Santiago_Gabriela

February 6, 2022

[18]:
```
!pip install missingno
```

```
Requirement already satisfied: missingno in
/Users/gabby/opt/anaconda3/lib/python3.9/site-packages (0.5.0)
Requirement already satisfied: matplotlib in
/Users/gabby/opt/anaconda3/lib/python3.9/site-packages (from missingno) (3.4.3)
Requirement already satisfied: numpy in
/Users/gabby/opt/anaconda3/lib/python3.9/site-packages (from missingno) (1.20.3)
Requirement already satisfied: seaborn in
/Users/gabby/opt/anaconda3/lib/python3.9/site-packages (from missingno) (0.11.2)
Requirement already satisfied: scipy in
/Users/gabby/opt/anaconda3/lib/python3.9/site-packages (from missingno) (1.7.1)
Requirement already satisfied: cycler>=0.10 in
/Users/gabby/opt/anaconda3/lib/python3.9/site-packages (from
matplotlib->missingno) (0.10.0)
Requirement already satisfied: kiwisolver>=1.0.1 in
/Users/gabby/opt/anaconda3/lib/python3.9/site-packages (from
matplotlib->missingno) (1.3.1)
Requirement already satisfied: pillow>=6.2.0 in
/Users/gabby/opt/anaconda3/lib/python3.9/site-packages (from
matplotlib->missingno) (8.4.0)
Requirement already satisfied: python-dateutil>=2.7 in
/Users/gabby/opt/anaconda3/lib/python3.9/site-packages (from
matplotlib->missingno) (2.8.2)
Requirement already satisfied: pyparsing>=2.2.1 in
/Users/gabby/opt/anaconda3/lib/python3.9/site-packages (from
matplotlib->missingno) (3.0.4)
Requirement already satisfied: six in
/Users/gabby/opt/anaconda3/lib/python3.9/site-packages (from
cycler>=0.10->matplotlib->missingno) (1.16.0)
Requirement already satisfied: pandas>=0.23 in
/Users/gabby/opt/anaconda3/lib/python3.9/site-packages (from seaborn->missingno)
(1.3.4)
Requirement already satisfied: pytz>=2017.3 in
/Users/gabby/opt/anaconda3/lib/python3.9/site-packages (from
pandas>=0.23->seaborn->missingno) (2021.3)
```

[1]:
```
#import libraries: pandas, numpy, matplotlib (set %matplotlib inline),␣
↪matplotlib's pyplot, seaborn, missingno, scipy's stats, sklearn
#This jupyter notebook is prepared by "Gabriela Santiago".
%matplotlib inline
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
import scipy.stats as st
import sklearn
import missingno as msno
```

[2]:
```
#import the data to a dataframe and show how many rows and columns does it have
df = pd.read_csv('hrdata.csv')
```

[3]:
```
print("Rows: ", len(df))
print("Columns: ", len(df.columns))
```

```
Rows:  21287
Columns:  18
```

[9]:
```
#call the describe method of dataframe to see some summary statistics of the␣
↪numerical columns
df.describe()
```

[9]:
```
        Unnamed: 0      rec_num   enrollee_id  city_development_index  \
count  21287.000000  21287.000000  21287.000000            21287.000000
mean   10643.000000  10644.000000  16873.983652                0.828462
std     6145.171926   6145.171926   9612.131237                0.123537
min        0.000000      1.000000      1.000000                0.448000
25%     5321.500000   5322.500000   8554.500000                0.739000
50%    10643.000000  10644.000000  16967.000000                0.903000
75%    15964.500000  15965.500000  25161.500000                0.920000
max    21286.000000  21287.000000  33380.000000                0.949000

       training_hours        target  city_development_matrics
count    21287.000000  19158.000000              21287.000000
mean        65.328510      0.249348                  8.284615
std         60.075201      0.432647                  1.235365
min          1.000000      0.000000                  4.480000
25%         23.000000      0.000000                  7.390000
50%         47.000000      0.000000                  9.030000
75%         88.000000      0.000000                  9.200000
max        336.000000      1.000000                  9.490000
```

[10]:
```
#Explain in words if you find any column's statistics interesting and good to␣
↪know
```

```
#I think it's good to know the training hours' statistics to know if an␣
↪employee has average or above average training time
```

[11]:
```
#Show the top 5 rows and last 5 rows of the data frame
df.head()
```

[11]:
```
   Unnamed: 0  rec_num  enrollee_id      city  city_development_index gender  \
0           0        1         8949  city_103                   0.920   Male
1           1        2        29725   city_40                   0.776   Male
2           2        3        11561   city_21                   0.624    NaN
3           3        4        33241  city_115                   0.789    NaN
4           4        5          666  city_162                   0.767   Male

       relevent_experience enrolled_university education_level  \
0  Has relevent experience       no_enrollment        Graduate
1   No relevent experience       no_enrollment        Graduate
2   No relevent experience    Full time course        Graduate
3   No relevent experience                 NaN        Graduate
4  Has relevent experience       no_enrollment         Masters

  major_discipline experience company_size    company_type last_new_job  \
0             STEM        >20          NaN             NaN            1
1             STEM         15        50-99         Pvt Ltd           >4
2             STEM          5          NaN             NaN        never
3  Business Degree         <1          NaN         Pvt Ltd        never
4             STEM        >20        50-99  Funded Startup            4

   training_hours  target state  city_development_matrics
0              36     1.0    CA                      9.20
1              47     0.0    CA                      7.76
2              83     0.0    CA                      6.24
3              52     1.0    CA                      7.89
4               8     0.0    CA                      7.67
```

[12]:
```
df.tail()
```

[12]:
```
       Unnamed: 0  rec_num  enrollee_id      city  city_development_index  \
21282       21282    21283         1289  city_103                   0.920
21283       21283    21284          195  city_136                   0.897
21284       21284    21285        31762  city_100                   0.887
21285       21285    21286         7873  city_102                   0.804
21286       21286    21287        12215  city_102                   0.804

      gender      relevent_experience enrolled_university education_level  \
21282   Male   No relevent experience       no_enrollment        Graduate
21283   Male  Has relevent experience       no_enrollment         Masters
21284   Male   No relevent experience       no_enrollment  Primary School
```

```
21285   Male  Has relevent experience    Full time course     High School
21286   Male  Has relevent experience       no_enrollment         Masters

      major_discipline experience company_size   company_type last_new_job  \
21282       Humanities         16          NaN  Public Sector            4
21283             STEM         18          NaN            NaN            2
21284              NaN          3          NaN        Pvt Ltd        never
21285              NaN          7      100-500  Public Sector            1
21286             STEM         15       10000+        Pvt Ltd            2

       training_hours  target state  city_development_matrics
21282              15     NaN    CA                      9.20
21283              30     NaN    CA                      8.97
21284              18     NaN    CA                      8.87
21285              84     NaN    CA                      8.04
21286              11     NaN    CA                      8.04
```

[13]:
```python
#List all the numerical columns
numerical = df.select_dtypes(include=[np.number])
numerical.columns
```

[13]:
```
Index(['Unnamed: 0', 'rec_num', 'enrollee_id', 'city_development_index',
       'training_hours', 'target', 'city_development_matrics'],
      dtype='object')
```

[14]:
```python
#List all the categorial columns
categorical = df.select_dtypes(include=[object])
categorical.columns
```

[14]:
```
Index(['city', 'gender', 'relevent_experience', 'enrolled_university',
       'education_level', 'major_discipline', 'experience', 'company_size',
       'company_type', 'last_new_job', 'state'],
      dtype='object')
```

[15]:
```python
#Show a list with column wise count of missing values and display the list in␣
↪count wise descending order
nulls = df.isnull().sum().to_frame('nulls')
nulls.sort_values("nulls", inplace = True, ascending = False)
for index, row in nulls.iterrows():
    print(index, row[0])
```

```
company_type 6774
company_size 6560
gender 5016
major_discipline 3125
target 2129
education_level 512
last_new_job 463
```

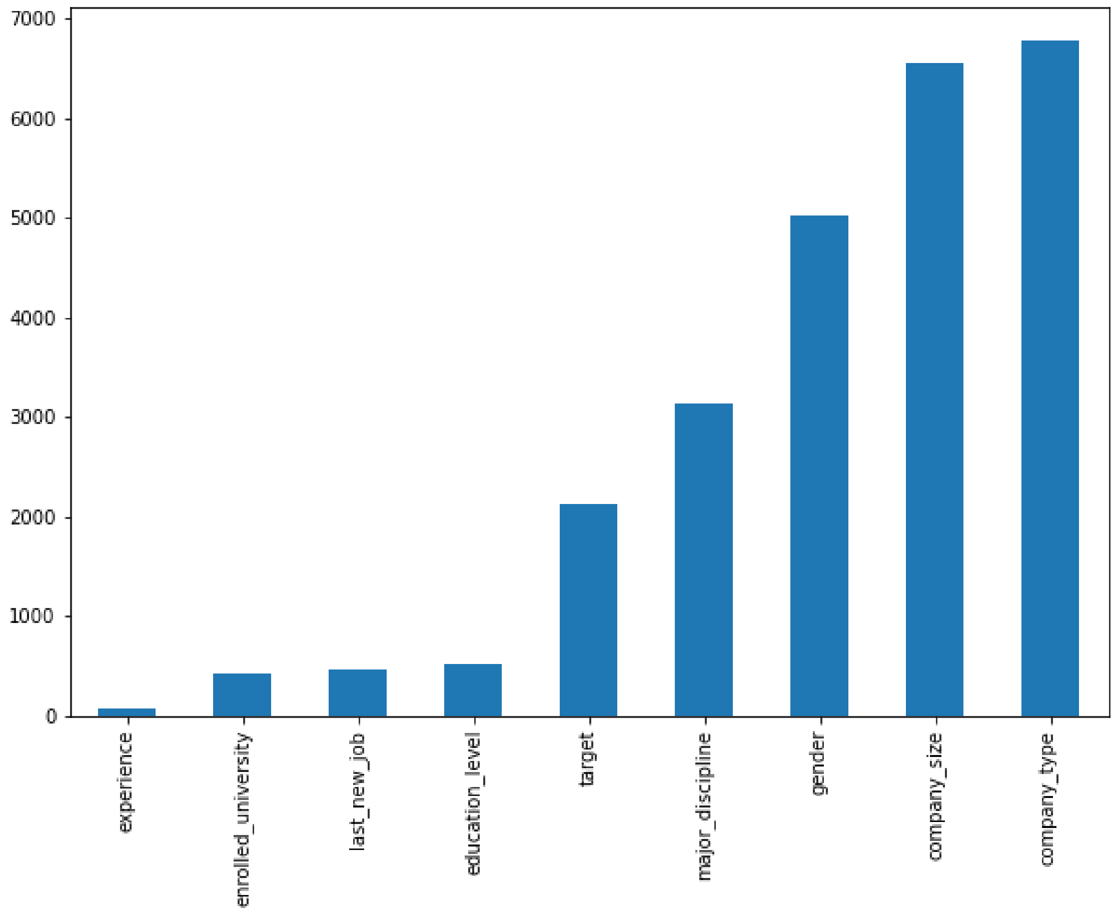
```
enrolled_university 417
experience 70
state 0
training_hours 0
Unnamed: 0 0
rec_num 0
relevent_experience 0
city_development_index 0
city 0
enrollee_id 0
city_development_matrics 0
```

[16]:
```python
#Show a list with column wise percentage of missing values and display the list␣
↪in percentage wise descending order
percentage = df.isnull().mean()*100
percentage = percentage.to_frame("nulls")
percentage.sort_values("nulls", inplace = True, ascending = False)
for index, row in percentage.iterrows():
    print(index, row[0])
```

```
company_type 31.822238925165593
company_size 30.816930520975244
gender 23.563677361770093
major_discipline 14.680321322873116
target 10.001409310846995
education_level 2.405223845539531
last_new_job 2.1750364071968806
enrolled_university 1.9589420773241883
experience 0.3288391976323578
state 0.0
training_hours 0.0
Unnamed: 0 0.0
rec_num 0.0
relevent_experience 0.0
city_development_index 0.0
city 0.0
enrollee_id 0.0
city_development_matrics 0.0
```

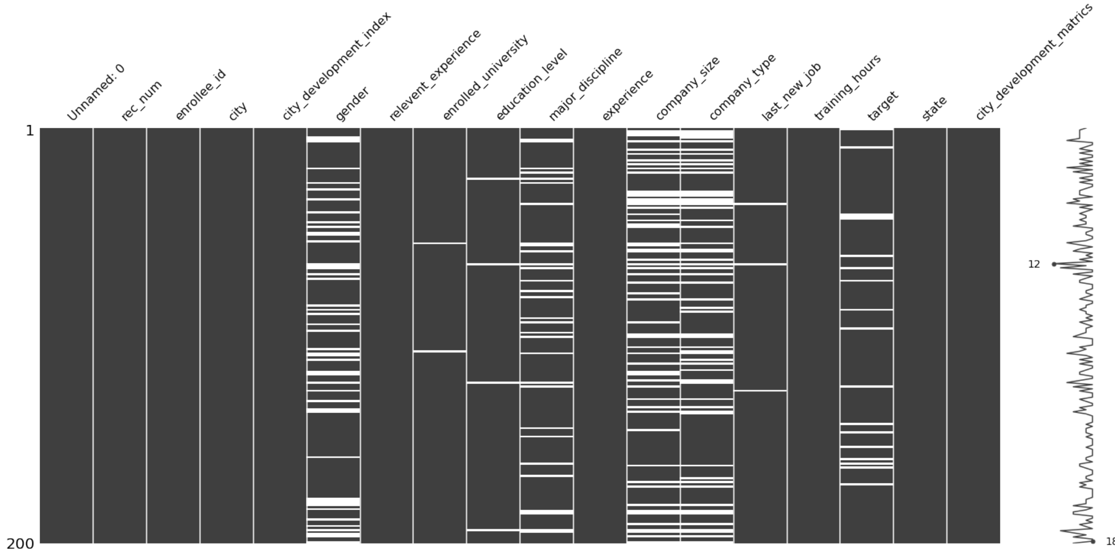
[17]:
```python
#Display a bar plot to visualize only the columns with missing values and their␣
↪count. The plot should display from less missing value columns in the left␣
↪and then more missing value columns to the right side of the plot
missing = df.isnull().sum()
missing = missing[missing>0]
missing.sort_values(inplace = True)
plt.figure(figsize = (10, 7))
missing.plot.bar()
```

