=col,data=df,ax=ax,color='tab:blue')
    else:
        sns.histplot(x=col,data=df,ax=ax,color='tab:blue')
    ax.set(title=col.title())
    plt.show()
```

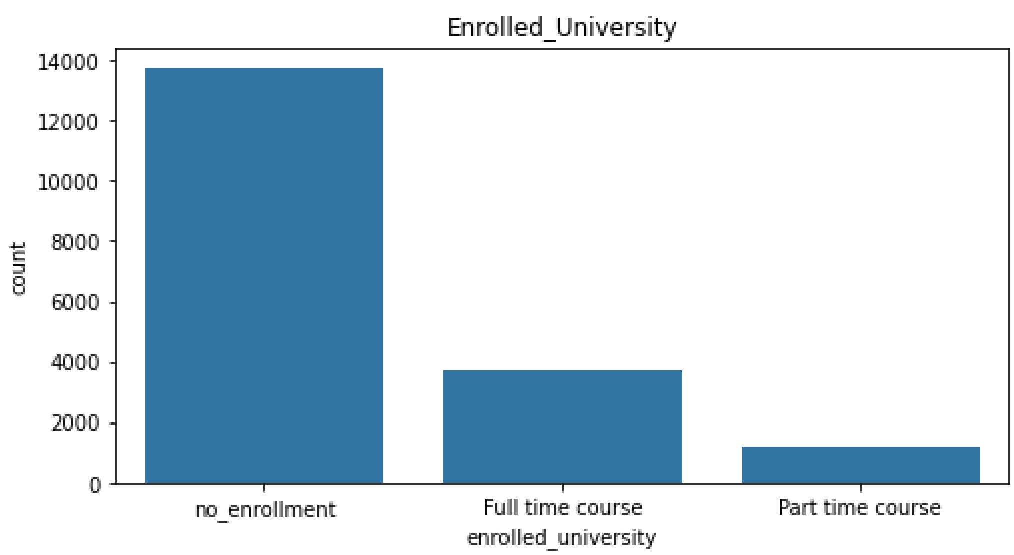
executed in 4.12s, finished 07:59:52 2022-01-10

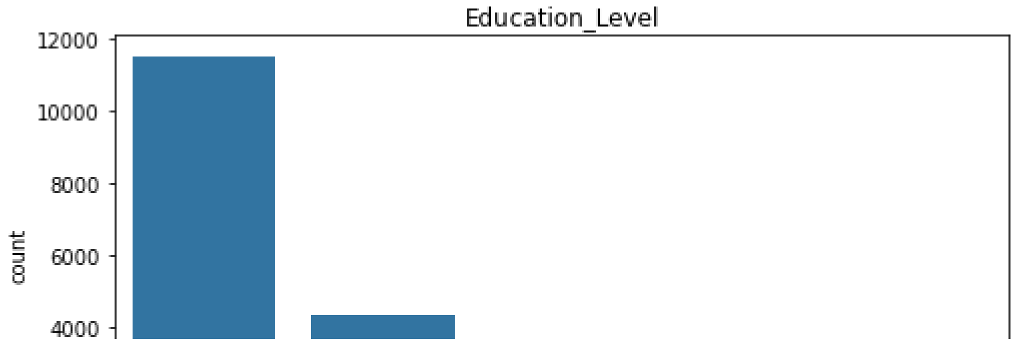


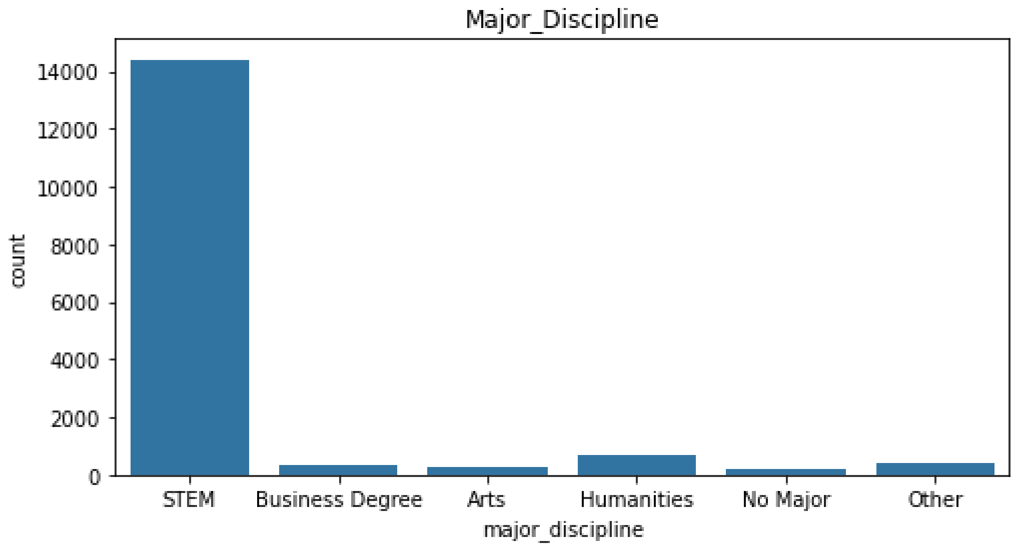


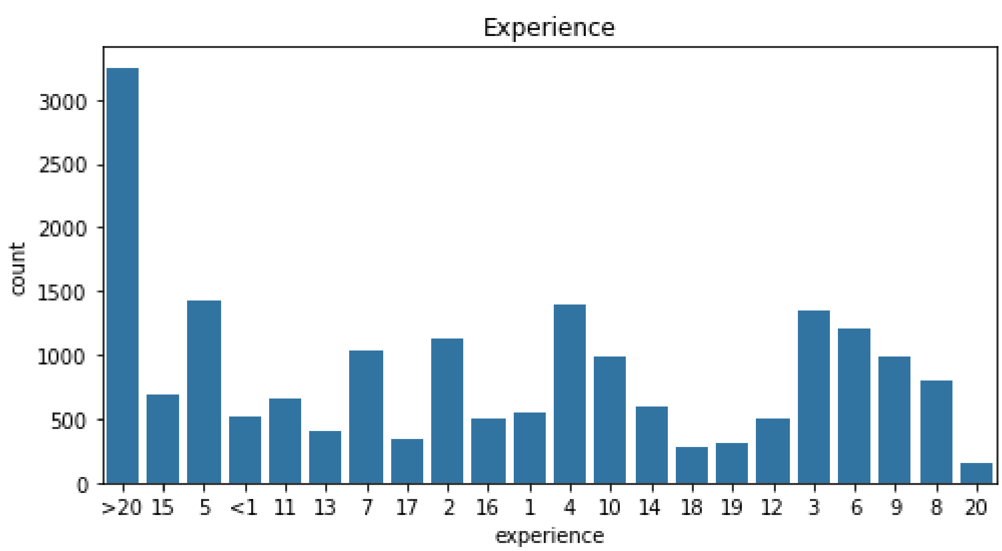

Gender
count
12000
10000
8000
6000
4000
2000
0
Male
Female
Other
gender


Relevent_Experience
count
14000
12000
10000
8000
6000
4000
2000
0
Has relevent experience
No relevent experience
relevent_experience

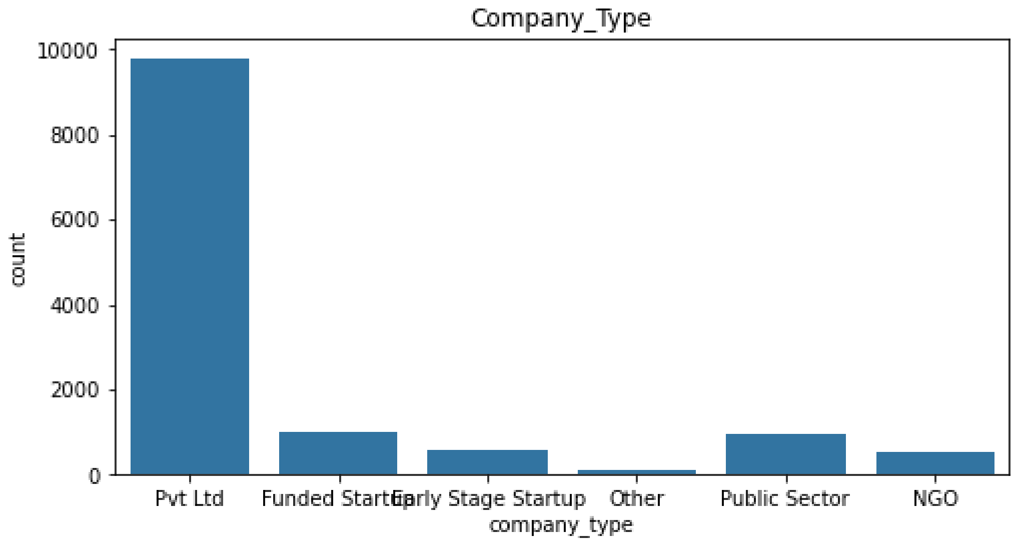

Enrolled_University
count
14000
12000
10000
8000
6000
4000
2000
0
no_enrollment
Full time course
Part time course
enrolled_university

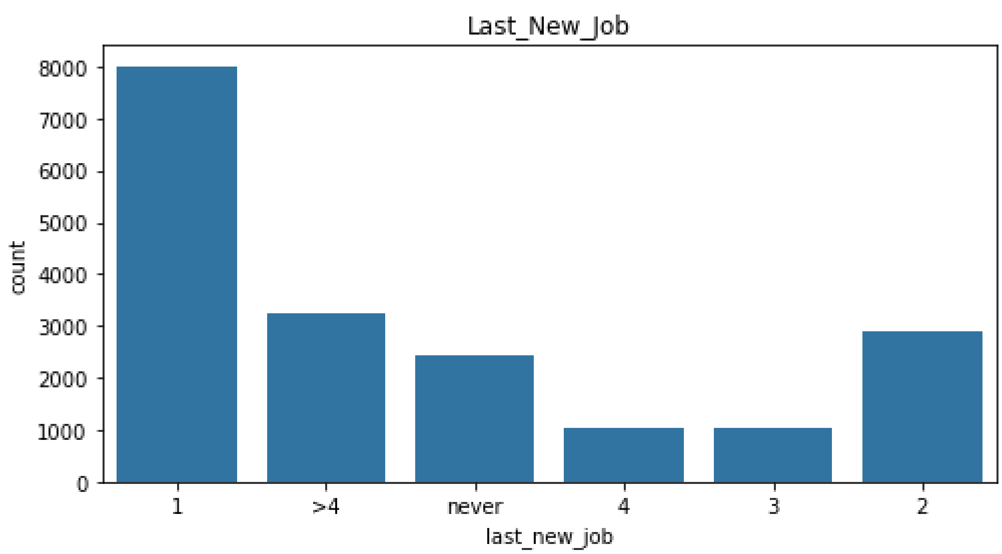

Education_Level
count
12000
10000
8000
6000
4000

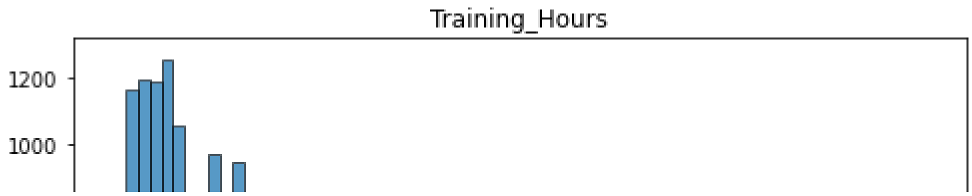

Major_Discipline
count
14000
12000
10000
8000
6000
4000
2000
0
STEM
Business Degree
Arts
Humanities
No Major
Other
major_discipline

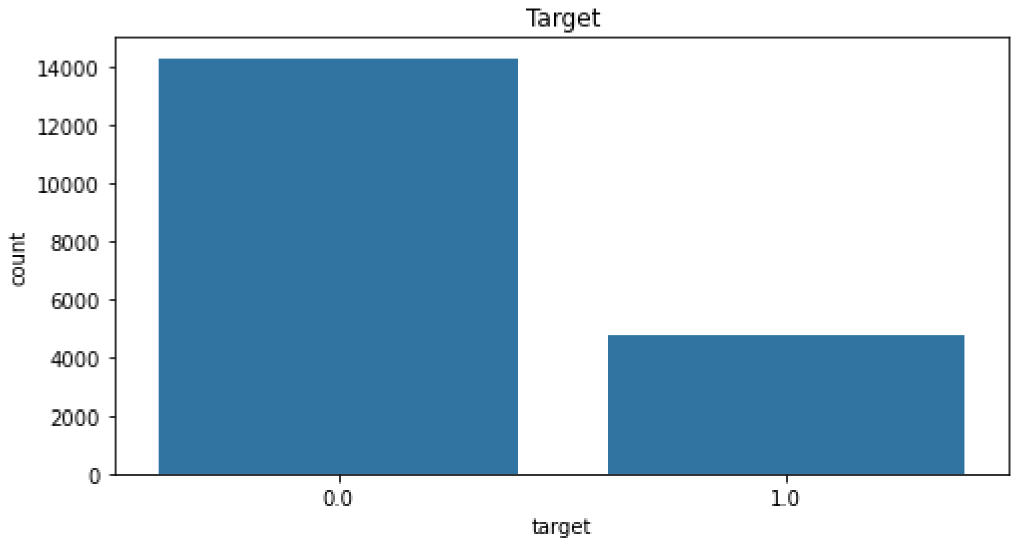

Experience
count
3000
2500
2000
1500
1000
500
0
>20 15 5 <1 11 13 7 17 2 16 1 4 10 14 18 19 12 3 6 9 8 20
experience


Company_Size
3000
2500


Company_Type
count
10000
8000
6000
4000
2000
0
Pvt Ltd
Funded Startup
Early Stage Startup
Other
Public Sector
NGO
company_type


Last_New_Job
count
8000
7000
6000
5000
4000
3000
2000
1000
0
1
>4
never
4
3
2
last_new_job



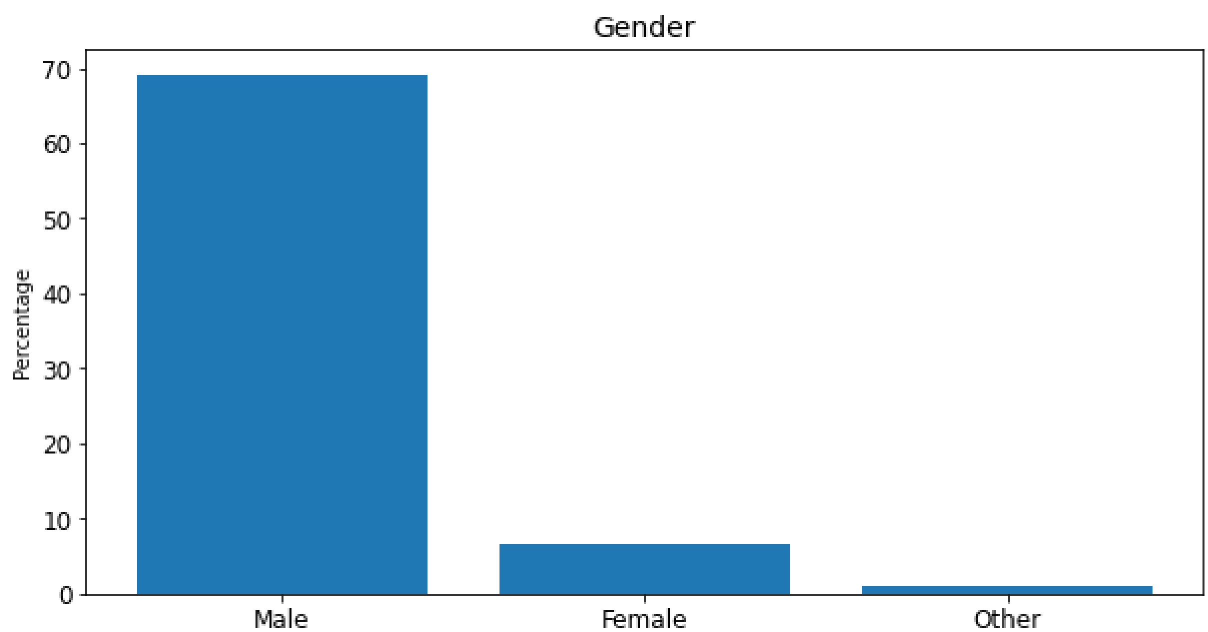


In [17]:
```
# Calculate % of Gender

gender_percent = (df['gender'].value_counts()/len(df['gender']))*100
gender_percent
```
executed in 7ms, finished 07:59:52 2022-01-10

Out[17]:
```
Male      69.108381
Female     6.490233
Other      0.987188
Name: gender, dtype: float64
```

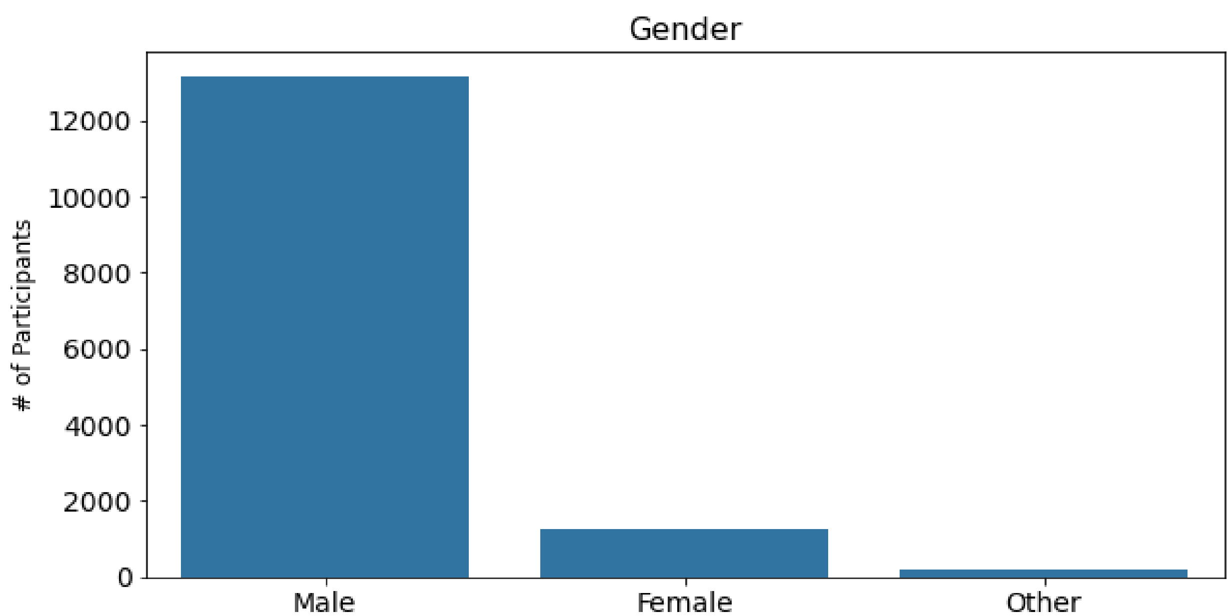
In [18]:
```
# Create cleaner visualizations for presentation
# Gender - Graph #1

data = {'Male':69.1, 'Female':6.5, 'Other':1}
gender = list(data.keys())
values = list(data.values())

fig = plt.figure(figsize = (10, 5))

plt.bar(gender, values, color ='tab:blue')

plt.ylabel("Percentage", fontsize=10)
plt.title("Gender",fontsize=14)
plt.xticks(fontsize=12)
plt.yticks(fontsize=12)
ax.grid(False)
plt.show()
```

executed in 100ms, finished 07:59:52 2022-01-10



In [19]:
```
# Create cleaner visualizations for presentation
# Gender - Graph #2

fig, ax = plt.subplots(figsize=(10,5))
sns.countplot(x='gender',data=df, color='tab:blue');
ax.grid(False)

plt.xlabel(None)
plt.ylabel("# of Participants", fontsize=12)
plt.title("Gender",fontsize=16)
plt.xticks(fontsize=14)
plt.yticks(fontsize=14)
ax.grid(False)
plt.show()
```

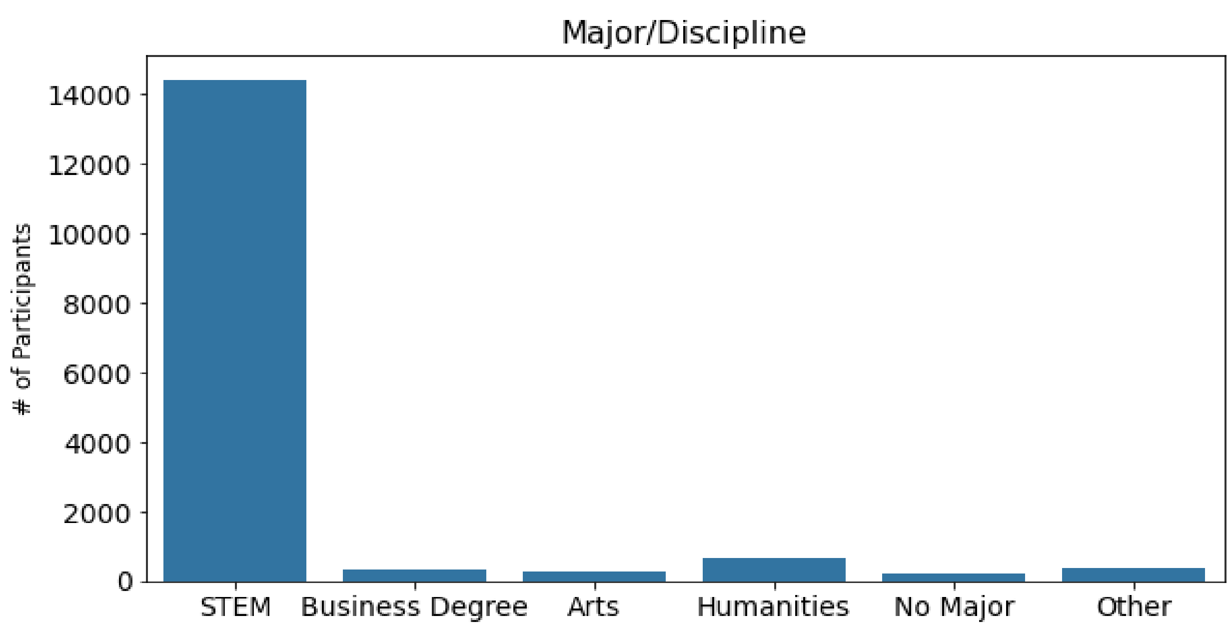
executed in 117ms, finished 07:59:52 2022-01-10



In [20]:
```
# Calculate % of each major_discipline

major_percent = (df['major_discipline'].value_counts()/len(df['major_discip
major_percent
```
executed in 7ms, finished 07:59:52 2022-01-10

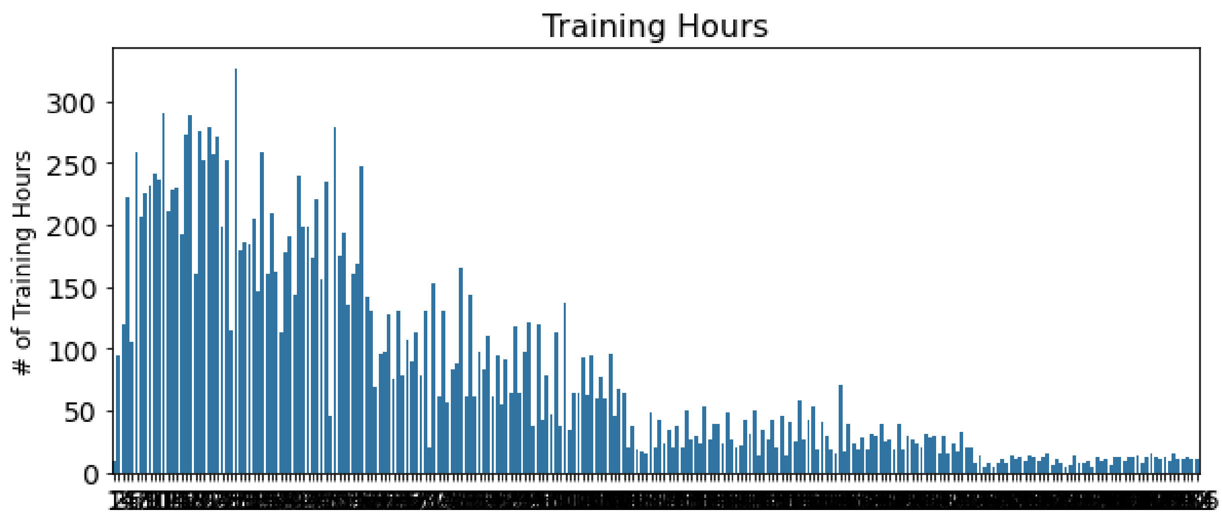
Out[20]:
```
STEM               75.645873
Humanities          3.507666
Other               1.979626
Business Degree     1.711825
Arts                1.323251
No Major            1.170972
Name: major_discipline, dtype: float64
```

In [21]:
```
# Create cleaner visualizations for presentation
# Major/Discipline

fig, ax = plt.subplots(figsize=(10,5))
sns.countplot(x='major_discipline',data=df, color='tab:blue');
ax.grid(False)

plt.xlabel(None)
plt.ylabel("# of Participants", fontsize=12)
plt.title("Major/Discipline",fontsize=16)
plt.xticks(fontsize=14)
plt.yticks(fontsize=14)
ax.grid(False)
plt.show()
```
executed in 133ms, finished 07:59:52 2022-01-10



In [22]:
```
# Create cleaner visualizations for presentation
# Training Hours - original graph is cleaner

fig, ax = plt.subplots(figsize=(10,4))
sns.countplot(x='training_hours',data=df, color='tab:blue');
ax.grid(False)

plt.xlabel(None)
plt.ylabel("# of Training Hours", fontsize=12)
plt.title("Training Hours",fontsize=16)
plt.xticks(fontsize=14)
plt.yticks(fontsize=14)
ax.grid(False)
plt.show()
plt.tight_layout()
```

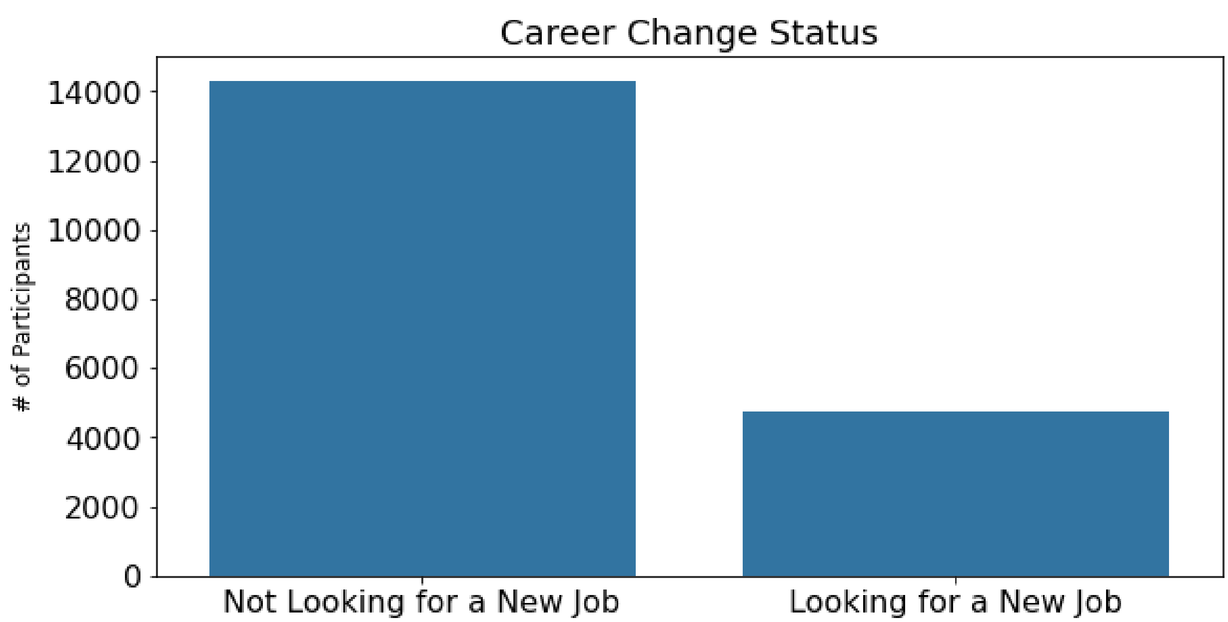
executed in 2.77s, finished 07:59:55 2022-01-10