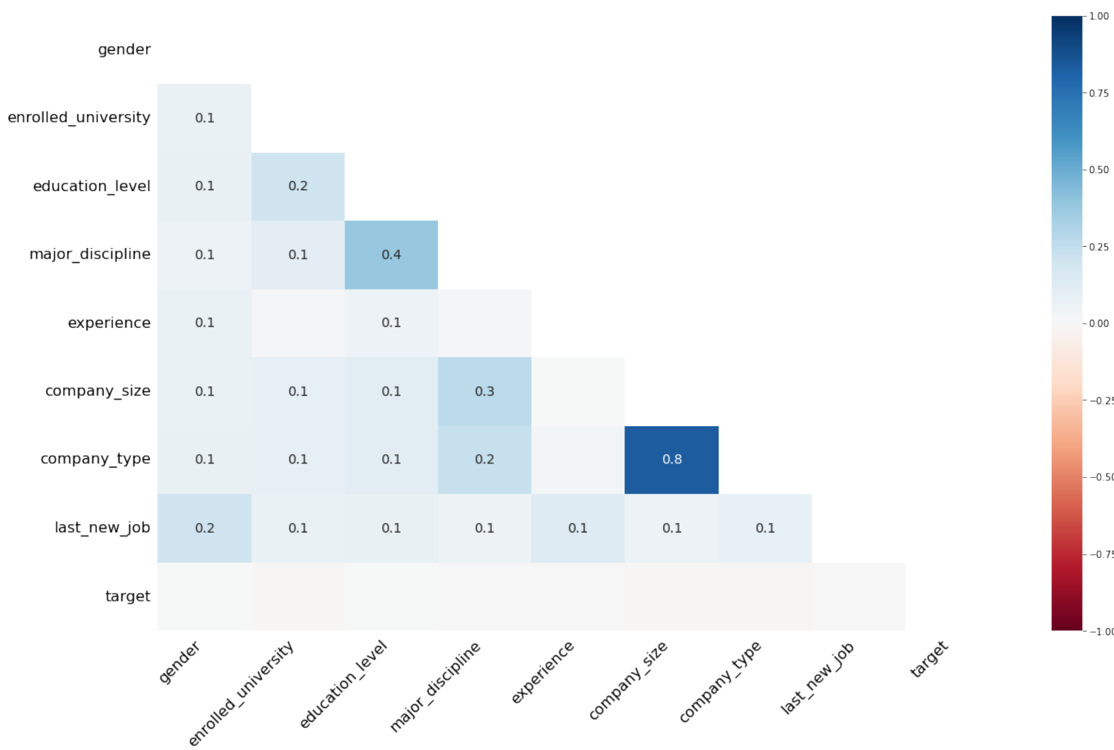
[17]: <AxesSubplot:>



[31]:
```
#Use missingno's bar plot, matrix plot with 200 sample, and heatmap
msno.matrix(df.sample(200))
msno.heatmap(df)
```

[31]: <AxesSubplot:>

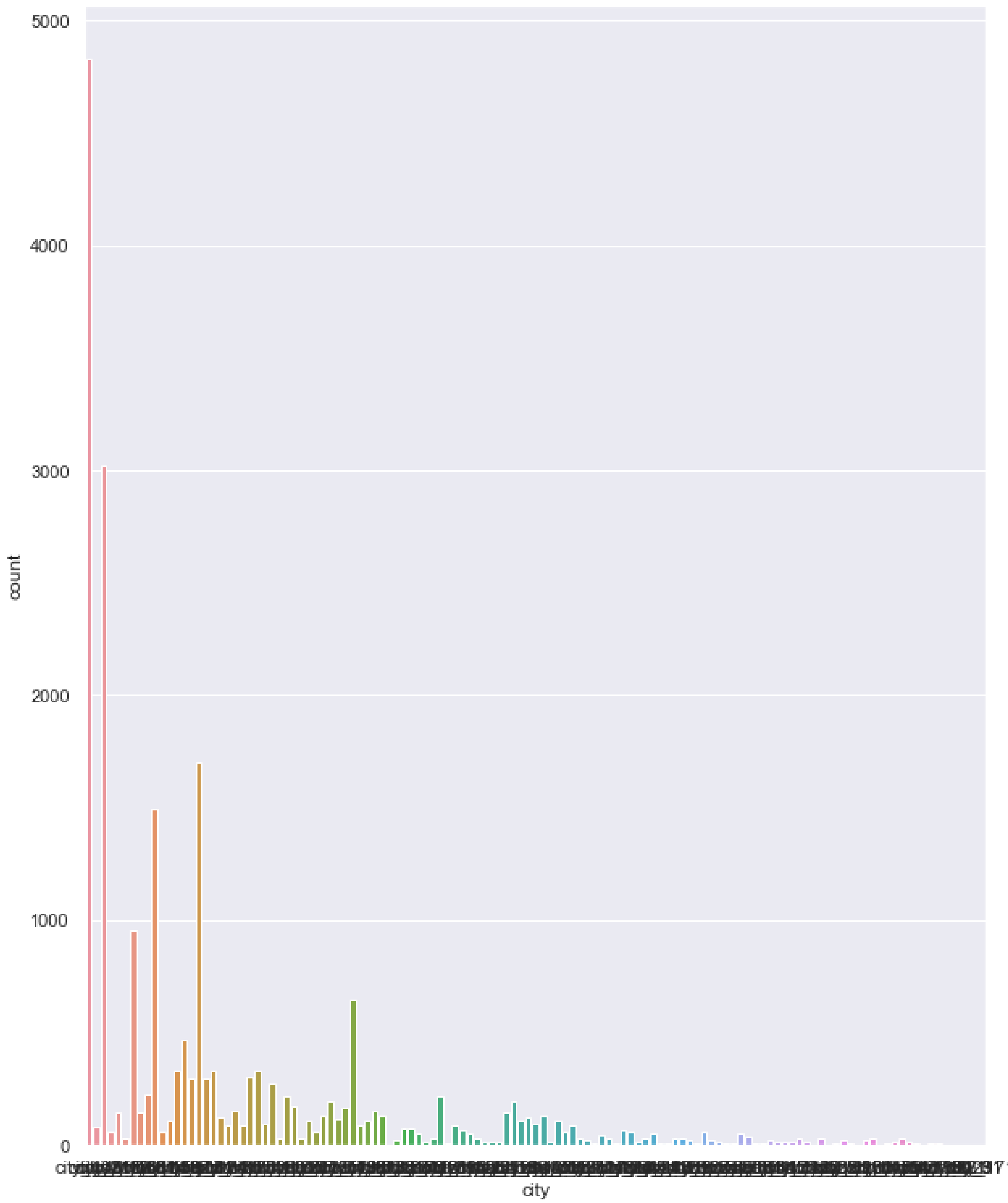




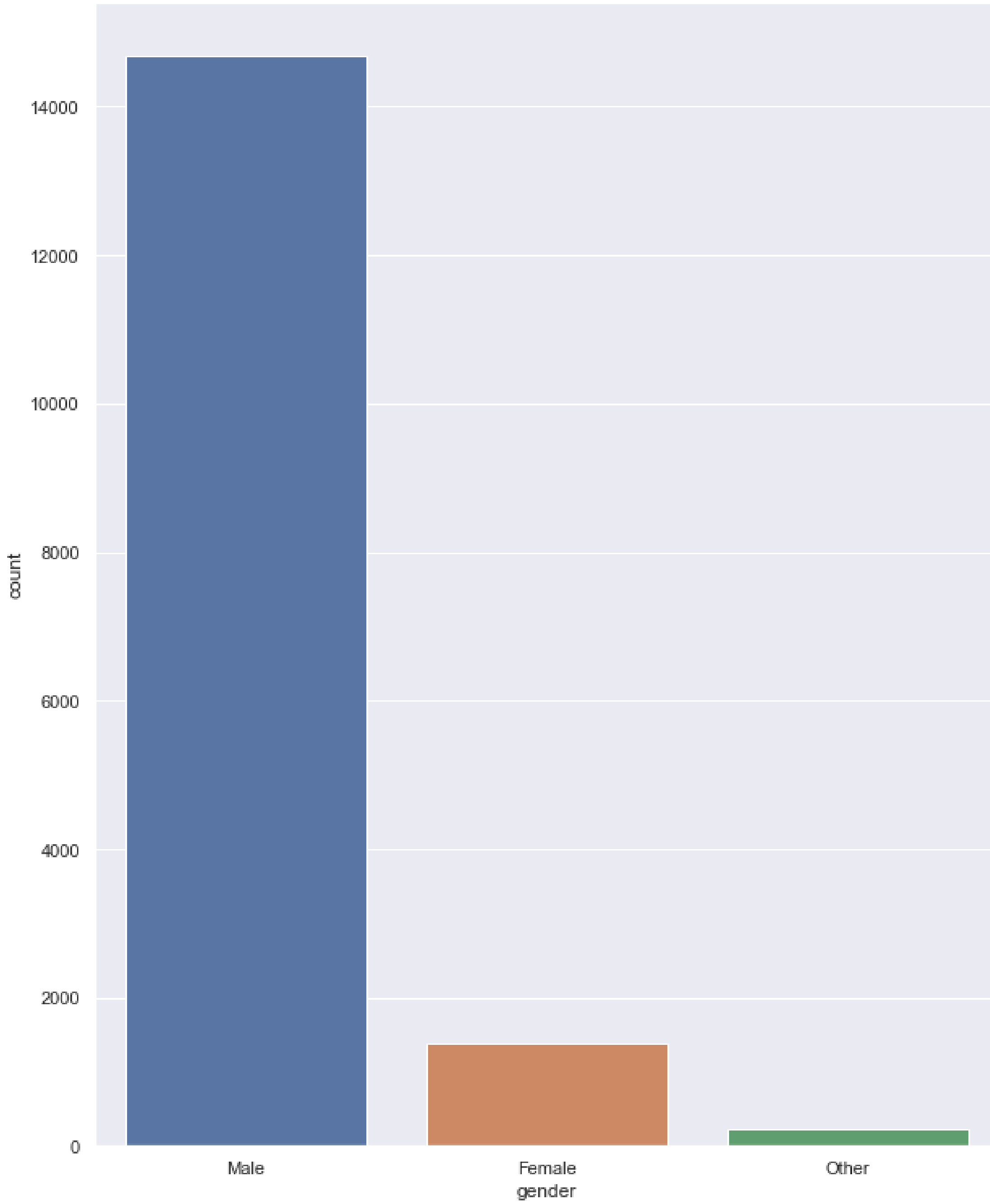
[32]:
```
#Interpret any interesting information you found in the heatmap and any one plot
#It's noticeable that there is a relatively strong correlation between the␣
↪'company_size' values and the "company_type" category
```

```
#It's also noticeable that those two very categories happen to be the columns␣
↪with the most missingno variables, this may have biased the heatmap
```

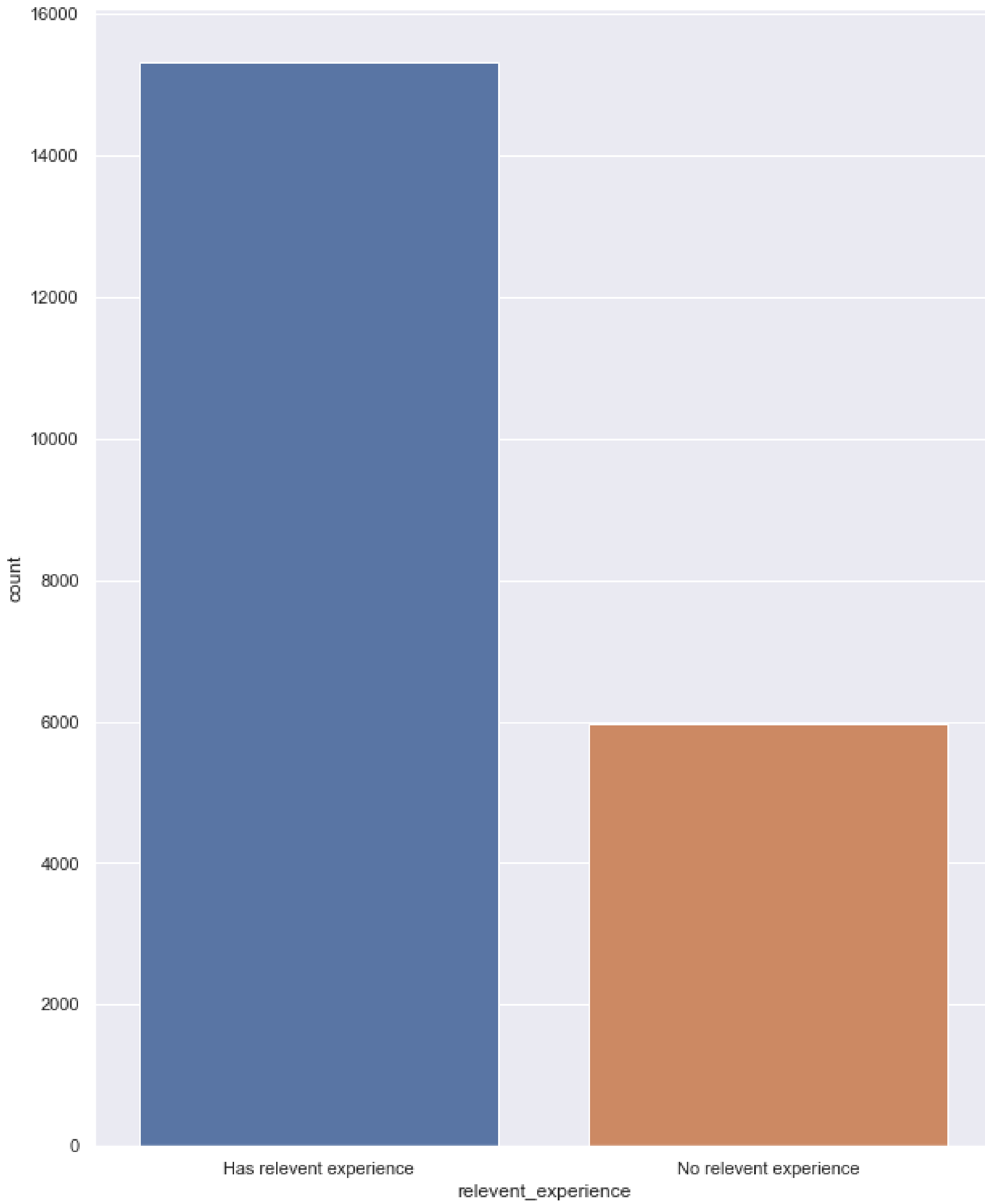
[20]:
```
#Use seaborn bar plot for the categorical feature to see different values and␣
↪count
#I used countplots instead as the bar plots required a y value
sns.countplot(x = 'city', data = categorical)
sns.set(rc={'figure.figsize':(1, 13)})
```



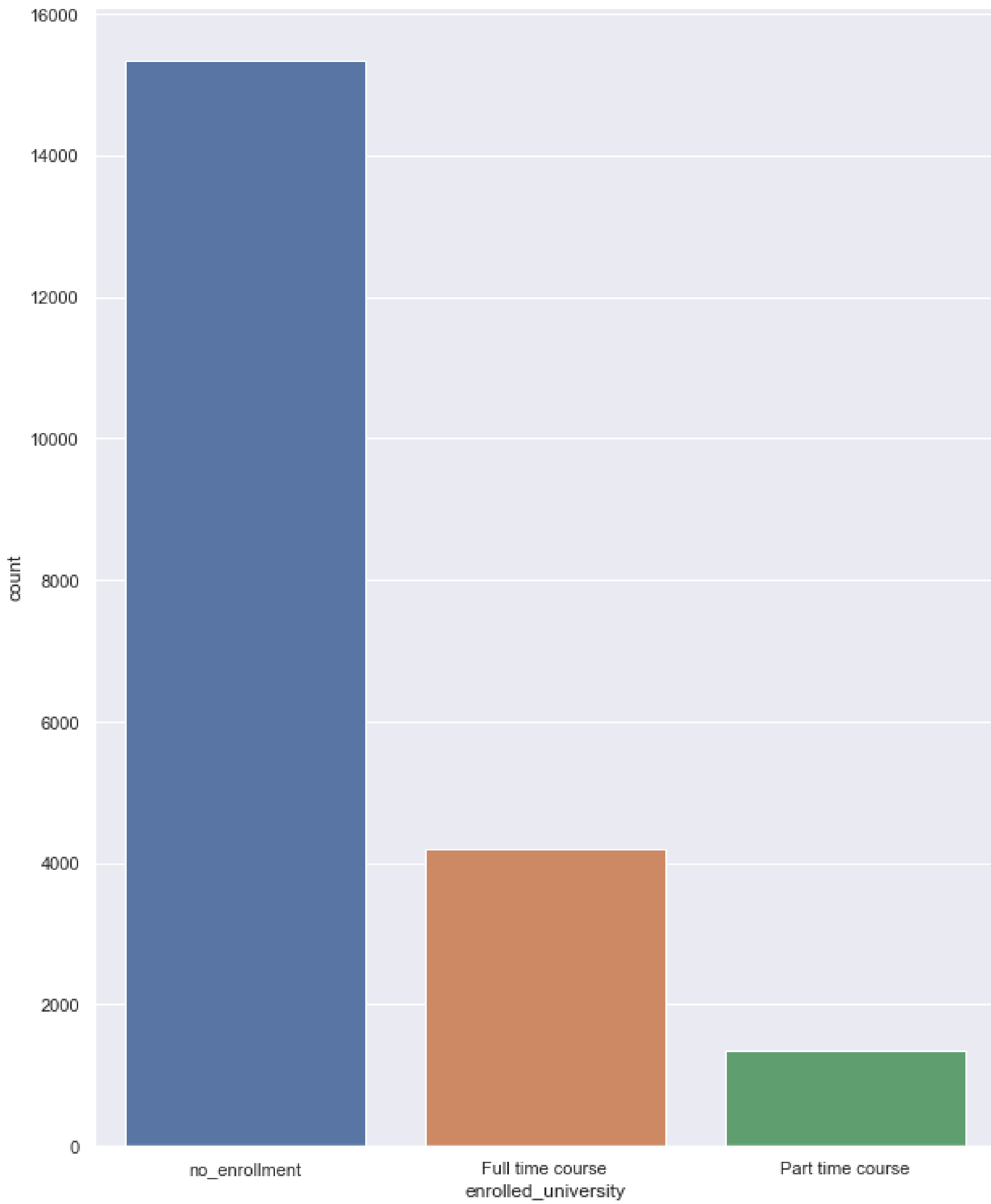
[83]:
```
sns.countplot(x = 'gender', data = categorical)
sns.set(rc={'figure.figsize':(10, 13)})
```



[35]:
```
sns.countplot(x = 'relevent_experience', data = categorical)
sns.set(rc={'figure.figsize':(10, 13)})
```

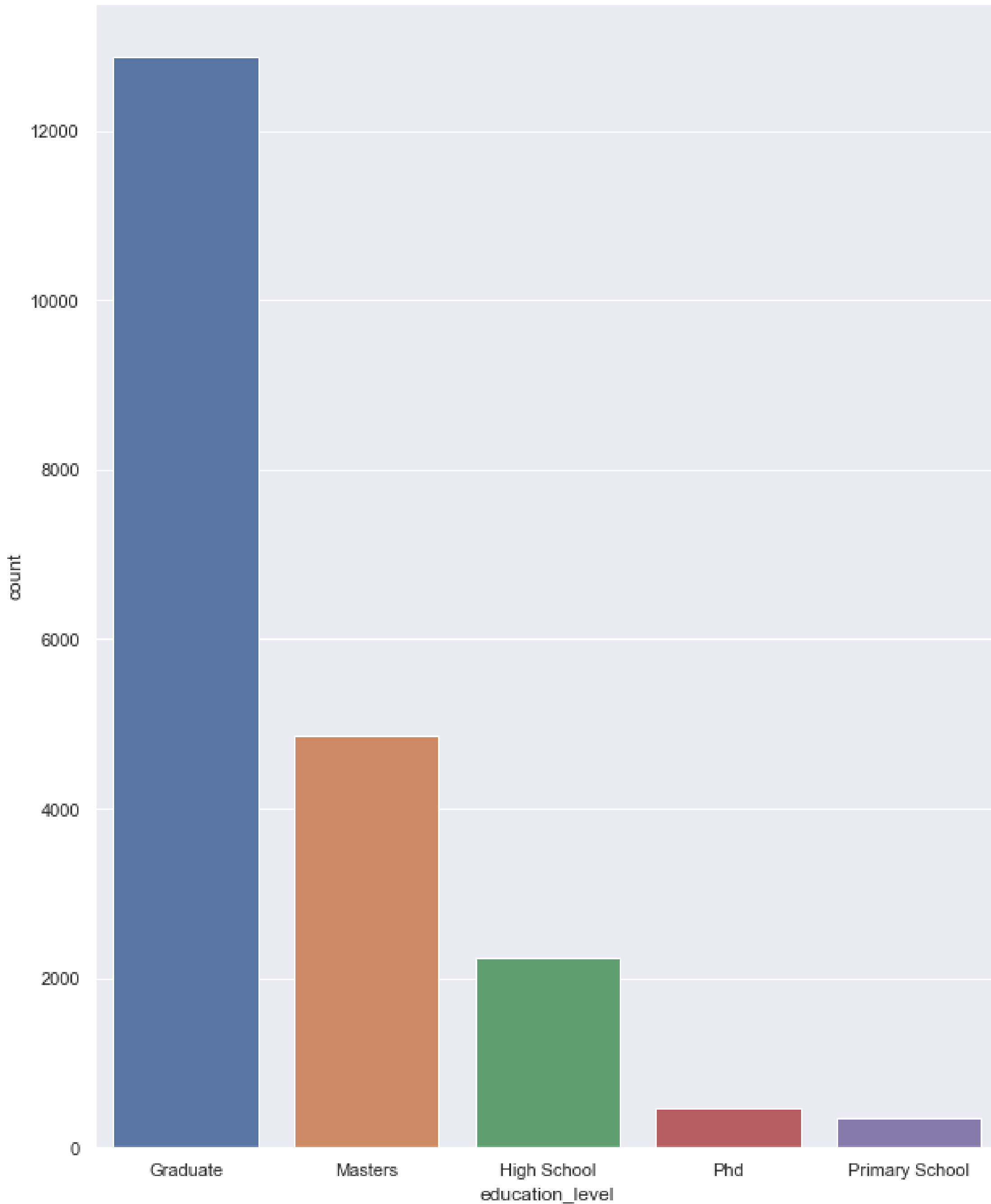


[36]:
```
sns.countplot(x = 'enrolled_university', data = categorical)
sns.set(rc={'figure.figsize':(10, 13)})
```



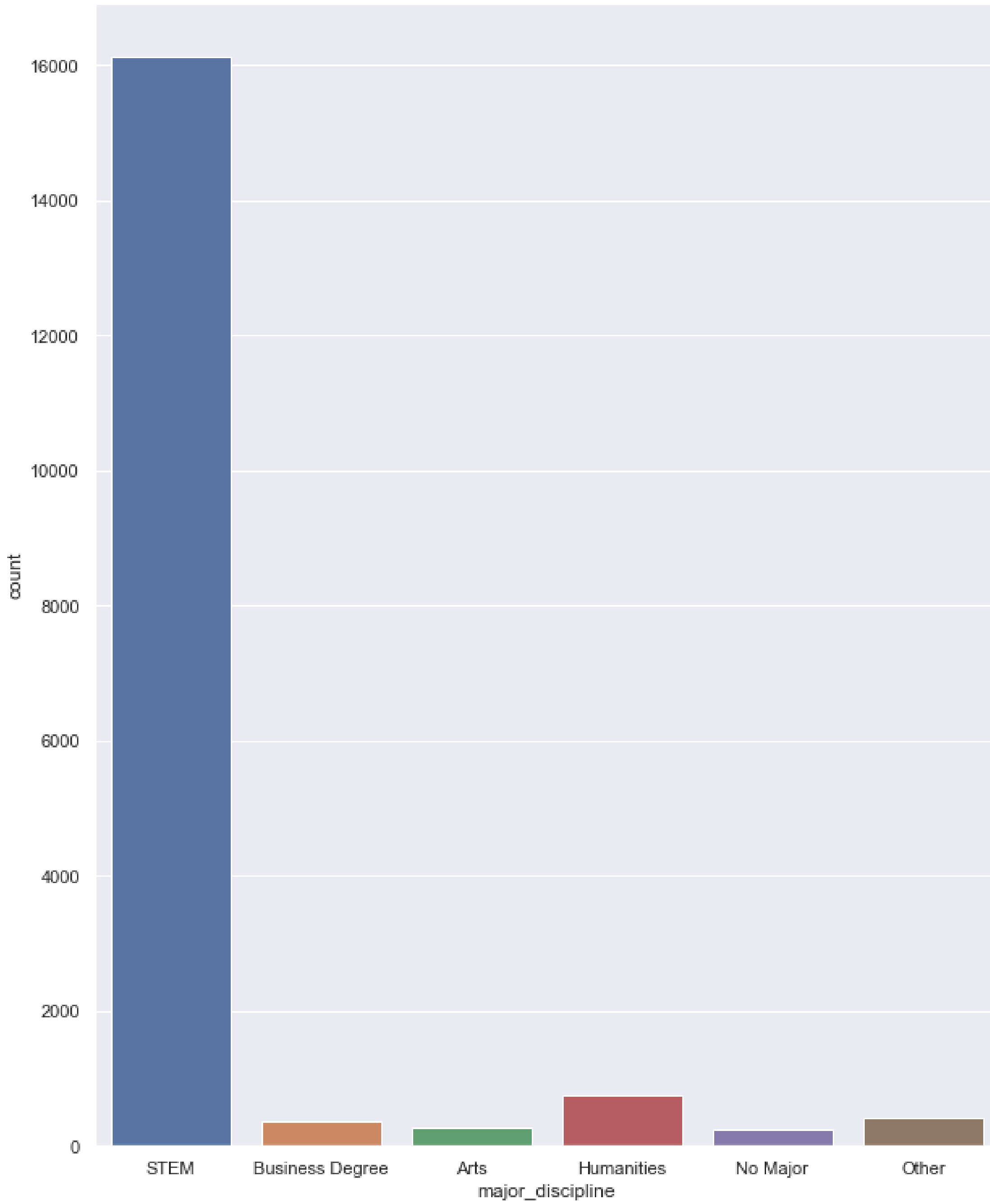
[37]:
```
sns.countplot(x = 'education_level', data = categorical)
```

[37]: <AxesSubplot:xlabel='education_level', ylabel='count'>



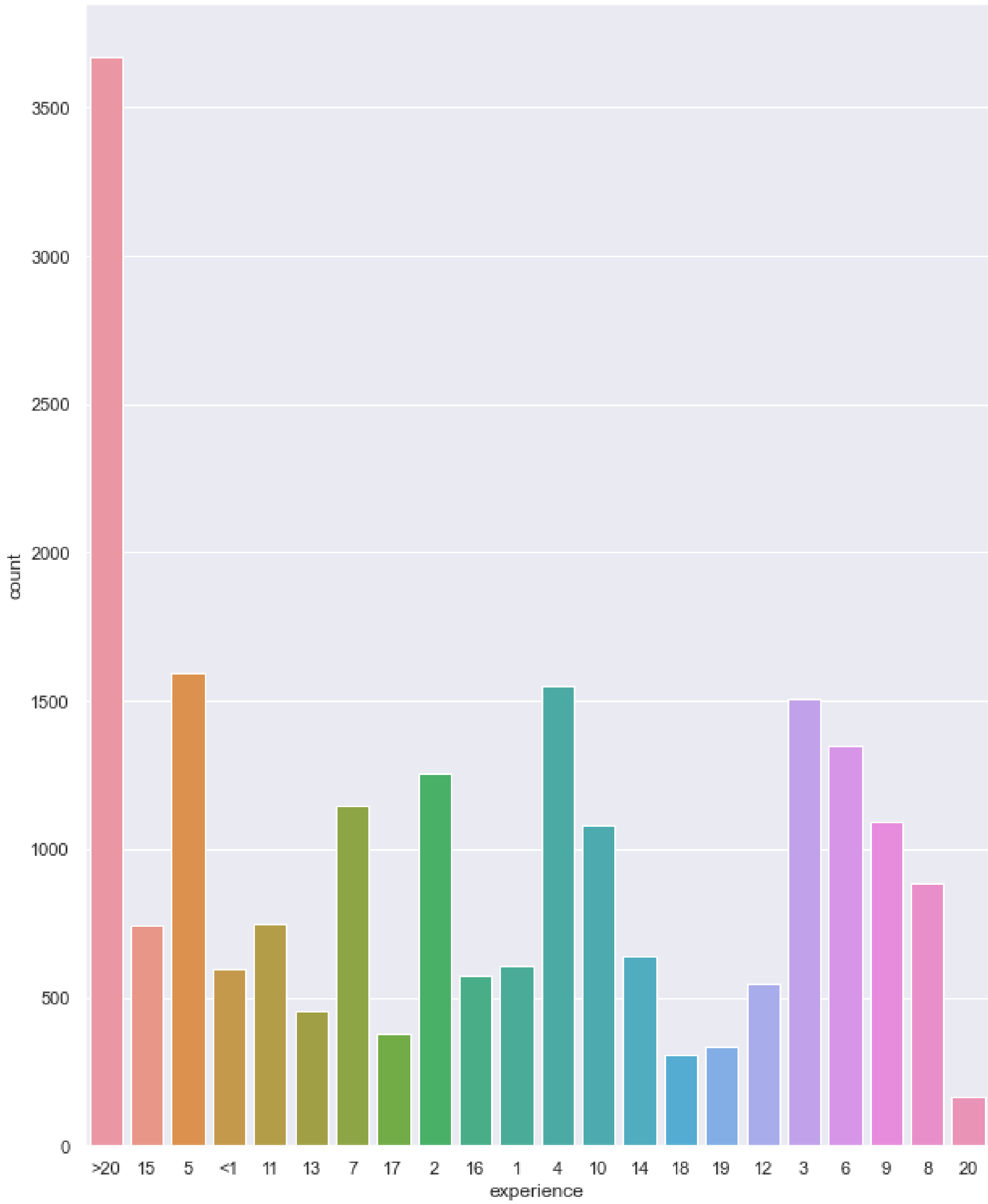

```
[38]: sns.countplot(x = 'major_discipline', data = categorical)
```

```
[38]: <AxesSubplot:xlabel='major_discipline', ylabel='count'>
```