```
<Figure size 432x288 with 0 Axes>
```

In [23]:
```
# Create cleaner visualizations for presentation
# Career Change Status

fig, ax = plt.subplots(figsize=(10,5))
sns.countplot(x='target',data=df, color='tab:blue');
ax.grid(False)
#ax.set_title('Target');
#ax.set(xlabel=None, ylabel = "Count");
ax.xaxis.set_ticklabels(['Not Looking for a New Job',
                         'Looking for a New Job']);

plt.xlabel(None)
plt.ylabel("# of Participants", fontsize=12)
plt.title("Career Change Status",fontsize=18)
plt.xticks(fontsize=16)
plt.yticks(fontsize=16)
plt.show()
```

executed in 104ms, finished 07:59:55 2022-01-10



2.3 Data Preparation

2.3.1 Create y (Target) and X

In [24]:
```
# Create y (Target)
# Create X

y = df['target']
X = df.drop(columns=['target'])
```
executed in 4ms, finished 07:59:55 2022-01-10

2.3.2 Check for Class Imbalance

In [25]:
```
# Check for class imbalance

y.value_counts(normalize=True)
```
executed in 5ms, finished 07:59:55 2022-01-10

Out[25]:
```
0.0    0.750998
1.0    0.249002
Name: target, dtype: float64
```

The data is imbalanced

2.3.3 Train Test Split the Data

In [26]:
```
# Create Train and Test data subsets using train_test_split
# Check shape of each data set

X_train, X_test, y_train, y_test = train_test_split(
    X, y, random_state=100, stratify=y)

X_train.shape, X_test.shape, y_train.shape, y_test.shape
```
executed in 13ms, finished 07:59:55 2022-01-10

Out[26]:
```
((14283, 12), (4761, 12), (14283,), (4761,))
```

In [27]:
```
# Check the shape of the data is the same

X_train.shape[0]+X_test.shape[0]==df.shape[0]
```
executed in 2ms, finished 07:59:55 2022-01-10

Out[27]:
```
True
```

2.3.4 Impute, Fit, and Transform the Data

- We believe the missing values in the dataset will be useful for our modeling
- Impute NaN values to "Missing" vs. not using the data

In [28]:
```
# Impute NaN values to "Missing"

X_train_processed = X_train.fillna('Missing')
X_test_processed = X_test.fillna('Missing')
```
executed in 12ms, finished 07:59:55 2022-01-10

In [29]:
```
# Check Train data - no missing values remaining

X_train_processed.isna().sum()
```
executed in 10ms, finished 07:59:55 2022-01-10

Out[29]:
```
city                      0
city_development_index    0
gender                    0
relevent_experience       0
enrolled_university       0
education_level           0
major_discipline          0
experience                0
company_size              0
company_type              0
last_new_job              0
training_hours            0
dtype: int64
```

In [30]:
```
# Check Train data - no missing values remaining

X_test_processed.isna().sum()
```
executed in 6ms, finished 07:59:55 2022-01-10

Out[30]:
```
city                      0
city_development_index    0
gender                    0
relevent_experience       0
enrolled_university       0
education_level           0
major_discipline          0
experience                0
company_size              0
company_type              0
last_new_job              0
training_hours            0
dtype: int64
```

In [31]:
```
# Explore data and datatypes

X_train_processed.info()
```
executed in 13ms, finished 07:59:55 2022-01-10

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 14283 entries, 3921 to 1762
Data columns (total 12 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   city                    14283 non-null  object 
 1   city_development_index  14283 non-null  float64
 2   gender                  14283 non-null  object 
 3   relevent_experience     14283 non-null  object 
 4   enrolled_university     14283 non-null  object 
 5   education_level         14283 non-null  object 
 6   major_discipline        14283 non-null  object 
 7   experience              14283 non-null  object 
 8   company_size            14283 non-null  object 
 9   company_type            14283 non-null  object 
 10  last_new_job            14283 non-null  object 
 11  training_hours          14283 non-null  int64  
dtypes: float64(1), int64(1), object(10)
memory usage: 1.4+ MB
```

In [32]:
```
# Look at X_train_processed dataframe

X_train_processed
```
executed in 15ms, finished 07:59:55 2022-01-10

Out[32]:

	city	city_development_index	gender	relevent_experience	enrolled_university	educ
enrollee_id						
3921	city_36	0.893	Missing	No relevent experience	no_enrollment	
21627	city_21	0.624	Missing	No relevent experience	Full time course	
24478	city_83	0.923	Male	Has relevent experience	no_enrollment	
32459	city_114	0.926	Male	No relevent experience	Full time course	
4033	city_114	0.926	Male	Has relevent experience	no_enrollment	
...	...	...	...	...	...	
17425	city_136	0.897	Male	Has relevent	Part time course	

In [33]:
```
# Clean 'experience' feature
# Change from string to integer

for df in (X_train_processed, X_test_processed):
    df['experience'] = df['experience'].apply(lambda x: x.replace('>',''))
    df['experience'] = df['experience'].apply(lambda x: x.replace('<',''))
    df['experience'] = df['experience'].astype(int)
```
executed in 14ms, finished 07:59:55 2022-01-10

In [34]:
```
# Look at 'experience' data column

X_train_processed['experience']
```
executed in 4ms, finished 07:59:55 2022-01-10

Out[34]:
```
enrollee_id
3921     20
21627     1
24478    16
32459     6
4033     20
         ..
17425     7
22588    20
9372     20
18874     6
1762      6
Name: experience, Length: 14283, dtype: int64
```

In [35]:
```
# Explore the Train data using .describe()

X_train_processed.describe()
```
executed in 15ms, finished 07:59:55 2022-01-10

Out[35]:

	city_development_index	experience	training_hours
count	14283.000000	14283.000000	14283.000000
mean	0.828626	9.940209	65.323461
std	0.123131	6.435927	59.952557
min	0.448000	1.000000	1.000000
25%	0.740000	4.000000	23.000000
50%	0.899000	9.000000	47.000000
75%	0.920000	16.000000	88.000000
max	0.949000	20.000000	336.000000

In [36]:
```
# Explore the Test data using .describe()

X_test_processed.describe()
```
executed in 14ms, finished 07:59:55 2022-01-10

Out[36]:

	city_development_index	experience	training_hours
count	4761.000000	4761.000000	4761.000000
mean	0.829697	9.940559	65.712665
std	0.123812	6.524810	60.515681
min	0.448000	1.000000	1.000000
25%	0.740000	4.000000	23.000000
50%	0.910000	8.000000	47.000000
75%	0.920000	16.000000	89.000000
max	0.949000	20.000000	336.000000

In [37]:
```
# Create variable for "number" columns (integers, floats)
# Create variable for "category" columns (objects, strings)
# Check CATEGORY COLUMNS

NUMBER_COLUMNS = X_train_processed.select_dtypes('number').columns

CATEGORY_COLUMNS = X_train_processed.select_dtypes('object').columns
CATEGORY_COLUMNS
```
executed in 7ms, finished 07:59:55 2022-01-10

Out[37]:
```
Index(['city', 'gender', 'relevent_experience', 'enrolled_university',
       'education_level', 'major_discipline', 'company_size', 'company_ty
pe',
       'last_new_job'],
      dtype='object')
```

In [38]:
```
# Check NUMBER COLUMNS

NUMBER_COLUMNS
```
executed in 2ms, finished 07:59:55 2022-01-10

Out[38]:
```
Index(['city_development_index', 'experience', 'training_hours'], dtype
='object')
```

2.3.5 One Hot Encode Category Columns

In [39]:
```
# ONE HOT ENCODE

ohe = OneHotEncoder(handle_unknown='ignore',sparse=False)
X_train_ohe = ohe.fit_transform(X_train_processed[CATEGORY_COLUMNS])
X_test_ohe = ohe.transform(X_test_processed[CATEGORY_COLUMNS])

# CHECK
X_train_ohe = pd.DataFrame(
    X_train_ohe, columns=ohe.get_feature_names(CATEGORY_COLUMNS))
X_test_ohe = pd.DataFrame(
    X_test_ohe, columns=ohe.get_feature_names(CATEGORY_COLUMNS))
```
executed in 48ms, finished 07:59:55 2022-01-10

Reset Index

In [40]:
```
for df in (X_train_processed, X_test_processed,
            y_train, y_test, X_train_ohe, X_test_ohe):
    df.reset_index(drop=True, inplace=True)
```
executed in 2ms, finished 07:59:55 2022-01-10

2.3.6 CREATE X_train and X_test data

Concatenate OHE Data with Number Columns

In [41]:
```
# Concatenate Number Columns with One Hot Encoded Columns

X_train = pd.concat([X_train_processed[NUMBER_COLUMNS],
                        X_train_ohe],
                        axis=1)
X_test = pd.concat([X_test_processed[NUMBER_COLUMNS],
                        X_test_ohe],
                        axis=1)
```
executed in 23ms, finished 07:59:55 2022-01-10

In [42]:

```
# Look at X_train data

X_train
```

executed in 27ms, finished 07:59:55 2022-01-10

Out[42]:

	city_development_index	experience	training_hours	city_city_1	city_city_10	city_city_100	c
0	0.893	20	4	0.0	0.0	0.0	
1	0.624	1	17	0.0	0.0	0.0	
2	0.923	16	96	0.0	0.0	0.0	
3	0.926	6	16	0.0	0.0	0.0	
4	0.926	20	32	0.0	0.0	0.0	
...	...	...	...	...	...	...	
14278	0.897	7	65	0.0	0.0	0.0	
14279	0.913	20	39	0.0	0.0	0.0	
14280	0.910	20	39	0.0	0.0	0.0	
14281	0.866	6	144	0.0	0.0	0.0	

In [43]:

```
# Look at X_test data

X_test
```

executed in 25ms, finished 07:59:55 2022-01-10

Out[43]:

	city_development_index	experience	training_hours	city_city_1	city_city_10	city_city_100	city
0	0.579	7	30	0.0	0.0	0.0	
1	0.890	14	39	0.0	0.0	0.0	
2	0.920	12	80	0.0	0.0	0.0	
3	0.624	10	19	0.0	0.0	0.0	
4	0.766	7	54	0.0	0.0	0.0	
...	...	...	...	...	...	...	
4756	0.624	11	158	0.0	0.0	0.0	
4757	0.920	8	66	0.0	0.0	0.0	
4758	0.624	15	5	0.0	0.0	0.0	
4759	0.920	13	116	0.0	0.0	0.0	
4760	0.920	4	8	0.0	0.0	0.0	

4761 rows × 172 columns

In [44]:
```
# Ensure there are no remaining NaN values in Train data

X_train.isna().sum()
```
executed in 10ms, finished 07:59:55 2022-01-10

Out[44]:
```
city_development_index     0
experience                 0
training_hours             0
city_city_1                0
city_city_10               0
                          ..
last_new_job_3             0
last_new_job_4             0
last_new_job_>4            0
last_new_job_Missing       0
last_new_job_never         0
Length: 172, dtype: int64
```

In [45]:
```
# Ensure there are no remaining NaN values in Test data

X_test.isna().sum()
```
executed in 7ms, finished 07:59:56 2022-01-10

Out[45]:
```
city_development_index     0
experience                 0
training_hours             0
city_city_1                0
city_city_10               0
                          ..
last_new_job_3             0
last_new_job_4             0
last_new_job_>4            0
last_new_job_Missing       0
last_new_job_never         0
Length: 172, dtype: int64
```

3 CLASSIFICATION MODELS

3.1 Logistic Regression Model

In [46]:
```
logreg = LogisticRegression()
log_reg_model = logreg.fit(X_train, y_train)
log_reg_model
```
executed in 335ms, finished 07:59:56 2022-01-10

```
/Users/v/opt/anaconda3/envs/learn-env/lib/python3.8/site-packages/sklear
n/linear_model/_logistic.py:762: ConvergenceWarning: lbfgs failed to conv
erge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown i
n:
    https://scikit-learn.org/stable/modules/preprocessing.html (https://s
cikit-learn.org/stable/modules/preprocessing.html)
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-re
gression (https://scikit-learn.org/stable/modules/linear_model.html#logis
tic-regression)
  n_iter_i = _check_optimize_result(
```

Out[46]: LogisticRegression()

In [47]:
```
from sklearn.feature_selection import RFE

rfe = RFE(estimator = log_reg_model,
          n_features_to_select = 20, step=1)

rfe = rfe.fit(X_train, y_train)
```
executed in 25.1s, finished 08:00:21 2022-01-10

```
/Users/v/opt/anaconda3/envs/learn-env/lib/python3.8/site-packages/sklea
rn/linear_model/_logistic.py:762: ConvergenceWarning: lbfgs failed to c
onverge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown
in:
    https://scikit-learn.org/stable/modules/preprocessing.html (http
s://scikit-learn.org/stable/modules/preprocessing.html)
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression (https://scikit-learn.org/stable/modules/linear_model.html#l
ogistic-regression)
  n_iter_i = _check_optimize_result(
/Users/v/opt/anaconda3/envs/learn-env/lib/python3.8/site-packages/sklea
rn/linear_model/_logistic.py:762: ConvergenceWarning: lbfgs failed to c
onverge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown
```

In [48]:
```
ranking = rfe.ranking_
ranking
```
executed in 4ms, finished 08:00:21 2022-01-10