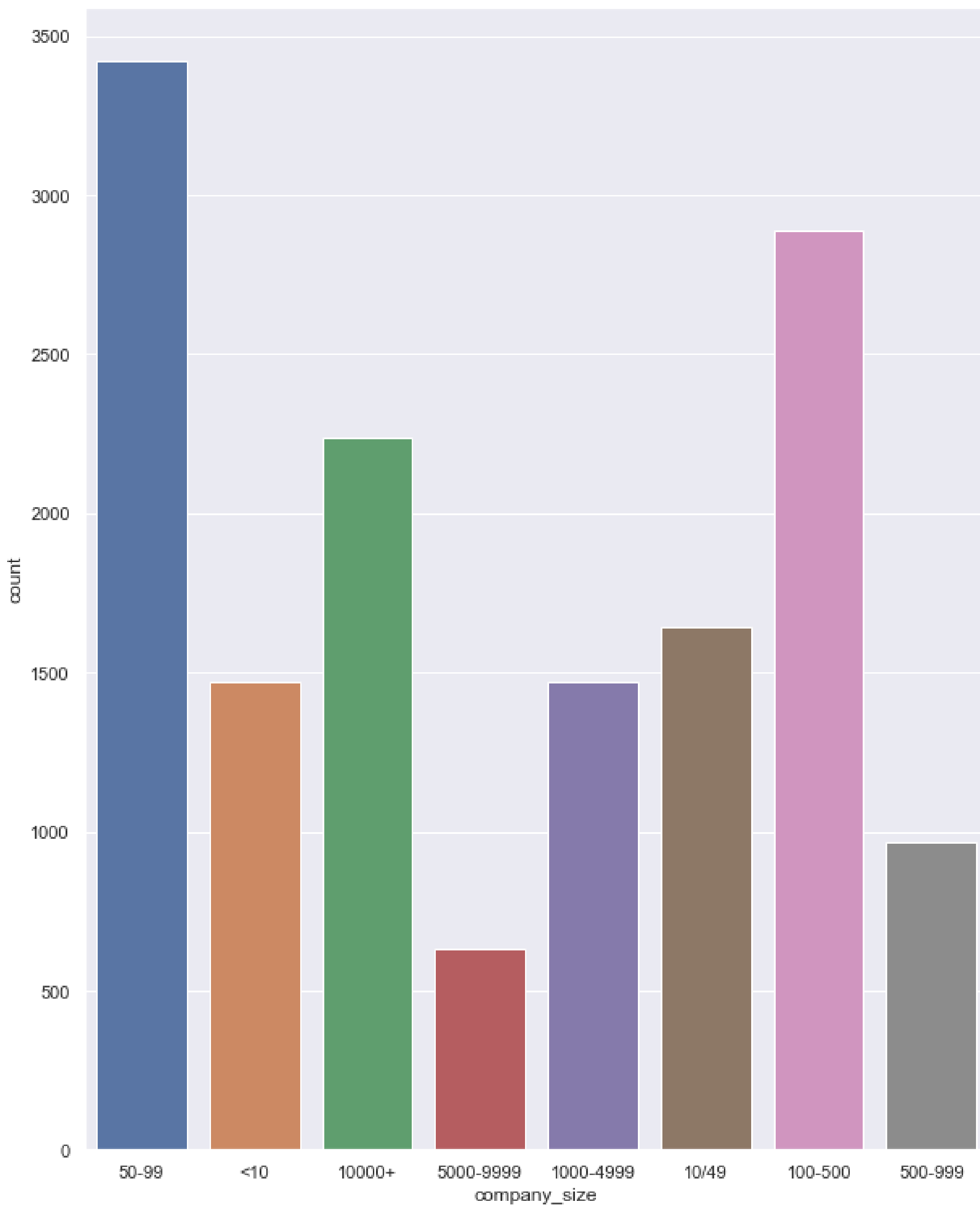
[39]:
```
sns.countplot(x = 'experience', data = categorical)
```

[39]: <AxesSubplot:xlabel='experience', ylabel='count'>



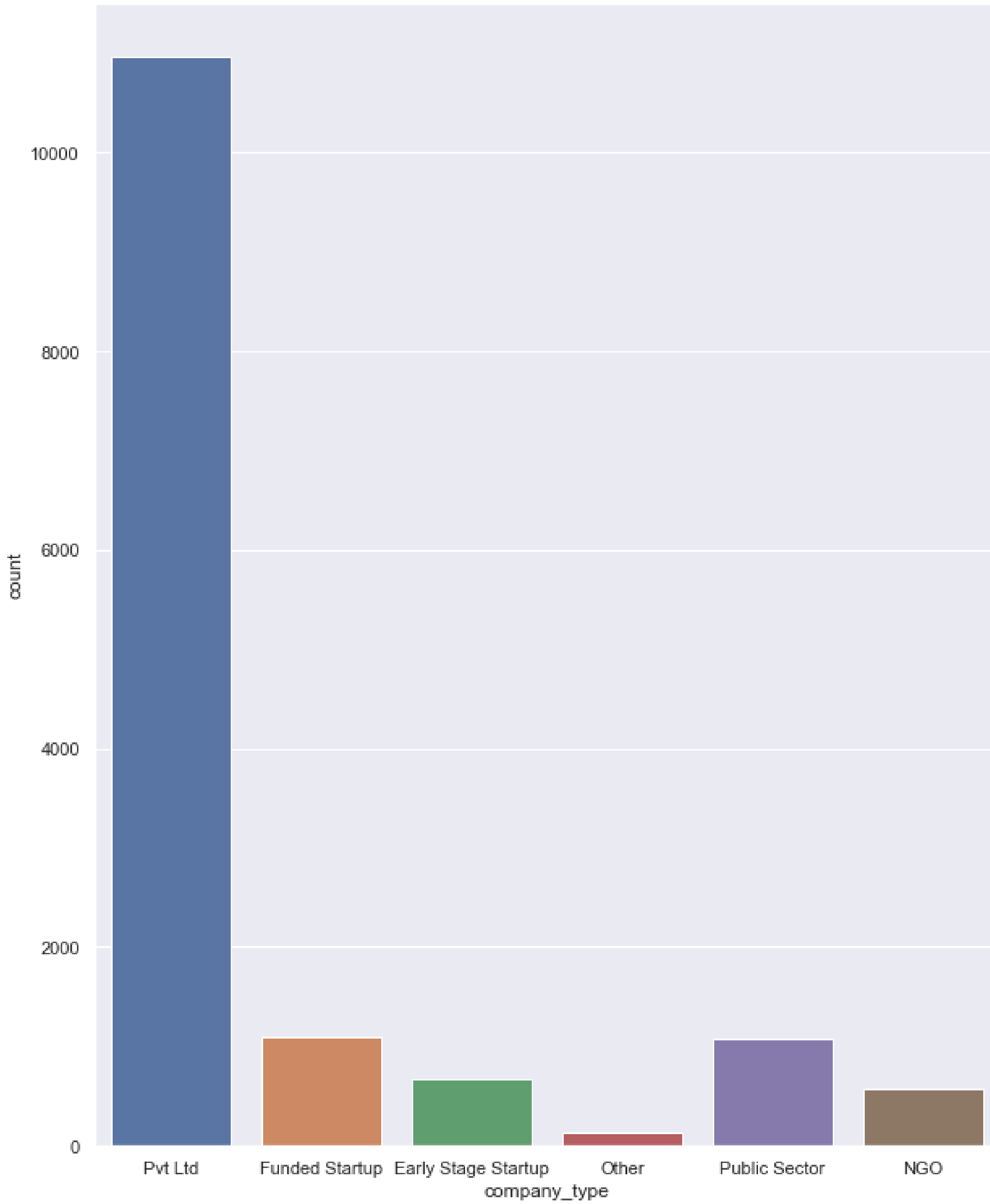

```
[40]: sns.countplot(x = 'company_size', data = categorical)
```

```
[40]: <AxesSubplot:xlabel='company_size', ylabel='count'>
```



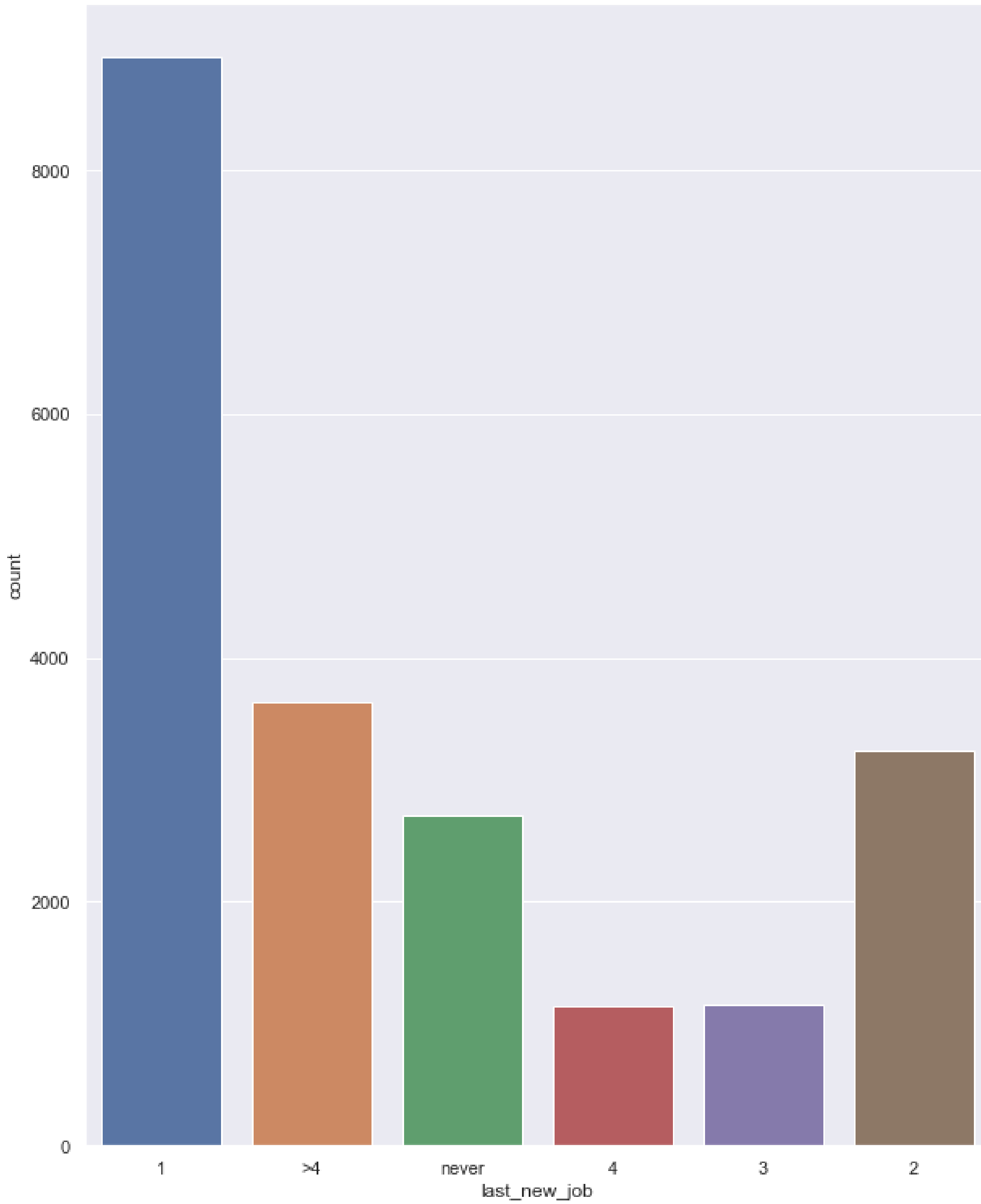
[41]:
```
sns.countplot(x = 'company_type', data = categorical)
```

[41]: <AxesSubplot:xlabel='company_type', ylabel='count'>



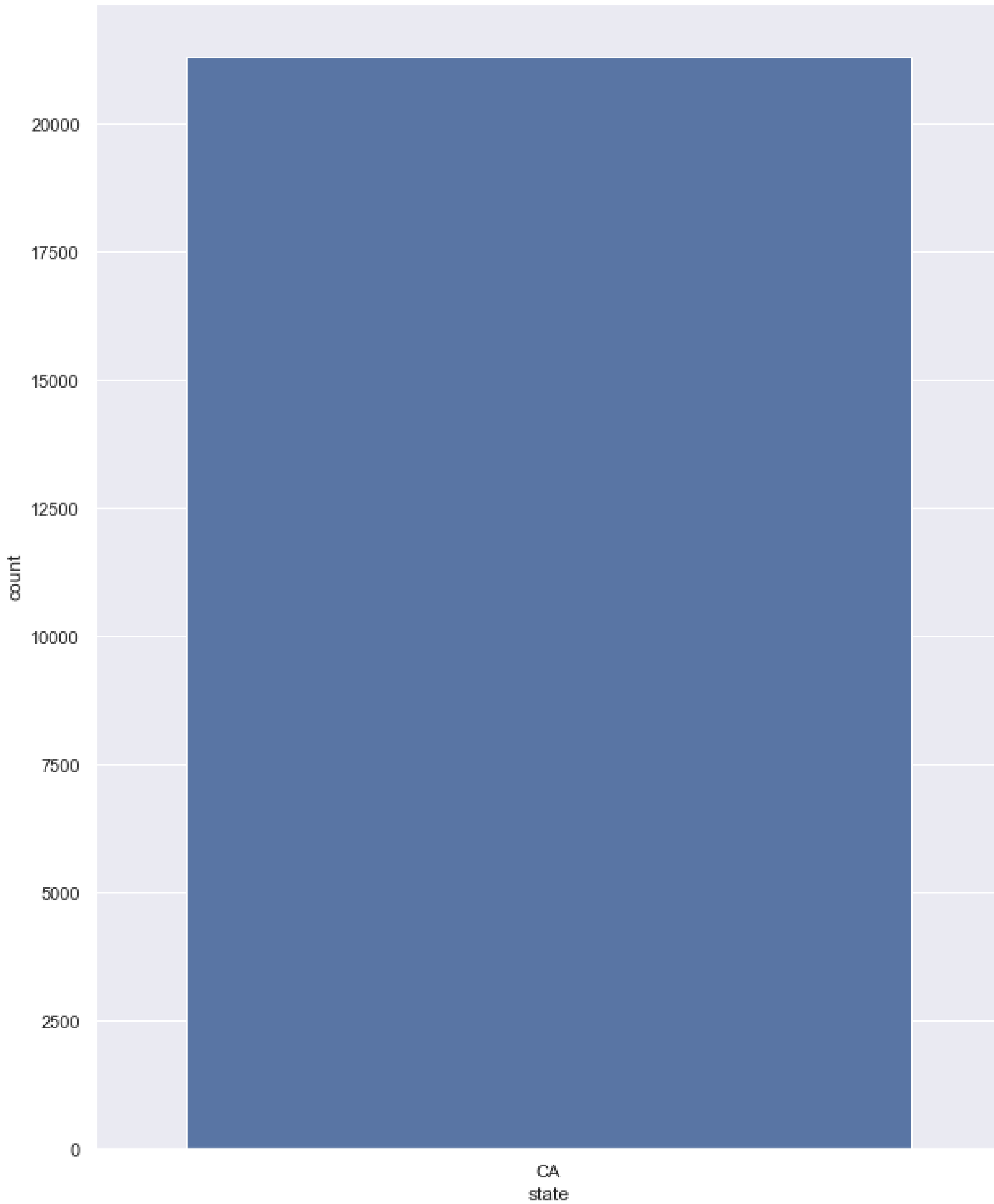
[42]:
```
sns.countplot(x = 'last_new_job', data = categorical)
```

[42]: <AxesSubplot:xlabel='last_new_job', ylabel='count'>

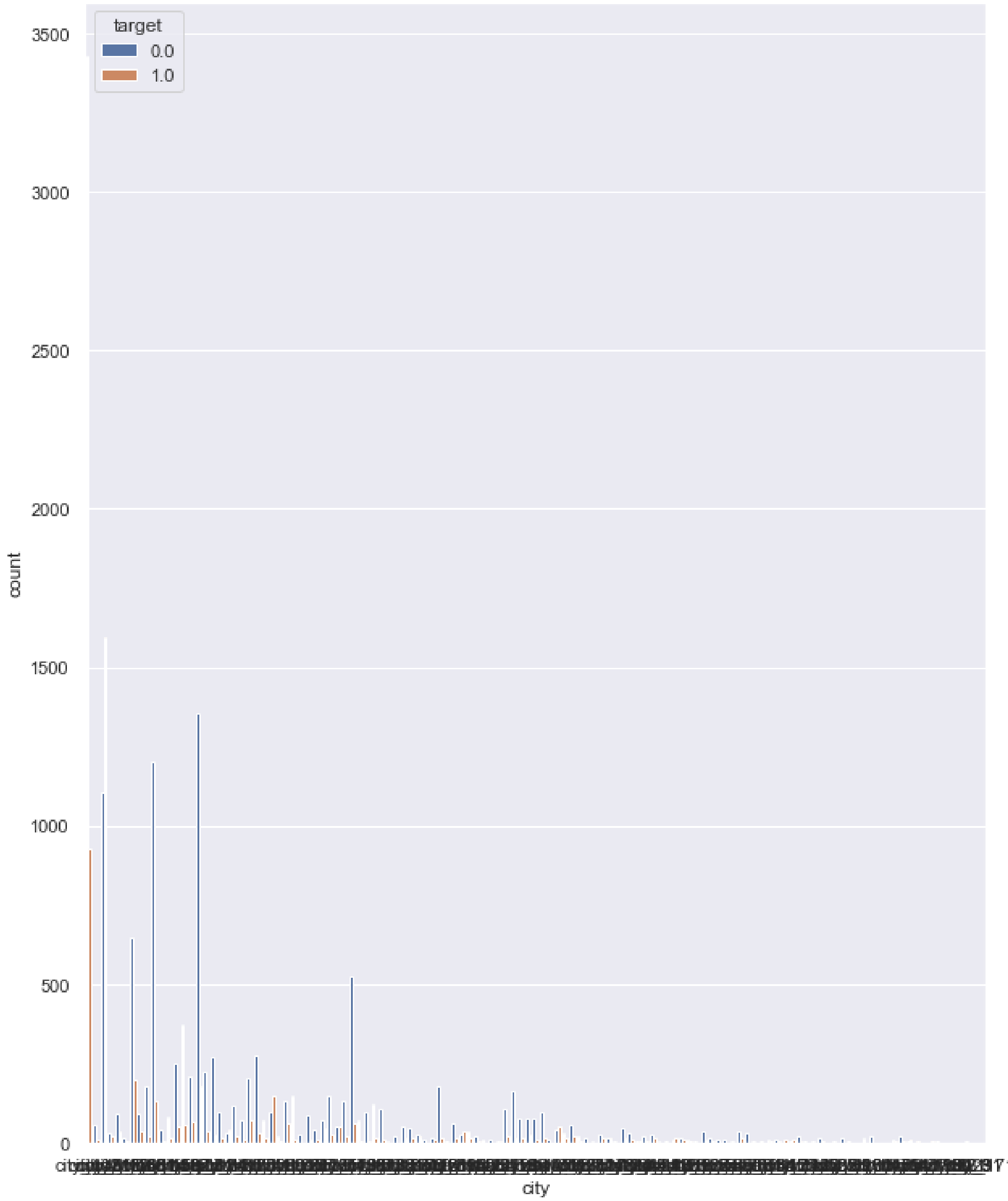


[43]:
```
sns.countplot(x = 'state', data = categorical)
```

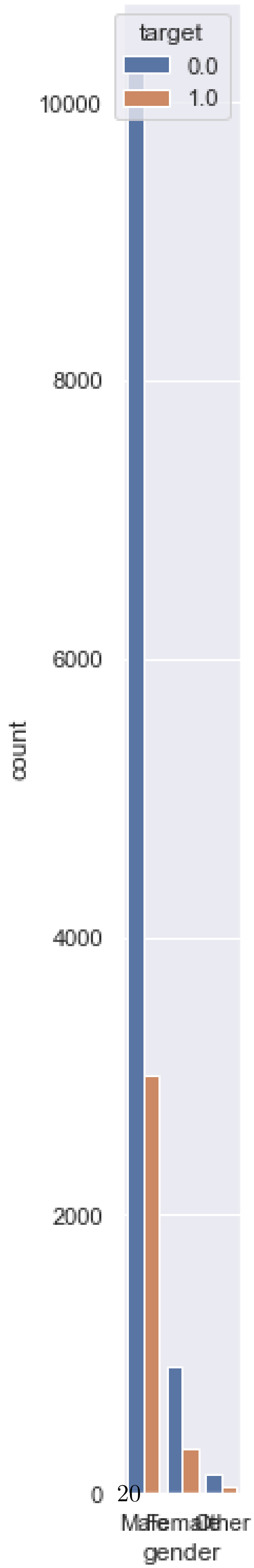
[43]: <AxesSubplot:xlabel='state', ylabel='count'>



[44]:
```
#Use seaborn countplot for the categorical feature against the values of the␣
↪target
sns.countplot(x = 'city', hue = df['target'], data = categorical)
sns.set(rc={'figure.figsize':(10, 130)})
```

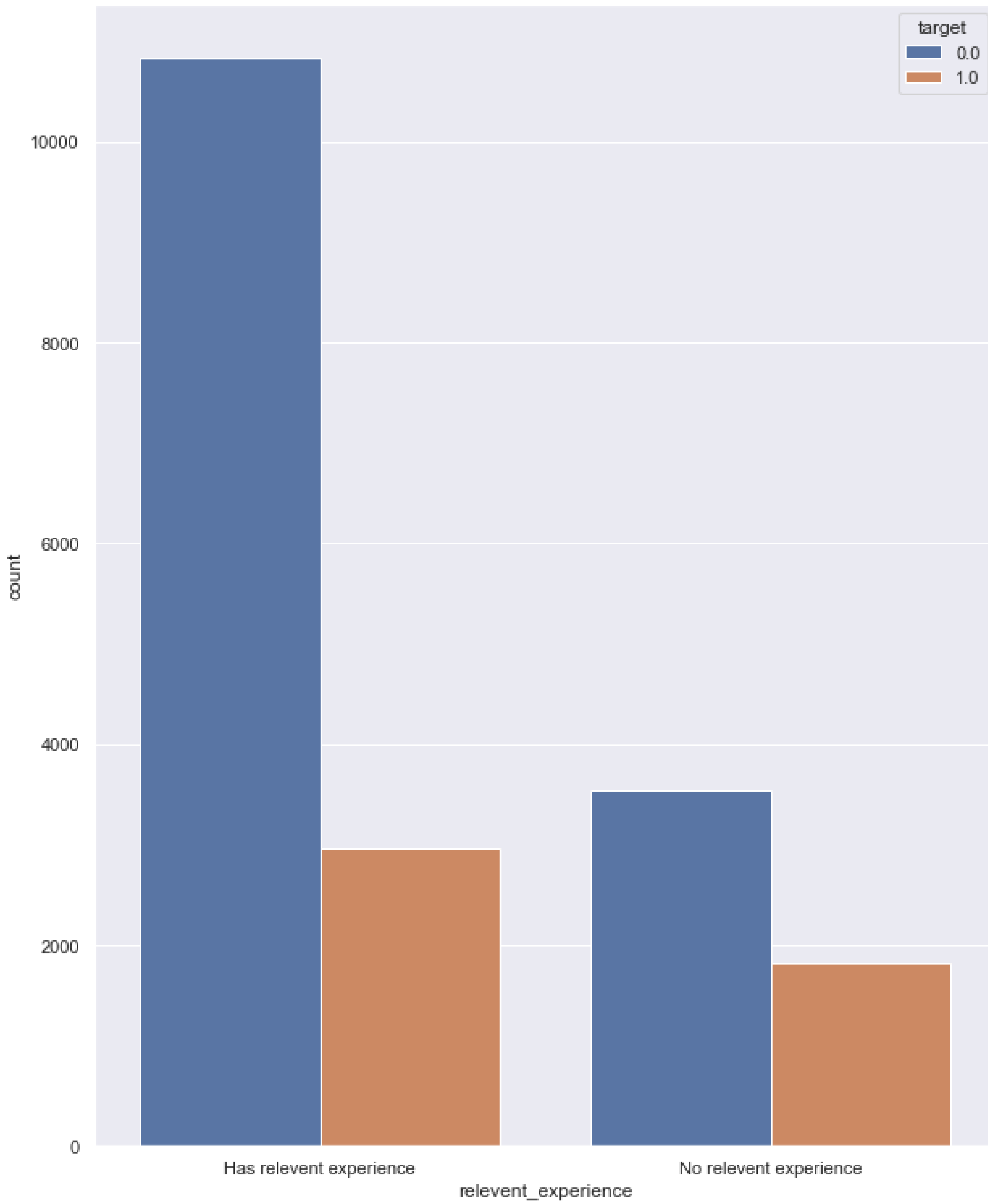


[21]:
```
sns.countplot(x = 'gender', hue = df['target'], data = categorical)
sns.set(rc={'figure.figsize':(10, 13)})
```