Out[48]:
```
array([  1, 128, 147,  35,  87,  12,  24,  76,   1,  53,  62,  85,  42,
       104,   1,  32,  78,   1,  46,  44, 124,  88, 150,  95, 101,  41,
        70,  23,  68,  74,  60,  56,  30,  55,  52,  19, 109, 129,  65,
       116,   1,   1,  67, 152,  48,  14, 136,   1,  89,   5,  59,  80,
         1,   6,   1,  96, 151,   7,  81,  57, 102,   1,  45,  37, 100,
         1,  61,   1,  97,  11,   9, 130,  22,  79, 121,   3,  43,  71,
        33,  28,  64,  20,   1,  54, 143, 103,  38, 111,  69,  40,  31,
       123,  47,  84,  72,   1,  10,  15,  51,  73,   8,  36,  82,  63,
       141,   1,  77, 125,   1,  29,  92,   1,  27, 153,  16,  13,  94,
       148,   2,  90,  34,   1, 139,  50,  75, 144, 137, 120, 134,  86,
        39, 149,  58, 145,  66, 142,  17,  93,  18, 132,  21,   1, 138,
       106, 108, 110, 119, 131, 107,  49,  98, 117, 146, 122, 133, 135,
       118,   1, 127,  83,  26, 140, 105,  25,  99, 115, 113, 112, 114,
       126,  91,   4])
```

In [49]:
```
y_pred_train = logreg.predict(X_train)
print('Accuracy of logistic regression classifier on test set: {:.2f}'
      .format(logreg.score(X_train, y_train)))
```
executed in 30ms, finished 08:00:21 2022-01-10

```
Accuracy of logistic regression classifier on test set: 0.78
```

In [50]:
```
y_pred_test = logreg.predict(X_test)
print('Accuracy of logistic regression classifier on test set: {:.2f}'
      .format(logreg.score(X_test, y_test)))
```
executed in 22ms, finished 08:00:21 2022-01-10

```
Accuracy of logistic regression classifier on test set: 0.79
```

3.1.1 Classification Report

Understanding the Classification Report

- The classification report assesses the quality of a model
- **Precision** measures how precise the predictors are
  Precision = Number of True Positives/Number of Predicted Positives
- **Recall** is the percentage of the class that is captured by the model
  Recall = Number of True Positives/Number of Actual Total Positives
- **F-1 Score** is a weighted average of Precision and Recall (also called the "Harmonic Mean")
  F-1 Score = 2 * (Precision * Recall)/(Precision + Recall)
- **Accuracy** is the percentage of predictions the model got right
  Accuracy = Number of Correct Predictions/Total Number of Predictions

Because our data is imbalanced and 75% of the candidates are "Not Looking for a Job Change," the metric we use to measure our models' performances is Recall because we care most about how our models predict True Positives (employees "Looking for a Job Change") that actually are looking for a job change

In [51]:
```
print('Classification Report for Training Data')

print(classification_report(y_train, y_pred_train,
                            target_names=['Not Looking for Job Change',
                                          'Looking for a Job Change']))

print('Classification Report for Test Data')

print(classification_report(y_test, y_pred_test,
                            target_names=['Not Looking for Job Change',
                                          'Looking for a Job Change']))
```

executed in 58ms, finished 08:00:21 2022-01-10

```
Classification Report for Training Data
                            precision    recall  f1-score   support

Not Looking for Job Change       0.82      0.91      0.86     10726
  Looking for a Job Change       0.60      0.39      0.48      3557

                  accuracy                           0.78     14283
                 macro avg       0.71      0.65      0.67     14283
              weighted avg       0.77      0.78      0.77     14283

Classification Report for Test Data
                            precision    recall  f1-score   support

Not Looking for Job Change       0.82      0.92      0.87      3576
  Looking for a Job Change       0.61      0.40      0.48      1185

                  accuracy                           0.79      4761
                 macro avg       0.72      0.66      0.67      4761
              weighted avg       0.77      0.79      0.77      4761
```

3.1.2 Confusion Matrixes

Understanding the Confusion Matrix

Every item in a Binary Classification dataset has a ground-truth value of 1 or 0. The Confusion Matrix helps us understand:

True Positives (TP): The number of observations where the model predicted the instance to be true (1), and it is actually true (1). In our case, where our model predicts a candidate is looking for a new job, and they are actually looking for a new job.

True Negatives (TN): The number of observations where the model predicted the instance to be not true (0), and the instance is actually not true (0). In our case, where our model predicts a candidate is not looking for a new job, and they are actually not looking for a new job.

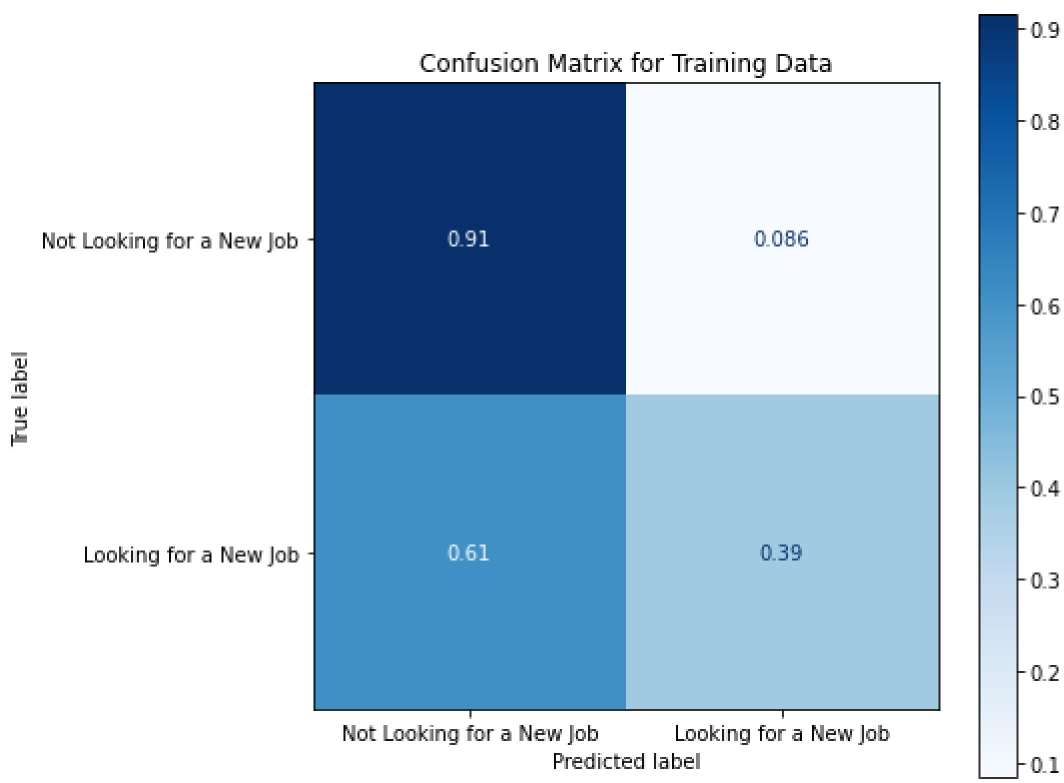
False Positives (FP): The number of observations where the model predicted the instance to be true (1), but the instance is actually not true (0). In our case, where our model predicts a candidate is looking for a new job, and they are actually not looking for a new job.

False Negatives (FN): The number of observations where the model predicted the instance to be not true (0), but the instance is actually true (1). In our case, where our model predicts a candidate is not looking for a new job, and they are actually looking for a new job.

In [52]:
```
train_data_confusion_matrix = confusion_matrix(y_train, y_pred_train)
print("Training Data Confusion Matrix")
print(train_data_confusion_matrix)

test_data_confusion_matrix = confusion_matrix(y_test, y_pred_test)
print("Test Data Confusion Matrix")
print(test_data_confusion_matrix)
```
executed in 23ms, finished 08:00:21 2022-01-10

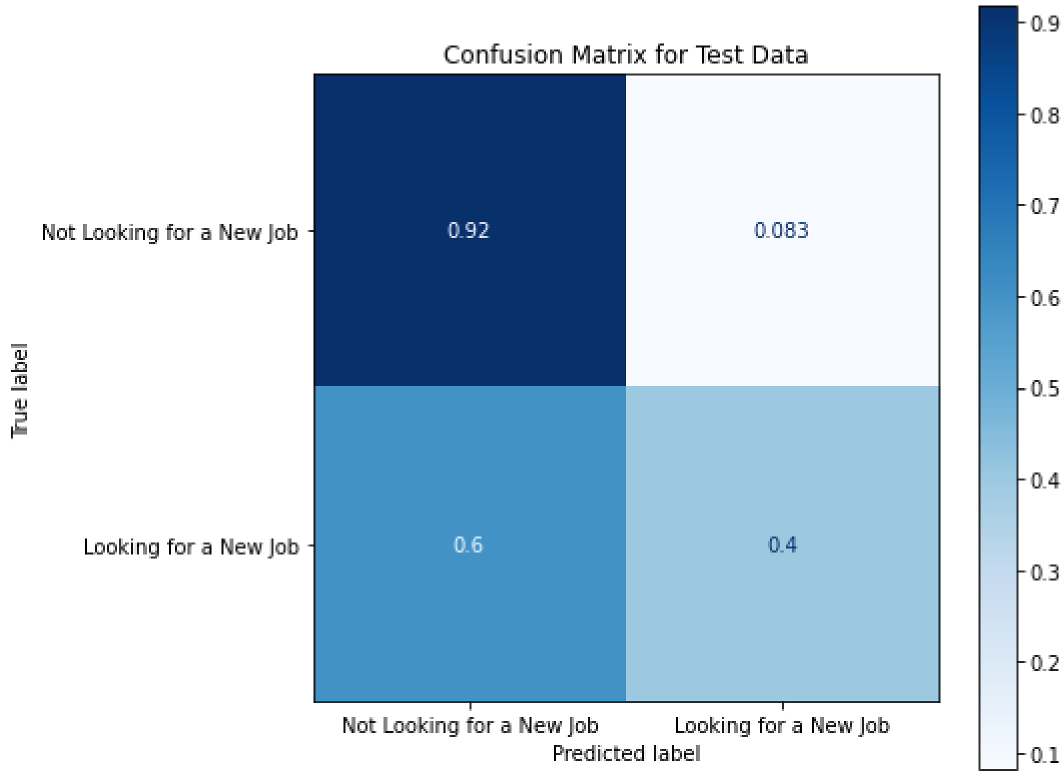
```
Training Data Confusion Matrix
[[9808  918]
 [2160 1397]]
Test Data Confusion Matrix
[[3280  296]
 [ 716  469]]
```

In [53]:
```
fig, ax = plt.subplots(figsize=(7,7))
plot_confusion_matrix(
    log_reg_model, X_train, y_train, cmap='Blues', ax=ax, normalize='true')
ax.grid(False)
ax.set_title('Confusion Matrix for Training Data');
ax.xaxis.set_ticklabels(['Not Looking for a New Job', 'Looking for a New Jo
ax.yaxis.set_ticklabels(['Not Looking for a New Job', 'Looking for a New Jo
```
executed in 223ms, finished 08:00:21 2022-01-10



In [54]:
```
fig, ax = plt.subplots(figsize=(7,7))
plot_confusion_matrix(
    log_reg_model, X_test, y_test, cmap='Blues', ax=ax, normalize='true')
ax.grid(False)
ax.set_title('Confusion Matrix for Test Data');
ax.xaxis.set_ticklabels(['Not Looking for a New Job', 'Looking for a New Jo
ax.yaxis.set_ticklabels(['Not Looking for a New Job', 'Looking for a New Jo
```

executed in 190ms, finished 08:00:22 2022-01-10



3.1.3 ROC Curve

Scikit-learn's built in roc_curve method returns the fpr, tpr, and thresholds for various decision boundaries given the case member probabilites

In [55]:
```
from sklearn.metrics import roc_curve, auc, roc_auc_score

# First calculate the probability scores of each of the datapoints:
y_score = logreg.fit(X_train, y_train).decision_function(X_test)

fpr, tpr, thresholds = roc_curve(y_test, y_score)
```

executed in 403ms, finished 08:00:22 2022-01-10

```
/Users/v/opt/anaconda3/envs/learn-env/lib/python3.8/site-packages/sklear
n/linear_model/_logistic.py:762: ConvergenceWarning: lbfgs failed to conv
erge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown i
n:
    https://scikit-learn.org/stable/modules/preprocessing.html (https://s
cikit-learn.org/stable/modules/preprocessing.html)
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-re
gression (https://scikit-learn.org/stable/modules/linear_model.html#logis
tic-regression)
  n_iter_i = _check_optimize_result(
```

In [56]:
```
print('AUC: {}'.format(auc(fpr, tpr)))
```

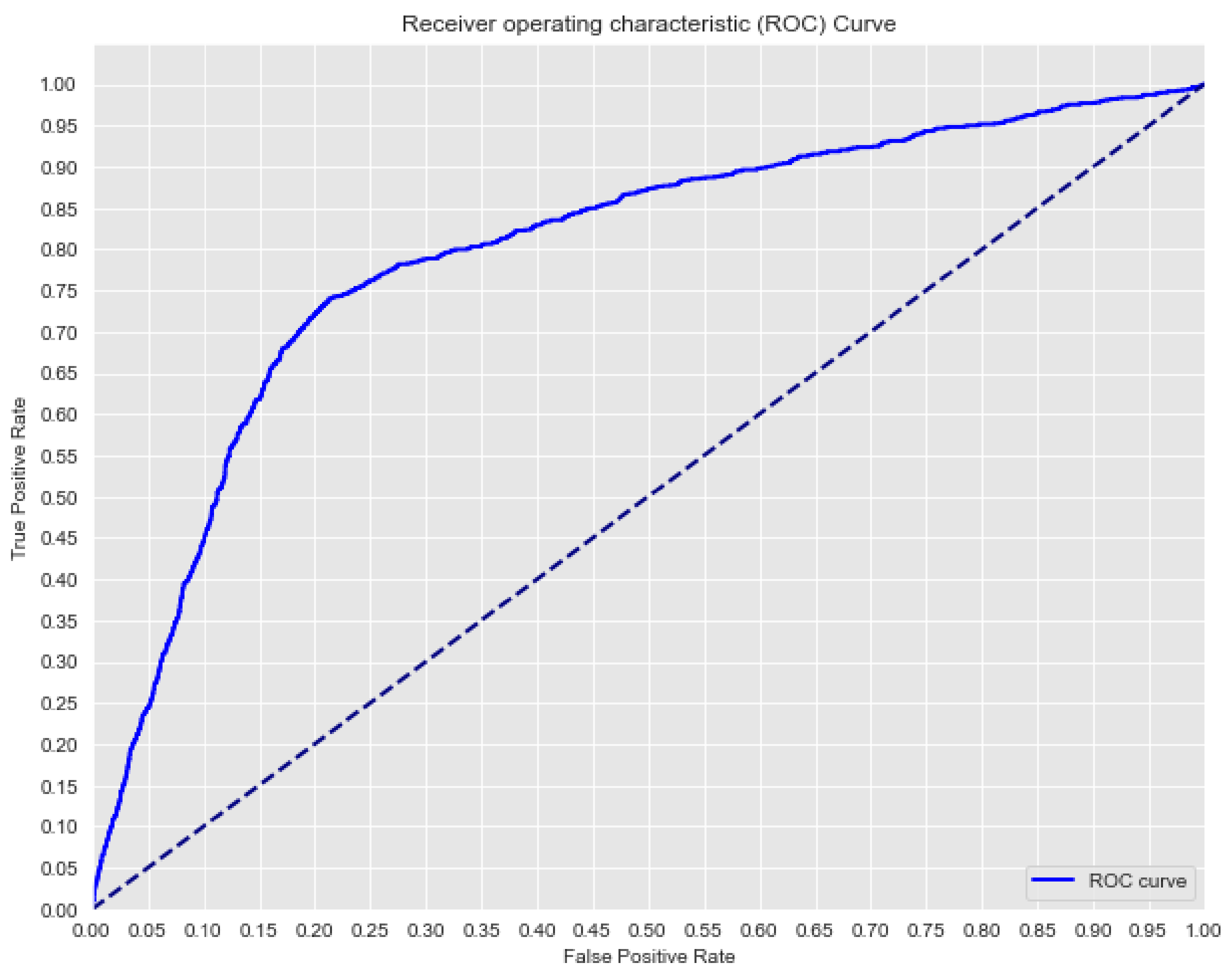
executed in 3ms, finished 08:00:22 2022-01-10

```
AUC: 0.7964694305213378
```

In [57]:
```
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

sns.set_style('darkgrid', {'axes.facecolor': '0.9'})

print('AUC: {}'.format(auc(fpr, tpr)))
plt.figure(figsize=(10, 8))
lw = 2
plt.plot(fpr, tpr, color='blue',
         lw=lw, label='ROC curve')
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.yticks([i/20.0 for i in range(21)])
plt.xticks([i/20.0 for i in range(21)])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic (ROC) Curve')
plt.legend(loc='lower right')
plt.show()
```

executed in 281ms, finished 08:00:22 2022-01-10

```
AUC: 0.7964694305213378
```

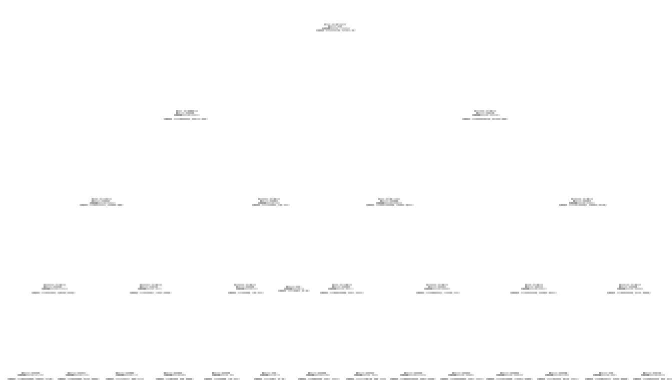


3.2 Decision Tree Classifier

In [58]:
```
decision_tree_model = DecisionTreeClassifier(
    max_depth=4,random_state=100, class_weight='balanced')

decision_tree_model.fit(X_train, y_train)
```
executed in 61ms, finished 08:00:22 2022-01-10

Out[58]:
```
DecisionTreeClassifier(class_weight='balanced', max_depth=4, random_state
=100)
```

In [59]:
```
tree.plot_tree(decision_tree_model);
```
executed in 837ms, finished 08:00:23 2022-01-10



In [60]:
```
y_pred_train = decision_tree_model.predict(X_train)
y_pred_test = decision_tree_model.predict(X_test)
```
executed in 18ms, finished 08:00:23 2022-01-10

3.2.1 Classification Report - Pre-Tuning

In [61]:
```
print('Classification Report for Training Data')

print(classification_report(y_train, y_pred_train,
                            target_names=['Not Looking for Job Change',
                                          'Looking for a Job Change']))

print('Classification Report for Test Data')

print(classification_report(y_test, y_pred_test,
                            target_names=['Not Looking for Job Change',
                                          'Looking for a Job Change']))
```
executed in 45ms, finished 08:00:23 2022-01-10

```
Classification Report for Training Data
                            precision    recall  f1-score   support

Not Looking for Job Change       0.91      0.74      0.81     10726
  Looking for a Job Change       0.49      0.77      0.60      3557

                  accuracy                           0.74     14283
                 macro avg       0.70      0.75      0.71     14283
              weighted avg       0.80      0.74      0.76     14283

Classification Report for Test Data
                            precision    recall  f1-score   support

Not Looking for Job Change       0.91      0.74      0.81      3576
  Looking for a Job Change       0.50      0.78      0.61      1185

                  accuracy                           0.75      4761
                 macro avg       0.70      0.76      0.71      4761
              weighted avg       0.81      0.75      0.76      4761
```

3.2.2 Grid Search

In [62]:
```
# Hyperparameter Tuning and Pruning
# Scoring on Recall

from sklearn.model_selection import GridSearchCV

my_param_grid = {'max_depth': [None, 2, 6, 10],
                 'min_samples_split': [2, 6, 12],
                 'criterion': ['gini','entropy'],
                 'max_features': ['auto','sqrt','log2']}

decision_tree_model_gridsearch = GridSearchCV(
    decision_tree_model, param_grid=my_param_grid,verbose=2,scoring='recall

decision_tree_model_gridsearch.fit(X_train, y_train)
```

executed in 11.9s, finished 08:00:35 2022-01-10

```
Fitting 5 folds for each of 72 candidates, totalling 360 fits
[CV] criterion=gini, max_depth=None, max_features=auto, min_samples_spl
it=2
[CV]  criterion=gini, max_depth=None, max_features=auto, min_samples_sp
lit=2, total=   0.1s
[CV] criterion=gini, max_depth=None, max_features=auto, min_samples_spl
it=2
[CV]  criterion=gini, max_depth=None, max_features=auto, min_samples_sp
lit=2, total=   0.1s
[CV] criterion=gini, max_depth=None, max_features=auto, min_samples_spl
it=2

[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent
workers.
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    0.1s remaining:
0.0s
```

In [63]:
```
decision_tree_model_gridsearch.best_params_
```

executed in 3ms, finished 08:00:35 2022-01-10

Out[63]:
```
{'criterion': 'entropy',
 'max_depth': 10,
 'max_features': 'log2',
 'min_samples_split': 6}
```

3.2.3 Tuned Model

In [64]:
```
best_decision_tree_model = decision_tree_model_gridsearch.best_estimator_
best_decision_tree_model
```
executed in 3ms, finished 08:00:35 2022-01-10

Out[64]:
```
DecisionTreeClassifier(class_weight='balanced', criterion='entropy',
                       max_depth=10, max_features='log2', min_samples_spl
it=6,
                       random_state=100)
```

In [65]:
```
best_decision_tree_model.feature_importances_
```
executed in 5ms, finished 08:00:35 2022-01-10

Out[65]:
```
array([1.08942966e-01, 8.65833868e-02, 1.37343614e-02, 0.00000000e+00,
       0.00000000e+00, 3.29523142e-04, 0.00000000e+00, 5.93109611e-04,
       2.53987360e-05, 1.29077732e-02, 0.00000000e+00, 0.00000000e+00,
       0.00000000e+00, 0.00000000e+00, 8.46194544e-04, 0.00000000e+00,
       3.44915753e-02, 1.13774359e-03, 5.77797972e-04, 0.00000000e+00,
       4.96375138e-04, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
       7.27856748e-04, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
       0.00000000e+00, 1.98171681e-03, 0.00000000e+00, 0.00000000e+00,
       0.00000000e+00, 4.36843843e-04, 3.63595177e-04, 0.00000000e+00,
       0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 1.63539917e-03,
       0.00000000e+00, 0.00000000e+00, 4.56318874e-03, 0.00000000e+00,
       2.14927049e-03, 0.00000000e+00, 9.61969904e-04, 5.40655952e-03,
       0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 2.22862330e-02,
       0.00000000e+00, 3.76533648e-04, 2.31157385e-04, 0.00000000e+00,
       0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 7.03021398e-04,
       0.00000000e+00, 2.84825320e-04, 0.00000000e+00, 0.00000000e+00,
       4.59063053e-04, 0.00000000e+00, 0.00000000e+00, 1.33877065e-02,
       1.18005691e-03, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
       0.00000000e+00, 9.26062413e-04, 0.00000000e+00, 0.00000000e+00,
```

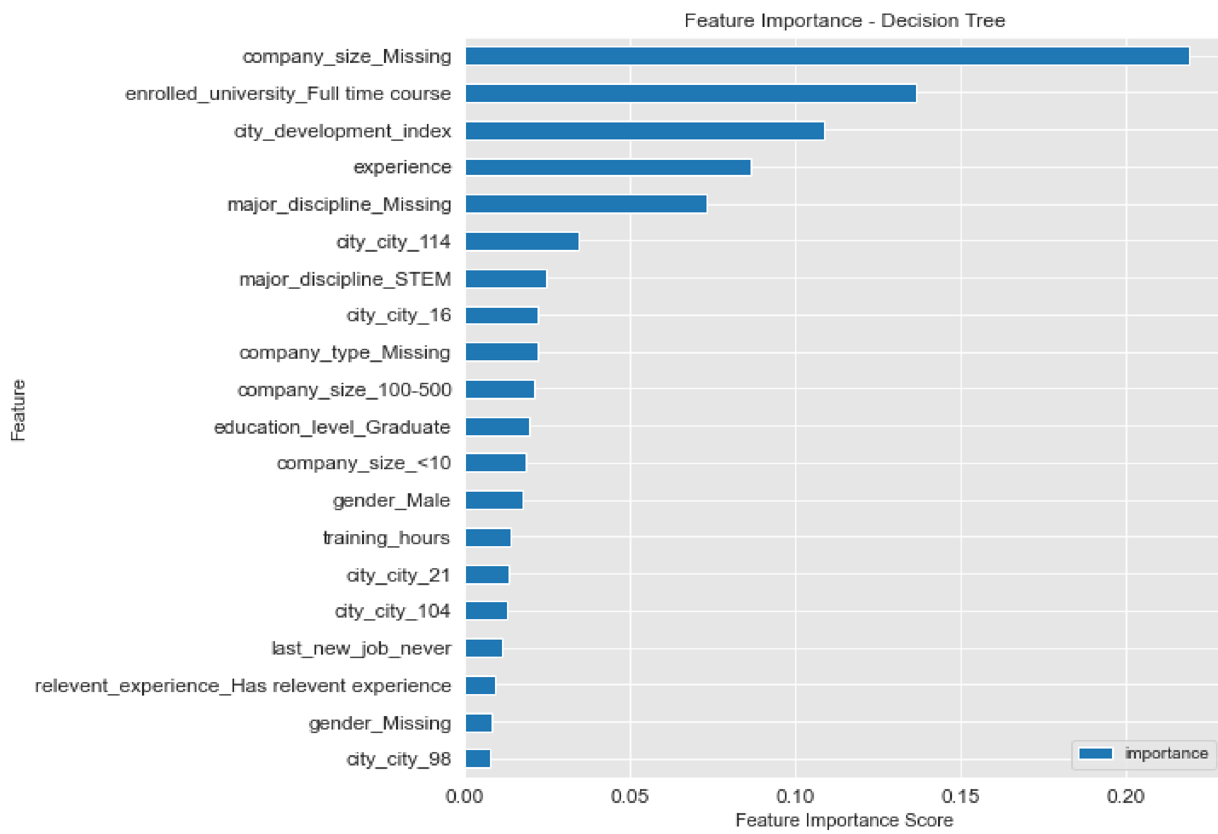
3.2.4 Feature Importance

In [66]:
```
feat_imp = list(
    zip(X_train.columns, best_decision_tree_model.feature_importances_))
sorted(feat_imp, key=lambda x: x[1], reverse=True)[:20]
```

executed in 4ms, finished 08:00:35 2022-01-10

Out[66]:
```
[('company_size_Missing', 0.2190993006764216),
 ('enrolled_university_Full time course', 0.13639426021184312),
 ('city_development_index', 0.10894296592786797),
 ('experience', 0.08658338675813584),
 ('major_discipline_Missing', 0.073057592809834),
 ('city_city_114', 0.03449157532091442 4),
 ('major_discipline_STEM', 0.02465044284696728),
 ('city_city_16', 0.02228623299445862),
 ('company_type_Missing', 0.022082570702650746),
 ('company_size_100-500', 0.021233108918187735),
 ('education_level_Graduate', 0.01952912904336569),
 ('company_size_<10', 0.01882646285864335),
 ('gender_Male', 0.017320075221763587),
 ('training_hours', 0.013734361387753208),
 ('city_city_21', 0.0133877065394416),
 ('city_city_104', 0.012907773155854403),
 ('last_new_job_never', 0.011431490812697441),
 ('relevent_experience_Has relevent experience', 0.009186648356389954),
 ('gender_Missing', 0.008096956254462896),
 ('city_city_98', 0.007675418182788548)]
```