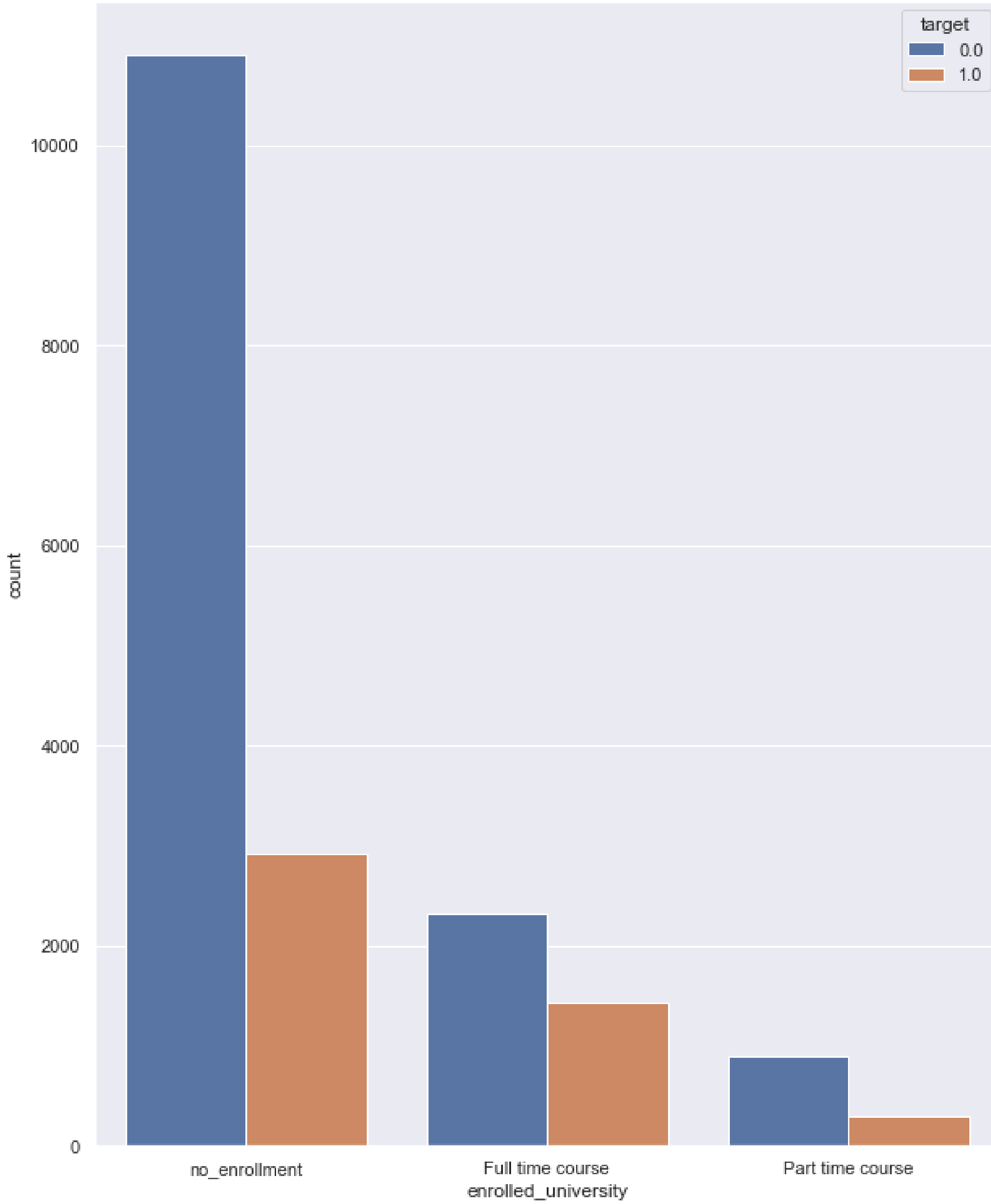
target
0.0
1.0
10000
8000
6000
4000
2000
0
count
Male
Female
Other
gender

[46]:
```
sns.countplot(x = 'relevent_experience', hue = df['target'], data = categorical)
sns.set(rc={'figure.figsize':(10, 13)})
```



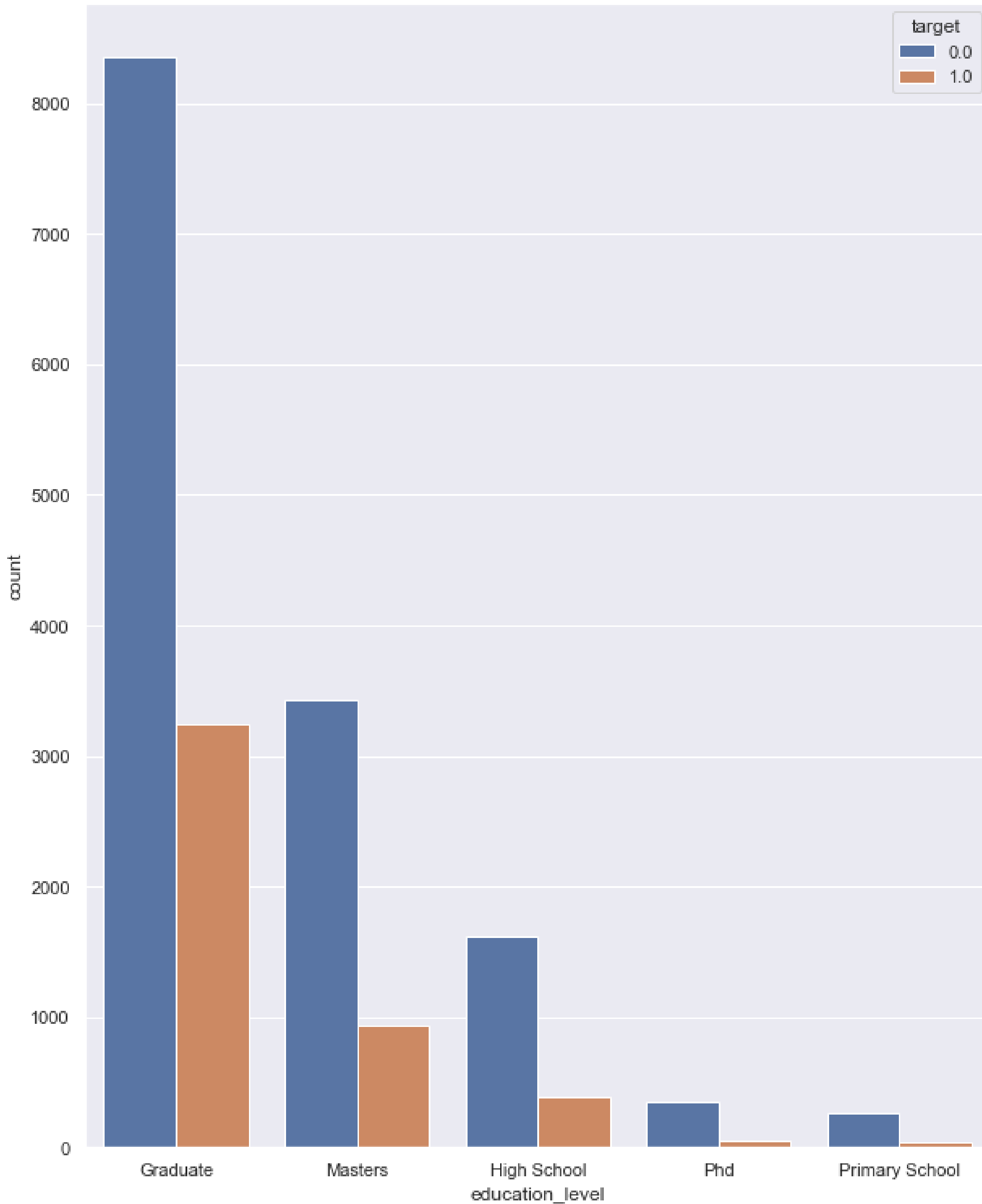
[47]:
```
sns.countplot(x = 'enrolled_university', hue = df['target'], data = categorical)
```

[47]: <AxesSubplot:xlabel='enrolled_university', ylabel='count'>



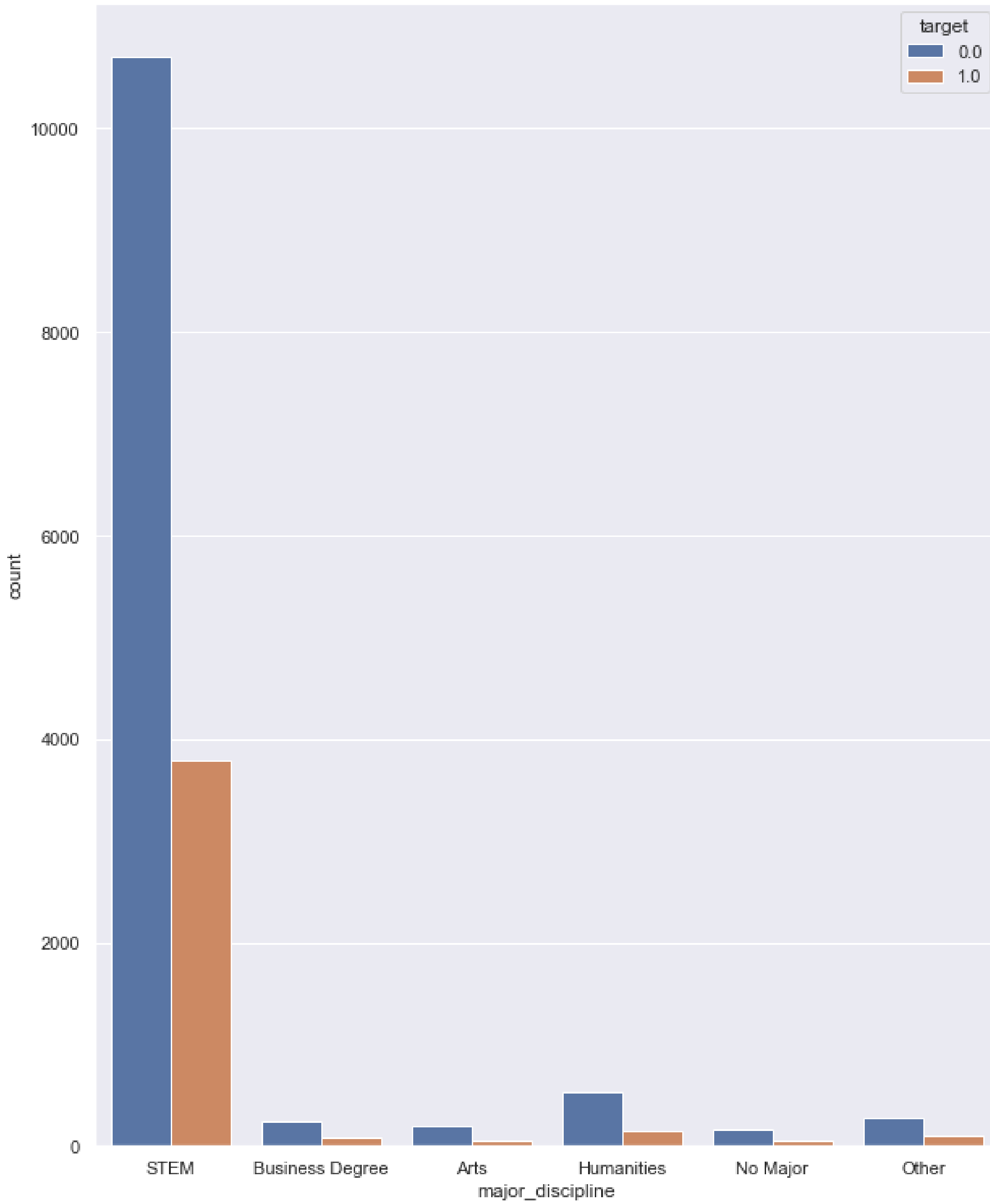
[48]:
```
sns.countplot(x = 'education_level', hue = df['target'], data = categorical)
```

[48]: <AxesSubplot:xlabel='education_level', ylabel='count'>



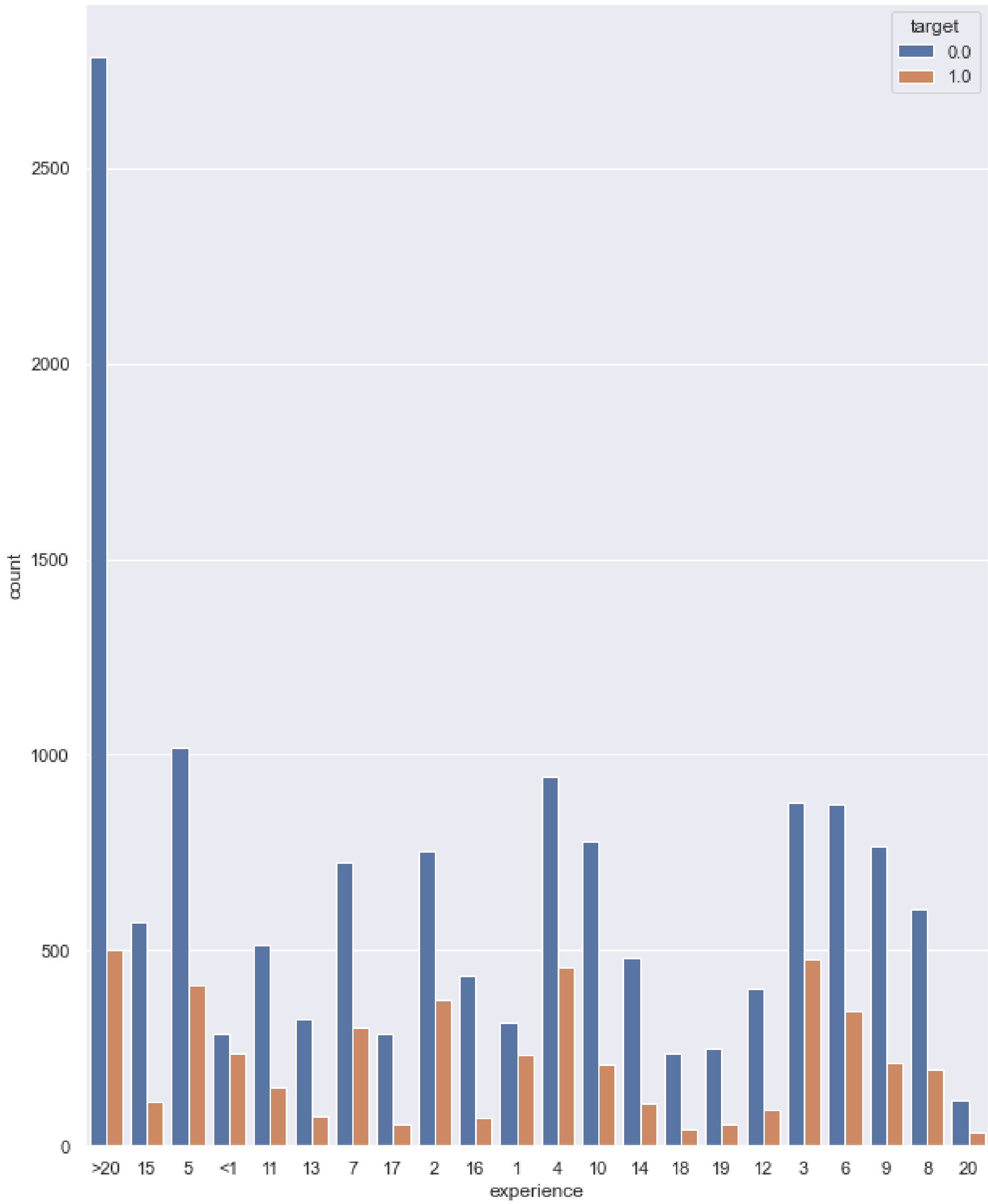
[49]:
```
sns.countplot(x = 'major_discipline', hue = df['target'], data = categorical)
```

[49]: <AxesSubplot:xlabel='major_discipline', ylabel='count'>



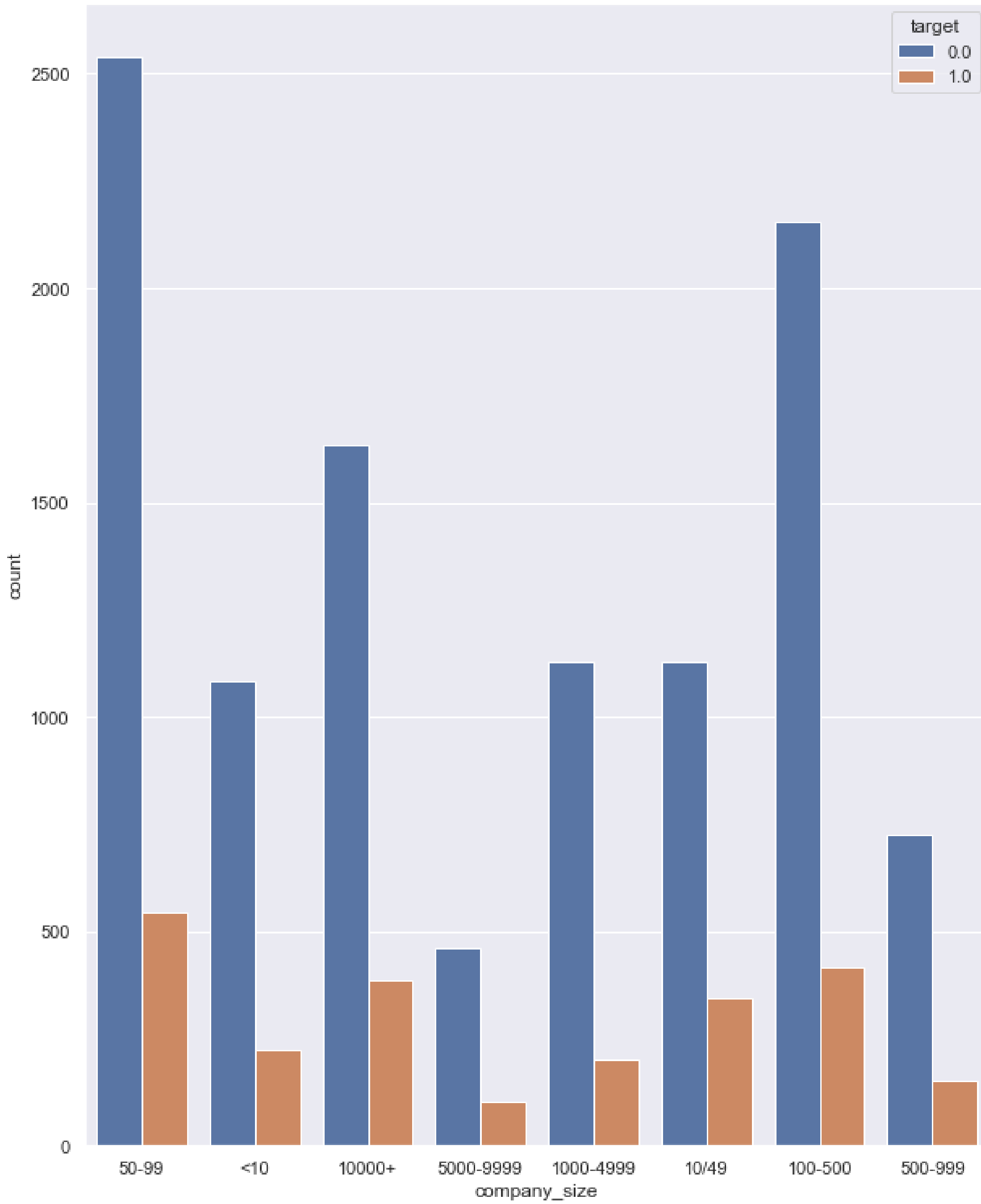
[50]:
```
sns.countplot(x = 'experience', hue = df['target'], data = categorical)
```

[50]: `<AxesSubplot:xlabel='experience', ylabel='count'>`



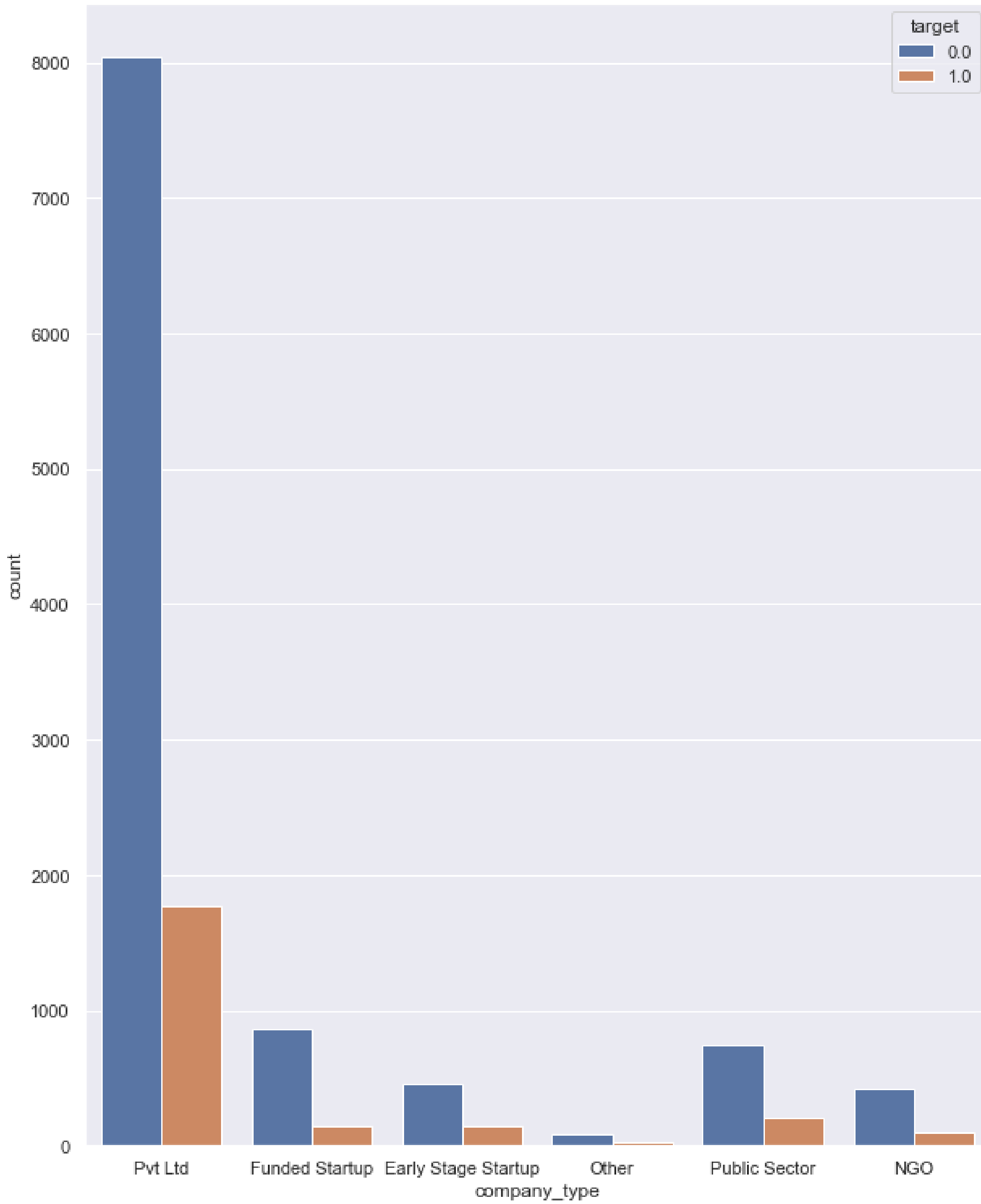

```
[51]: sns.countplot(x = 'company_size', hue = df['target'], data = categorical)
```

```
[51]: <AxesSubplot:xlabel='company_size', ylabel='count'>
```



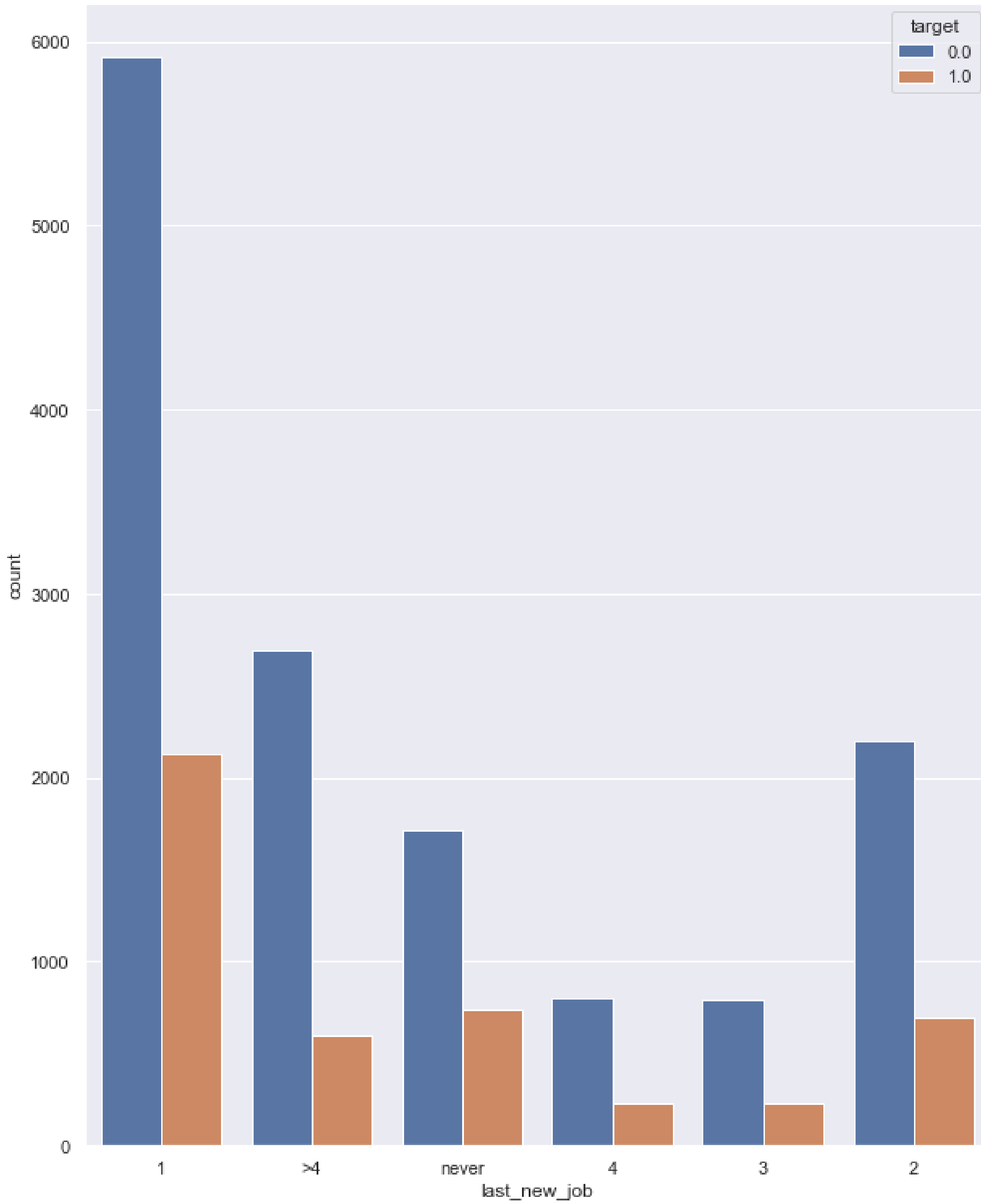

```
[52]: sns.countplot(x = 'company_type', hue = df['target'], data = categorical)
```

```
[52]: <AxesSubplot:xlabel='company_type', ylabel='count'>
```



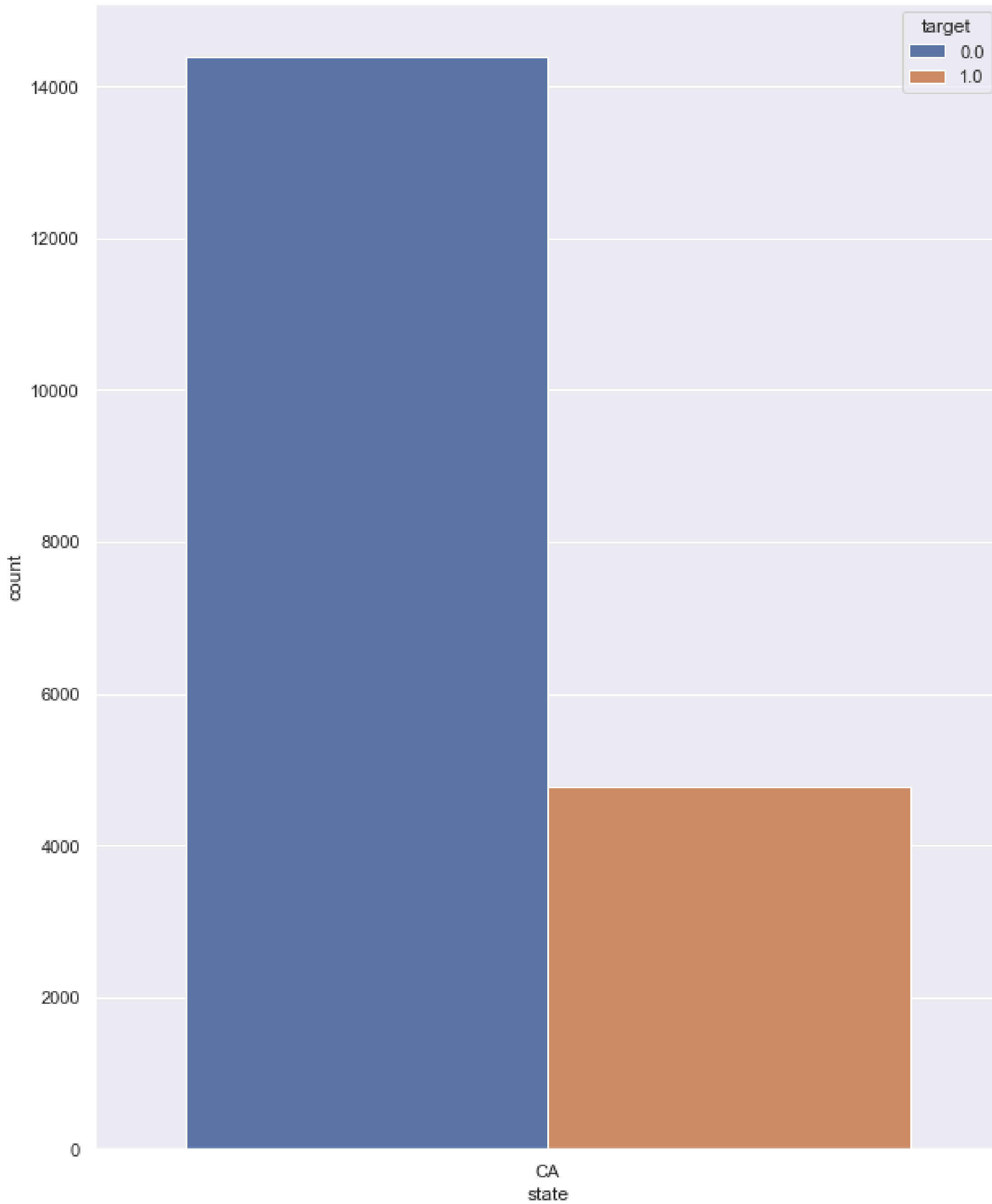
[53]:
```
sns.countplot(x = 'last_new_job', hue = df['target'], data = categorical)
```