In [67]:
```
feat_imp = pd.DataFrame(
    {'importance':best_decision_tree_model.feature_importances_}
)
feat_imp['feature'] = X_train.columns
feat_imp.sort_values(by='importance', ascending=False, inplace=True)
feat_imp = feat_imp.iloc[:20]

feat_imp.sort_values(by='importance', inplace=True)
feat_imp = feat_imp.set_index('feature', drop=True)
feat_imp.plot.barh(title='Feature Importance - Decision Tree',
                   figsize=(8,8),
                   fontsize=12)
plt.xlabel('Feature Importance Score', fontsize=11)
plt.ylabel('Feature', fontsize=11)
plt.show()
```
executed in 224ms, finished 08:00:35 2022-01-10



3.2.5 Classification Report - Tuned Decision Tree

In [68]:
```
print('Classification Report for Training Data')
print(classification_report(y_train, best_decision_tree_model.predict(X_tra
                                target_names=['Not Looking for Job Change',
                                              'Looking for a Job Change']))

print('Classification Report for Test Data')
print(classification_report(y_test, best_decision_tree_model.predict(X_test
                                target_names=['Not Looking for Job Change',
                                              'Looking for a Job Change']))
```

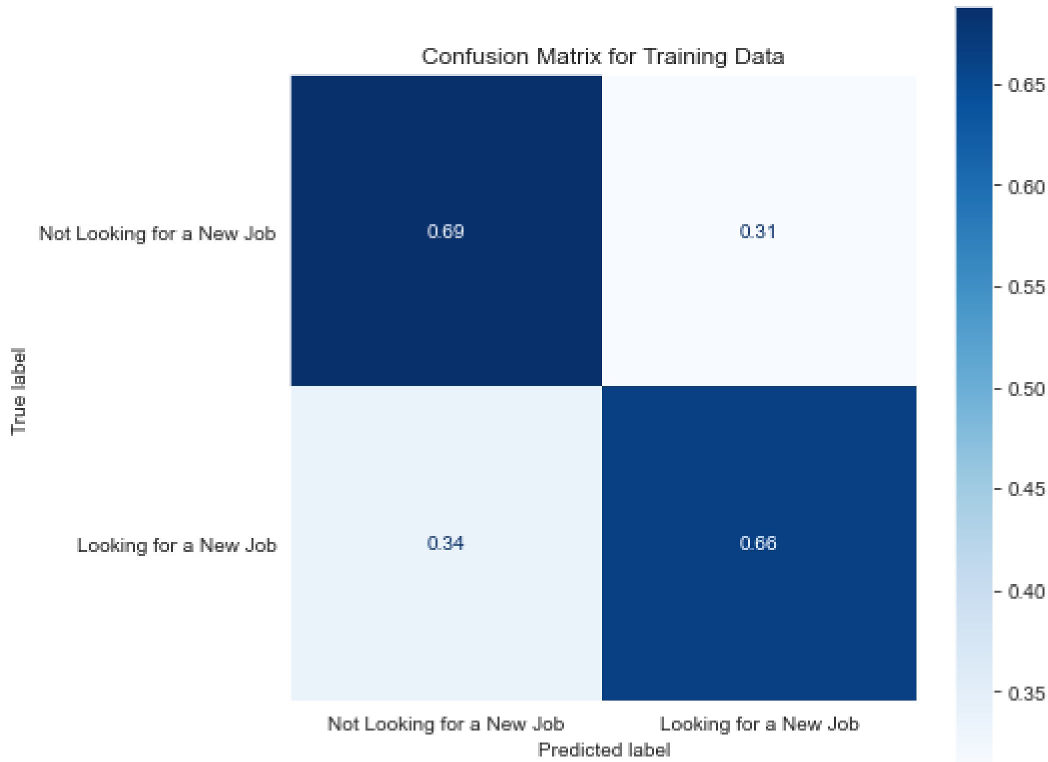
executed in 48ms, finished 08:00:35 2022-01-10

```
Classification Report for Training Data
                            precision    recall  f1-score   support

Not Looking for Job Change       0.86      0.69      0.76     10726
  Looking for a Job Change       0.41      0.66      0.51      3557

                  accuracy                           0.68     14283
                 macro avg       0.64      0.68      0.64     14283
              weighted avg       0.75      0.68      0.70     14283

Classification Report for Test Data
                            precision    recall  f1-score   support

Not Looking for Job Change       0.86      0.69      0.77      3576
  Looking for a Job Change       0.41      0.66      0.51      1185

                  accuracy                           0.68      4761
                 macro avg       0.64      0.67      0.64      4761
              weighted avg       0.75      0.68      0.70      4761
```

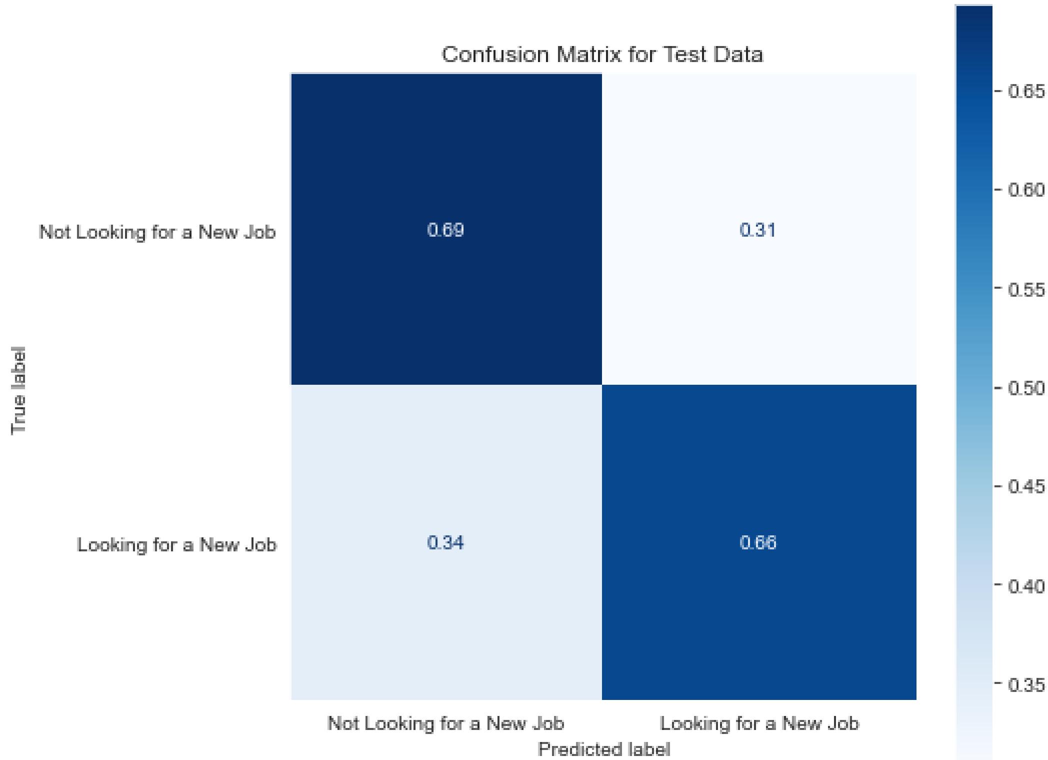
3.2.6 Confusion Matrixes

In [69]:
```
fig, ax = plt.subplots(figsize=(7,7))
plot_confusion_matrix(
    best_decision_tree_model, X_train, y_train, cmap='Blues', ax=ax, normal
ax.grid(False)
ax.set_title('Confusion Matrix for Training Data');
ax.xaxis.set_ticklabels(['Not Looking for a New Job', 'Looking for a New Jo
ax.yaxis.set_ticklabels(['Not Looking for a New Job', 'Looking for a New Jo
#ax.plot(legend=False)
#fig.tight_layout()
```

executed in 158ms, finished 08:00:36 2022-01-10



In [70]:
```
fig, ax = plt.subplots(figsize=(7,7))
plot_confusion_matrix(
    best_decision_tree_model, X_test, y_test, cmap='Blues', ax=ax, normaliz
ax.grid(False)
ax.set_title('Confusion Matrix for Test Data');
ax.xaxis.set_ticklabels(['Not Looking for a New Job', 'Looking for a New Jo
ax.yaxis.set_ticklabels(['Not Looking for a New Job', 'Looking for a New Jo
```
executed in 159ms, finished 08:00:36 2022-01-10



3.3 Random Forest Classifier

In [71]:
```
from sklearn.ensemble import BaggingClassifier, RandomForestClassifier
```
executed in 12ms, finished 08:00:36 2022-01-10

In [72]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.datasets import make_classification

random_forest_model = RandomForestClassifier(
    random_state=100, class_weight='balanced')

random_forest_model.fit(X_train, y_train)

y__pred_train = random_forest_model.predict(X_train)
y_pred_test = random_forest_model.predict(X_test)
```
executed in 2.43s, finished 08:00:38 2022-01-10

3.3.1 Classification Report - Pre-Tuning

In [73]:
```
print('Classification Report for Training Data')

print(classification_report(y_train, y_pred_train,
                            target_names=['Not Looking for Job Change',
                                          'Looking for a Job Change']))

print('Classification Report for Test Data')

print(classification_report(y_test, y_pred_test,
                            target_names=['Not Looking for Job Change',
                                          'Looking for a Job Change']))
```

executed in 34ms, finished 08:00:38 2022-01-10

```
Classification Report for Training Data
                            precision    recall  f1-score   support

Not Looking for Job Change       0.91      0.74      0.81     10726
  Looking for a Job Change       0.49      0.77      0.60      3557

                  accuracy                           0.74     14283
                 macro avg       0.70      0.75      0.71     14283
              weighted avg       0.80      0.74      0.76     14283

Classification Report for Test Data
                            precision    recall  f1-score   support

Not Looking for Job Change       0.83      0.90      0.86      3576
  Looking for a Job Change       0.58      0.44      0.50      1185

                  accuracy                           0.78      4761
                 macro avg       0.71      0.67      0.68      4761
              weighted avg       0.77      0.78      0.77      4761
```

3.3.2 Grid Search

In [74]:
```
param_grid = {
#    'n_estimators': [200, 500],
     'max_features': ['auto', 'sqrt', 'log2'],
     'max_depth' : [4,5,6,7,8],
     'criterion' :['gini', 'entropy']
}

random_forest_model_gridsearch = GridSearchCV(
    estimator=random_forest_model,
    param_grid=param_grid, scoring='recall', verbose=2)

random_forest_model_gridsearch.fit(X_train, y_train)
```

executed in 1m 10.1s, finished 08:01:48 2022-01-10

```
Fitting 5 folds for each of 30 candidates, totalling 150 fits
[CV] criterion=gini, max_depth=4, max_features=auto ..................

[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent
workers.

[CV] ... criterion=gini, max_depth=4, max_features=auto, total=   0.4s
[CV] criterion=gini, max_depth=4, max_features=auto ..................

[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    0.4s remaining:
0.0s
```

In [75]:
```
random_forest_model_gridsearch.best_params_
```

executed in 3ms, finished 08:01:48 2022-01-10

Out[75]:
```
{'criterion': 'gini', 'max_depth': 5, 'max_features': 'auto'}
```

3.3.3 Tuned Model

In [76]:
```
best_random_forest_model = random_forest_model_gridsearch.best_estimator_
```

executed in 2ms, finished 08:01:48 2022-01-10

3.3.4 Feature Importance

In [77]:
```
feat_imp = list(
    zip(X_train.columns, best_random_forest_model.feature_importances_))
sorted(feat_imp, key=lambda x: x[1], reverse=True)[:20]
```

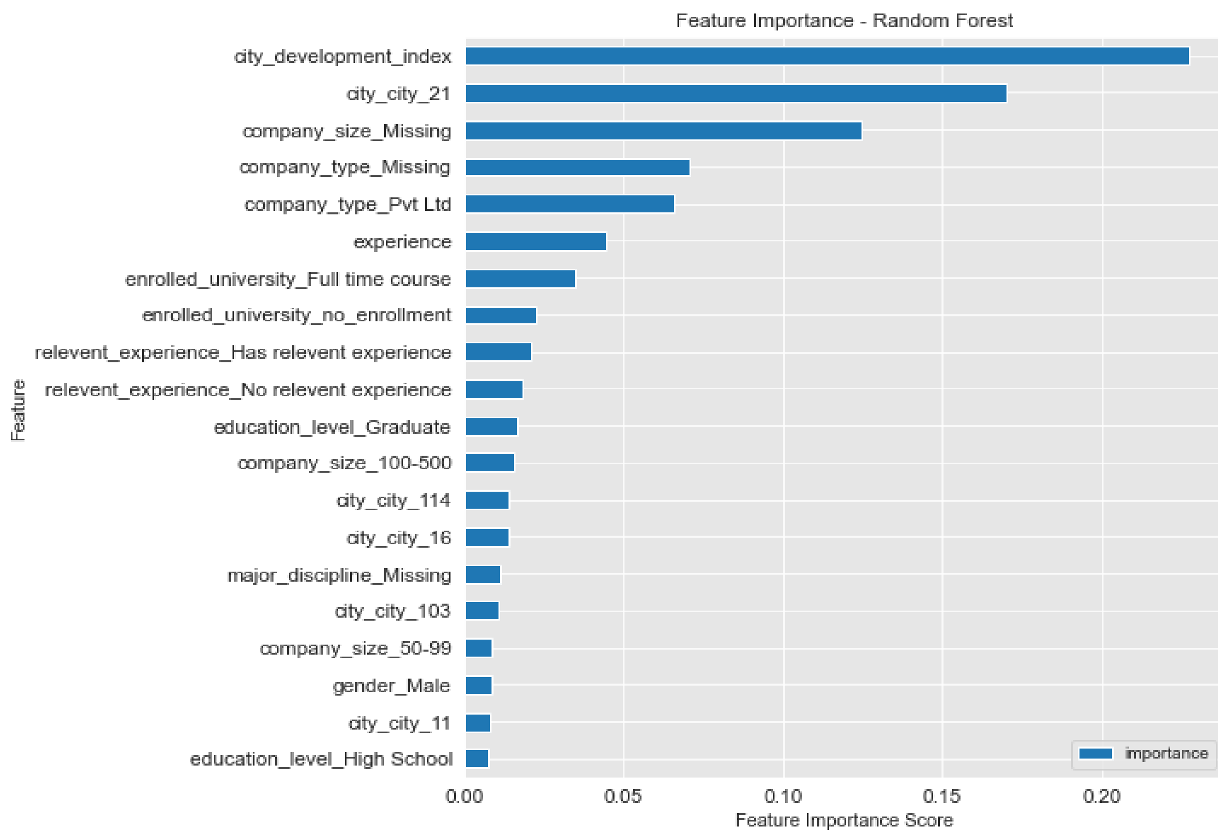
executed in 12ms, finished 08:01:48 2022-01-10

Out[77]:
```
[('city_development_index', 0.22740288904332817),
 ('city_city_21', 0.17010254010184192),
 ('company_size_Missing', 0.12485665123523287),
 ('company_type_Missing', 0.07039186963964708),
 ('company_type_Pvt Ltd', 0.06599291299775398),
 ('experience', 0.04436437517204363),
 ('enrolled_university_Full time course', 0.03466138198463109),
 ('enrolled_university_no_enrollment', 0.022758315122114934),
 ('relevent_experience_Has relevent experience', 0.020911139303026894),
 ('relevent_experience_No relevent experience', 0.017964797105444758),
 ('education_level_Graduate', 0.016538947979366413),
 ('company_size_100-500', 0.015319505097498543),
 ('city_city_114', 0.01393822136615138),
 ('city_city_16', 0.013709621233367523),
 ('major_discipline_Missing', 0.010996995730536467),
 ('city_city_103', 0.010899940231614908),
 ('company_size_50-99', 0.008633335029450571),
 ('gender_Male', 0.00862963684792497),
 ('city_city_11', 0.008070731806875397),
 ('education_level_High School', 0.007340281071872067)]
```

In [78]:

```
feat_imp = pd.DataFrame(
    {'importance':best_random_forest_model.feature_importances_}
)
feat_imp['feature'] = X_train.columns
feat_imp.sort_values(by='importance', ascending=False, inplace=True)
feat_imp = feat_imp.iloc[:20]

feat_imp.sort_values(by='importance', inplace=True)
feat_imp = feat_imp.set_index('feature', drop=True)
feat_imp.plot.barh(title='Feature Importance - Random Forest',
                   figsize=(8,8),
                   fontsize=12)
plt.xlabel('Feature Importance Score', fontsize=11)
plt.ylabel('Feature', fontsize=11)
plt.show()
```

executed in 218ms, finished 08:01:49 2022-01-10



3.3.5 Classification Report - Tuned Random Forest

In [79]:
```
print('Classification Report for Training Data')
print(classification_report(y_train, best_random_forest_model.predict(X_tra
                            target_names=['Not Looking for Job Change',
                                          'Looking for a Job Change']))

print('Classification Report for Test Data')
print(classification_report(y_test, best_random_forest_model.predict(X_test
                            target_names=['Not Looking for Job Change',
                                          'Looking for a Job Change']))
```

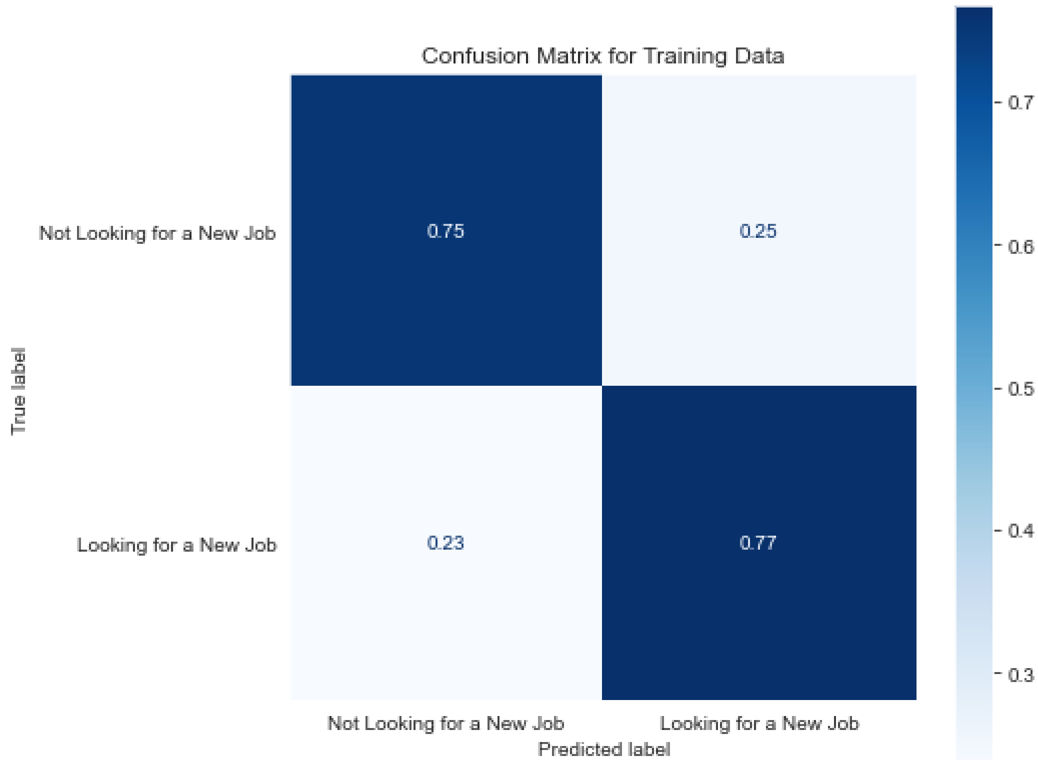
executed in 146ms, finished 08:01:49 2022-01-10

```
Classification Report for Training Data
                            precision    recall  f1-score   support

Not Looking for Job Change       0.91      0.75      0.82     10726
  Looking for a Job Change       0.51      0.77      0.61      3557

                  accuracy                           0.76     14283
                 macro avg       0.71      0.76      0.72     14283
              weighted avg       0.81      0.76      0.77     14283

Classification Report for Test Data
                            precision    recall  f1-score   support

Not Looking for Job Change       0.91      0.75      0.82      3576
  Looking for a Job Change       0.50      0.77      0.61      1185

                  accuracy                           0.75      4761
                 macro avg       0.71      0.76      0.71      4761
              weighted avg       0.81      0.75      0.77      4761
```

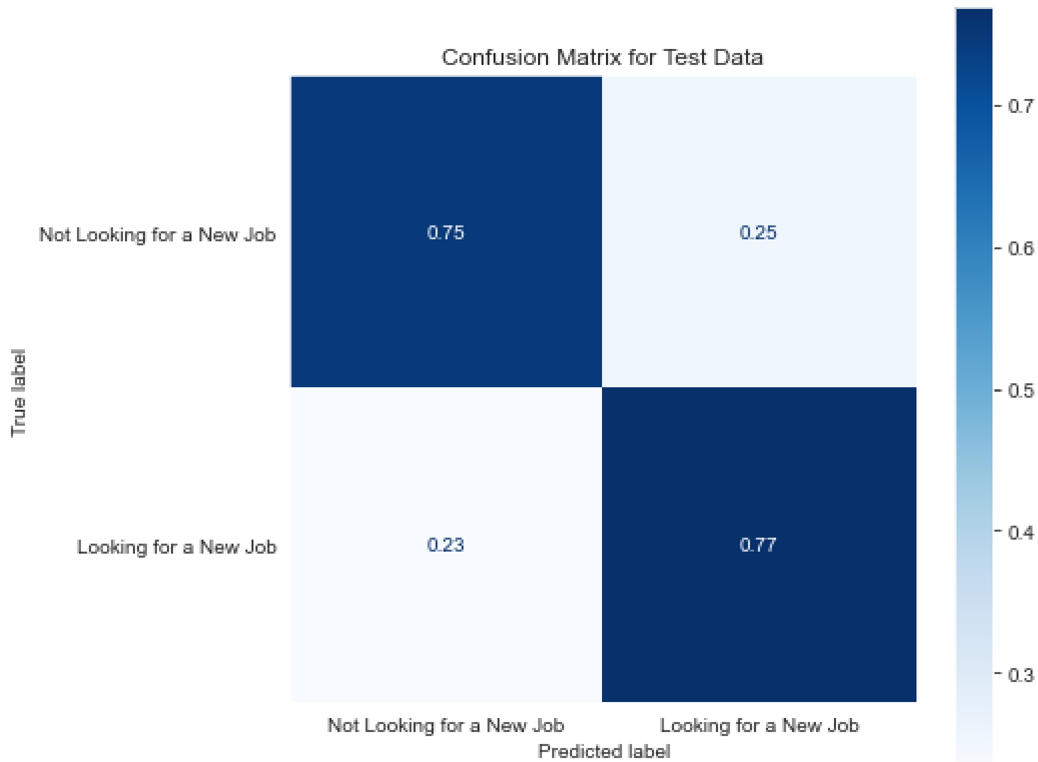
3.3.6 Confusion Matrixes

In [80]:
```
fig, ax = plt.subplots(figsize=(7,7))
plot_confusion_matrix(
    best_random_forest_model, X_train, y_train, cmap='Blues',
    ax=ax, normalize='true')
ax.grid(False)
ax.set_title('Confusion Matrix for Training Data');
ax.xaxis.set_ticklabels(['Not Looking for a New Job', 'Looking for a New Jo
ax.yaxis.set_ticklabels(['Not Looking for a New Job', 'Looking for a New Jo
#ax.plot(legend=False)
#fig.tight_layout()
```

executed in 246ms, finished 08:01:49 2022-01-10



In [81]:
```
fig, ax = plt.subplots(figsize=(7,7))
plot_confusion_matrix(
    best_random_forest_model, X_test, y_test, cmap='Blues',
    ax=ax, normalize='true')
ax.grid(False)
ax.set_title('Confusion Matrix for Test Data');
ax.xaxis.set_ticklabels(['Not Looking for a New Job', 'Looking for a New Jo
ax.yaxis.set_ticklabels(['Not Looking for a New Job', 'Looking for a New Jo
```
executed in 182ms, finished 08:01:49 2022-01-10



3.4 Gradient Boosting

In [82]:
```
from sklearn.ensemble import GradientBoostingClassifier

gradient_boost_model = GradientBoostingClassifier(
    learning_rate=0.1, n_estimators=100,max_depth=3, min_samples_split=2,
    min_samples_leaf=1, subsample=1,max_features='sqrt', random_state=100)

gradient_boost_model.fit(X_train, y_train)

gradient_boost_model.score(X_test, y_test)
```
executed in 471ms, finished 08:01:50 2022-01-10

Out[82]: 0.7889098928796471

In [83]:
```
y_pred_train = gradient_boost_model.predict(X_train)
y_pred_test = gradient_boost_model.predict(X_test)
```
executed in 56ms, finished 08:01:50 2022-01-10

3.4.1 Classification Report - Pre-Tuning

In [84]:
```
print('Classification Report for Training Data')

print(classification_report(y_train, y_pred_train,
                            target_names=['Not Looking for Job Change',
                                          'Looking for a Job Change']))

print('Classification Report for Test Data')

print(classification_report(y_test, y_pred_test,
                            target_names=['Not Looking for Job Change',
                                          'Looking for a Job Change']))
```

executed in 38ms, finished 08:01:50 2022-01-10

```
Classification Report for Training Data
                            precision    recall  f1-score   support

Not Looking for Job Change       0.83      0.90      0.87     10726
  Looking for a Job Change       0.62      0.46      0.53      3557

                  accuracy                           0.79     14283
                 macro avg       0.73      0.68      0.70     14283
              weighted avg       0.78      0.79      0.78     14283

Classification Report for Test Data
                            precision    recall  f1-score   support

Not Looking for Job Change       0.83      0.90      0.87      3576
  Looking for a Job Change       0.60      0.45      0.52      1185

                  accuracy                           0.79      4761
                 macro avg       0.72      0.68      0.69      4761
              weighted avg       0.77      0.79      0.78      4761
```

3.4.2 Grid Search

In [85]:
```
param_grid = {
    "loss":["deviance"],
    "max_depth":[3,5,8],
    "max_features":["log2","sqrt","auto"],
    "subsample":[.5,.75,1],
   }

gradient_boost_model_gridsearch = GridSearchCV(
    gradient_boost_model, param_grid=param_grid, cv=10, n_jobs=1,
    scoring='recall', verbose=2)

gradient_boost_model_gridsearch.fit(X_train, y_train)
```

executed in 6m 31s, finished 08:08:21 2022-01-10

```
Fitting 10 folds for each of 27 candidates, totalling 270 fits
[CV] loss=deviance, max_depth=3, max_features=log2, subsample=0.5 ....

[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent
workers.

[CV]  loss=deviance, max_depth=3, max_features=log2, subsample=0.5, tot
al=   0.4s
[CV] loss=deviance, max_depth=3, max_features=log2, subsample=0.5 ....

[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    0.4s remaining:
0.0s
```

In [86]:
```
gradient_boost_model_gridsearch.best_params_
```

executed in 3ms, finished 08:08:21 2022-01-10

Out[86]:
```
{'loss': 'deviance', 'max_depth': 5, 'max_features': 'auto', 'subsample':
1}
```

3.4.3 Tuned Model

In [87]:
```
best_gradient_boost_model = gradient_boost_model_gridsearch.best_estimator_
print(classification_report(y_train, best_gradient_boost_model.predict(X_tr
print(classification_report(y_test, best_gradient_boost_model.predict(X_tes
```
executed in 116ms, finished 08:08:21 2022-01-10

```
              precision    recall  f1-score   support

         0.0       0.88      0.89      0.89     10726
         1.0       0.67      0.64      0.66      3557

    accuracy                           0.83     14283
   macro avg       0.78      0.77      0.77     14283
weighted avg       0.83      0.83      0.83     14283

              precision    recall  f1-score   support

         0.0       0.86      0.86      0.86      3576
         1.0       0.58      0.56      0.57      1185

    accuracy                           0.79      4761
   macro avg       0.72      0.71      0.72      4761
weighted avg       0.79      0.79      0.79      4761
```

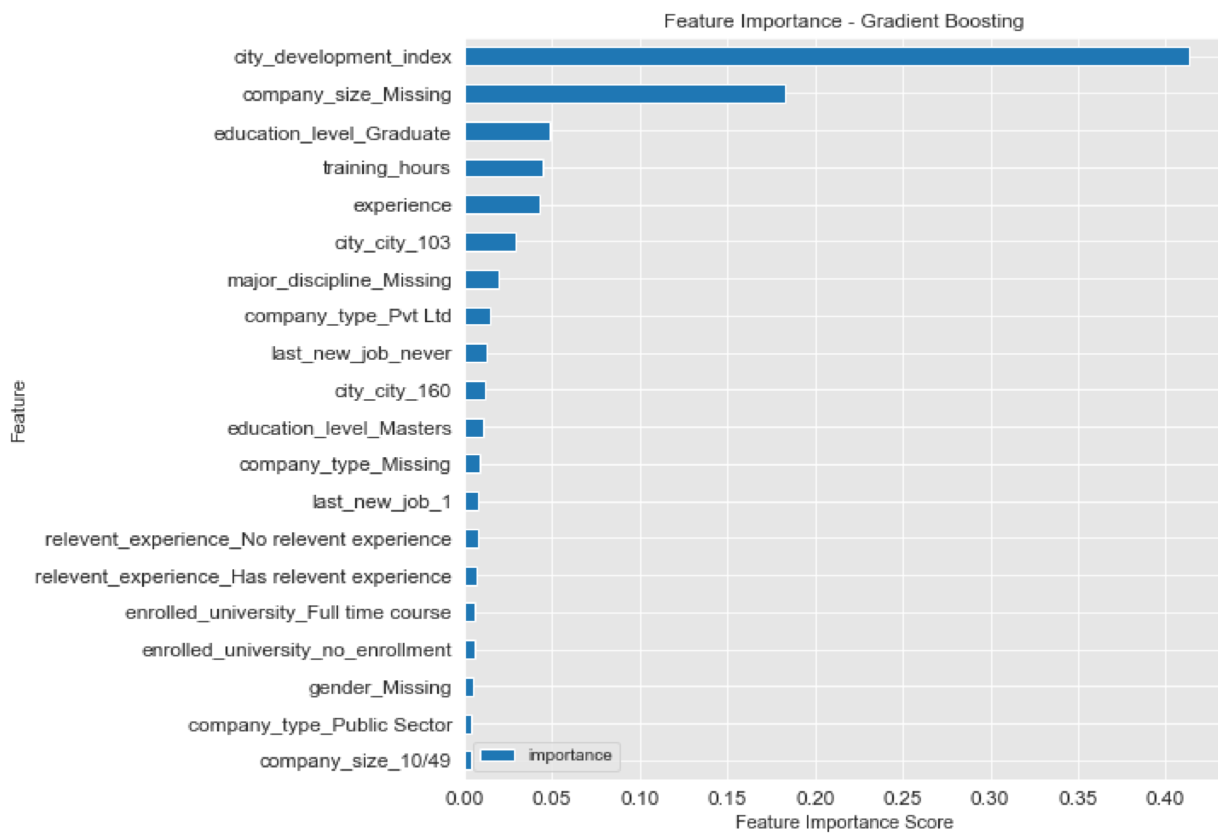
3.4.4 Feature Importance

In [88]:
```
feat_imp = list(
    zip(X_train.columns, best_gradient_boost_model.feature_importances_))
sorted(feat_imp, key=lambda x: x[1], reverse=True)[:20]
```
executed in 6ms, finished 08:08:21 2022-01-10

Out[88]:
```
[('city_development_index', 0.4132762929116181),
 ('company_size_Missing', 0.1828786241596875),
 ('education_level_Graduate', 0.04855039297895594),
 ('training_hours', 0.04520680966564507 4),
 ('experience', 0.04268205694237325),
 ('city_city_103', 0.02897024044778092 8),
 ('major_discipline_Missing', 0.019076822021671824),
 ('company_type_Pvt Ltd', 0.014943134624447822),
 ('last_new_job_never', 0.012863391338347588),
 ('city_city_160', 0.011568969187002846),
 ('education_level_Masters', 0.010483021668422741),
 ('company_type_Missing', 0.009114684169909572),
 ('last_new_job_1', 0.00822829735921949),
 ('relevent_experience_No relevent experience', 0.007787638960791248),
 ('relevent_experience_Has relevent experience', 0.007190143360342924),
 ('enrolled_university_Full time course', 0.006125375599436206),
 ('enrolled_university_no_enrollment', 0.005426261335473219 4),
 ('gender_Missing', 0.004519114013987973),
 ('company_type_Public Sector', 0.004071097578302900 4),
 ('company_size_10/49', 0.003969408713787684)]
```

In [89]:
```
feat_imp = pd.DataFrame(
    {'importance':best_gradient_boost_model.feature_importances_}
)
feat_imp['feature'] = X_train.columns
feat_imp.sort_values(by='importance', ascending=False, inplace=True)
feat_imp = feat_imp.iloc[:20]

feat_imp.sort_values(by='importance', inplace=True)
feat_imp = feat_imp.set_index('feature', drop=True)
feat_imp.plot.barh(title='Feature Importance - Gradient Boosting',
                   figsize=(8,8),
                   fontsize=12)
plt.xlabel('Feature Importance Score', fontsize=11)
plt.ylabel('Feature', fontsize=11)
plt.show()
```

executed in 249ms, finished 08:08:21 2022-01-10



3.4.5 Classification Report - Tuned Gradient Boosting

In [90]:
```
print('Classification Report for Training Data')
print(classification_report(y_train, best_gradient_boost_model.predict(X_tr
                            target_names=['Not Looking for Job Change',
                                          'Looking for a Job Change']))

print('Classification Report for Test Data')
print(classification_report(y_test, best_gradient_boost_model.predict(X_tes
                            target_names=['Not Looking for Job Change',
                                          'Looking for a Job Change']))
```

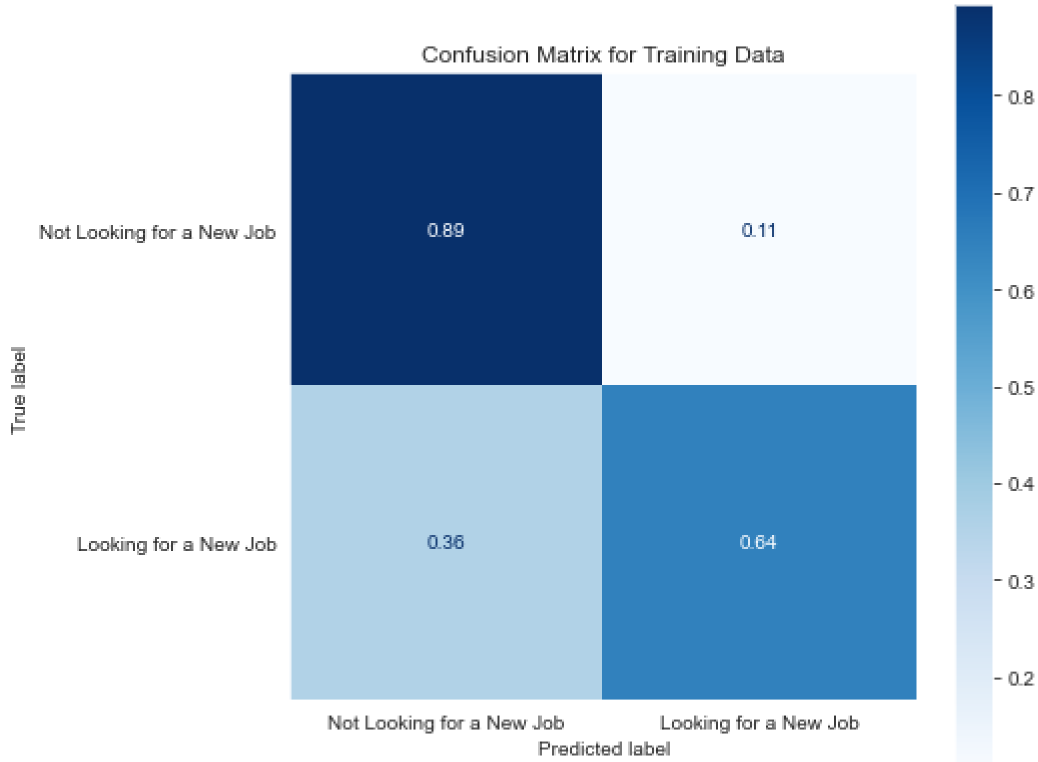
executed in 113ms, finished 08:08:21 2022-01-10

```
Classification Report for Training Data
                            precision    recall  f1-score   support

Not Looking for Job Change       0.88      0.89      0.89     10726
  Looking for a Job Change       0.67      0.64      0.66      3557

                  accuracy                           0.83     14283
                 macro avg       0.78      0.77      0.77     14283
              weighted avg       0.83      0.83      0.83     14283

Classification Report for Test Data
                            precision    recall  f1-score   support

Not Looking for Job Change       0.86      0.86      0.86      3576
  Looking for a Job Change       0.58      0.56      0.57      1185

                  accuracy                           0.79      4761
                 macro avg       0.72      0.71      0.72      4761
              weighted avg       0.79      0.79      0.79      4761
```

3.4.6 Confusion Matrixes

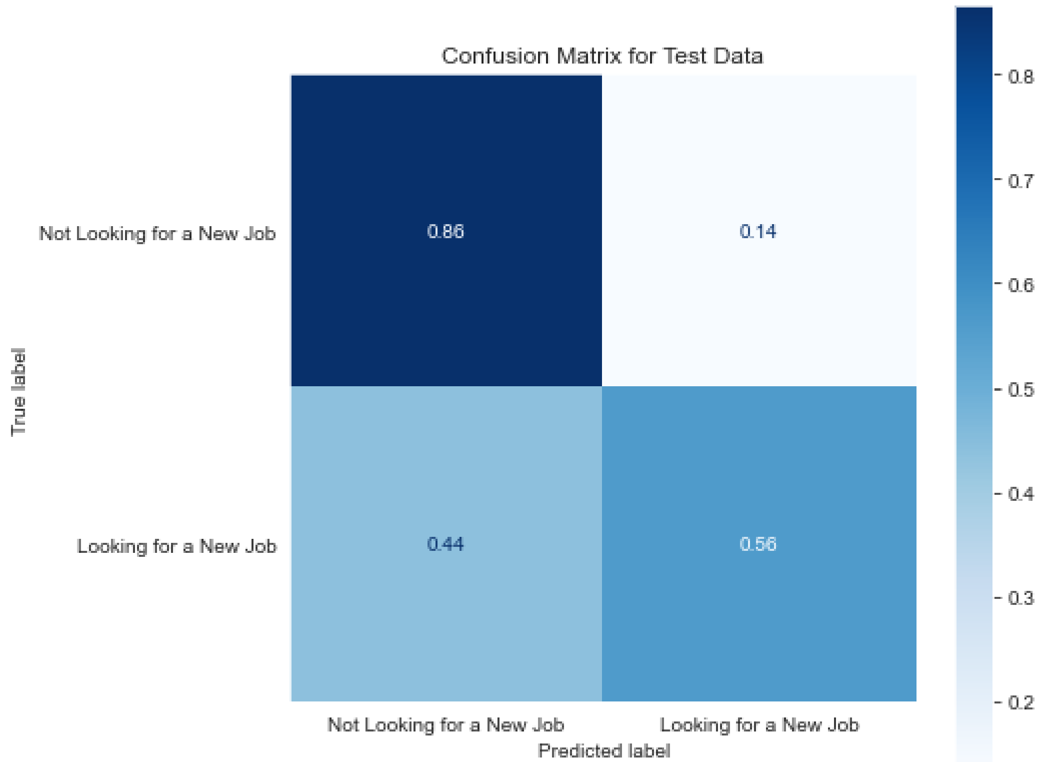
In [91]:
```
fig, ax = plt.subplots(figsize=(7,7))
plot_confusion_matrix(
    best_gradient_boost_model, X_train, y_train, cmap='Blues', ax=ax, norma
ax.grid(False)
ax.set_title('Confusion Matrix for Training Data');
ax.xaxis.set_ticklabels(['Not Looking for a New Job', 'Looking for a New Jo
ax.yaxis.set_ticklabels(['Not Looking for a New Job', 'Looking for a New Jo
```

executed in 259ms, finished 08:08:22 2022-01-10



In [92]:
```
fig, ax = plt.subplots(figsize=(7,7))
plot_confusion_matrix(
    best_gradient_boost_model, X_test, y_test, cmap='Blues', ax=ax, normali
ax.grid(False)
ax.set_title('Confusion Matrix for Test Data');
ax.xaxis.set_ticklabels(['Not Looking for a New Job', 'Looking for a New Jo
ax.yaxis.set_ticklabels(['Not Looking for a New Job', 'Looking for a New Jo
```

executed in 171ms, finished 08:08:22 2022-01-10



4 Evaluation and Conclusions

After evaluating several classification models (logistic regression, decision tree, random forest, and gradient boosting), we've chosen Random Forest as the model to determine whether candidates are likely to change careers.

Conclusions

- Because our data is imbalanced and 75% of candidates are "Not Looking for a Job Change," the metric we used to measure our models' performances was Recall because we care most about how our models predict True Positives (employees "Looking for a Job Change") that actually are looking for a job change
- The Recall using Random Forest is 77% (vs. Logistic Regression @ 40%, Decision Tree @ 66%, and Gradient Boosting @ 56%)
- Our model is expected to predict True Positives (i.e. predict employees "Looking for a Job Change" that are actually looking for a job change) 77% of the time

- Within our Random Forest model, City Development Index was the most important feature/determinant of whether a candidate was looking for a job change
- Overall, using this model is a more robust, data-driven approach compared with the company's current approach of scanning resumes for potential Data Science talent

5 Future Work

Future work:

- Work with the company to identify recruitment opportunities and strategies for their Data Science education program (recruit more females; recruit 'unlikely' candidates that do not have a background in STEM; recruit in various cities)
- Suggest another round of Data Science training curriculum following these suggestions
- Gather more data following Round 2 and re-run models
- Continue refining overall process and models
- Make sure all who want to explore Data Science have the opportunity!