[53]: <AxesSubplot:xlabel='last_new_job', ylabel='count'>




```
[54]: sns.countplot(x = 'state', hue = df['target'], data = categorical)
```

```
[54]: <AxesSubplot:xlabel='state', ylabel='count'>
```



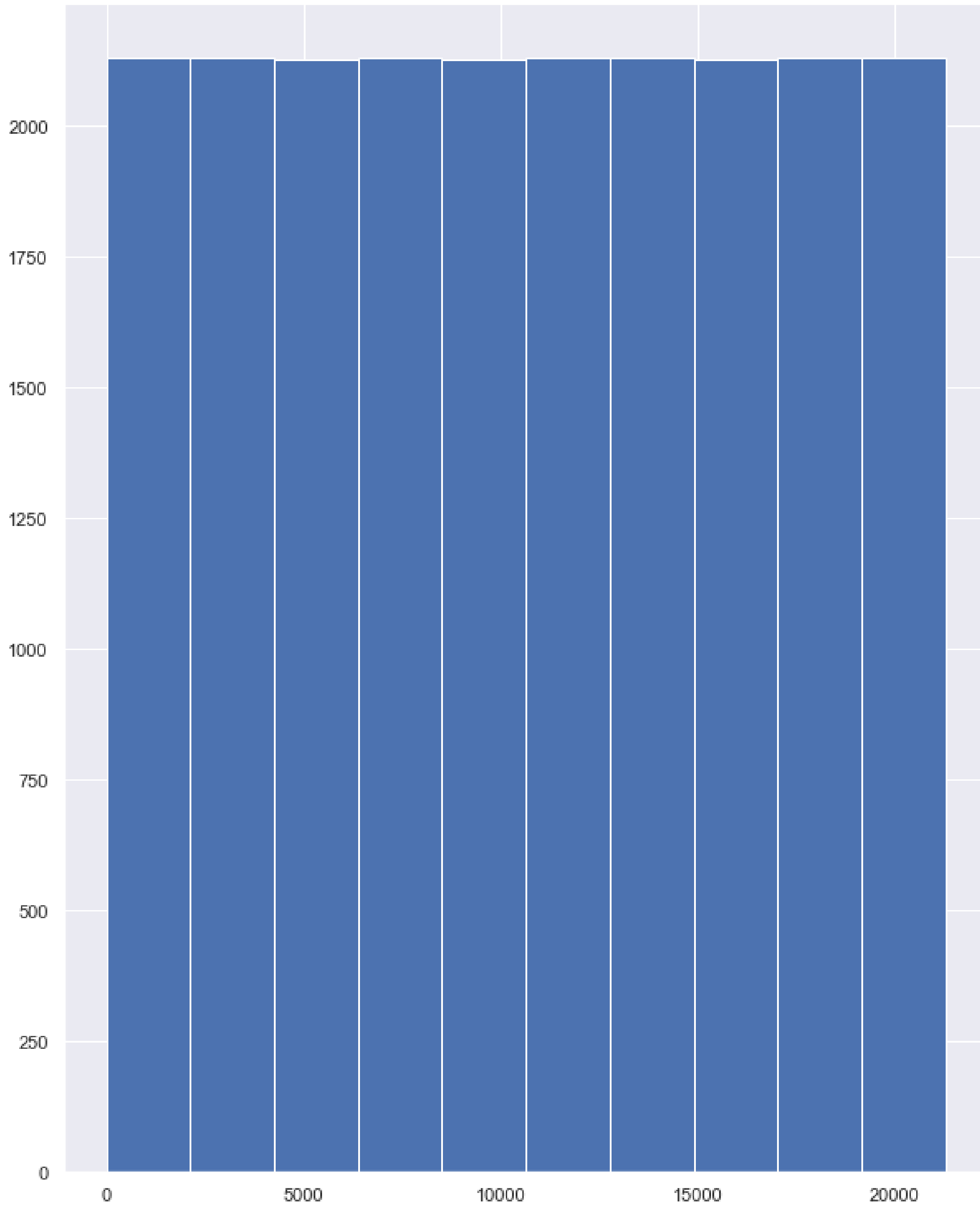
[55]:
```
#Interpret any interesting information and any information that might help you␣
↪to make any decision on combining, removing, or adding features based on␣
↪that, or any resampling maybe needed.
#Since everyone in the data is from California I don't believe we need to keep␣
↪that column at all as it doesn't contribute to any learning about the data␣
↪or its correlation to the target value.
```

```
#It also looks like STEM graduates not enrolled in a university make up for␣
↪most of the people who wish to stay with the company, which could be useful␣
↪for creating a predictive model
#City 103 has the most people willing to stay for the company, since every␣
↪other city has a miniscule amount of people, I would change the data to a␣
↪binary input of "living in city 103" and "not living in city 103"
```

[56]:
```
#For each numerical features, perform the following:
#Plot their distributions using histogram
print(numerical.columns)
plt.hist(df['rec_num'])
```

```
Index(['Unnamed: 0', 'rec_num', 'enrollee_id', 'city_development_index',
       'training_hours', 'target', 'city_development_matrics'],
      dtype='object')
```

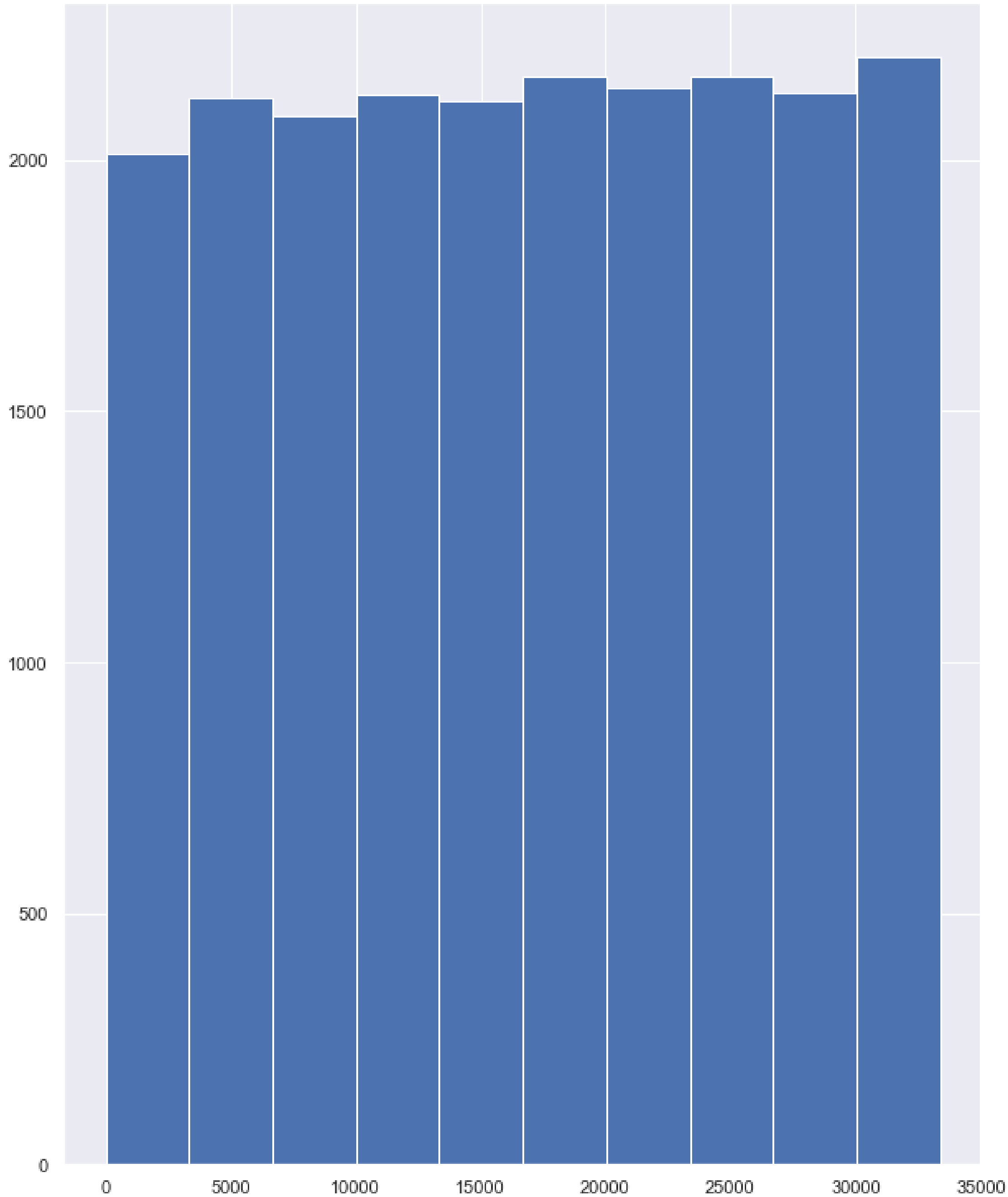
[56]:
```
(array([2129., 2129., 2128., 2129., 2128., 2129., 2129., 2128., 2129.,
        2129.]),
 array([1.00000e+00, 2.12960e+03, 4.25820e+03, 6.38680e+03, 8.51540e+03,
        1.06440e+04, 1.27726e+04, 1.49012e+04, 1.70298e+04, 1.91584e+04,
        2.12870e+04]),
 <BarContainer object of 10 artists>)
```



[57]:
```
plt.hist(df['enrollee_id'])
```

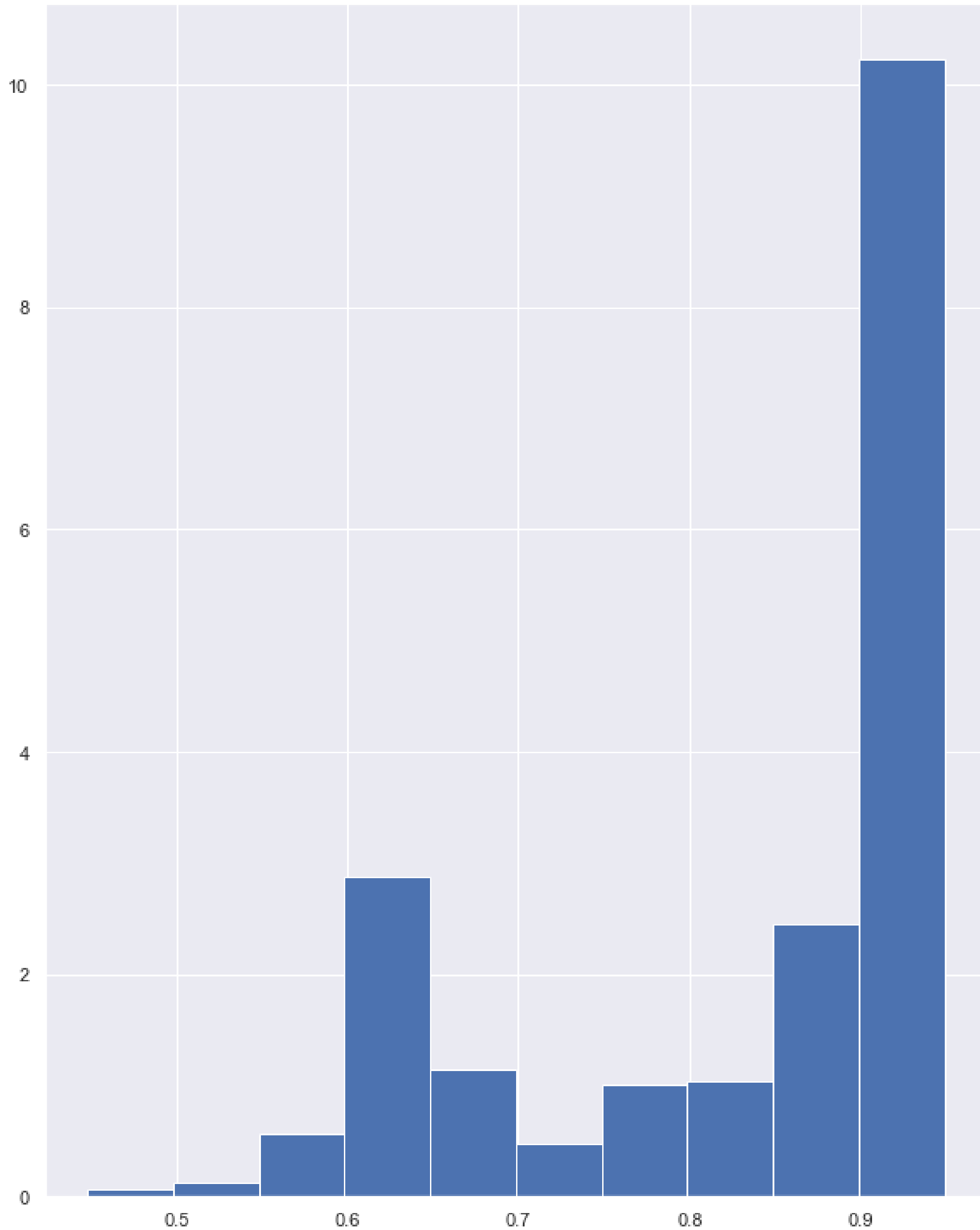
[57]:
```
(array([2013., 2123., 2087., 2130., 2118., 2167., 2144., 2165., 2135.,
        2205.]),
 array([1.00000e+00, 3.33890e+03, 6.67680e+03, 1.00147e+04, 1.33526e+04,
        1.66905e+04, 2.00284e+04, 2.33663e+04, 2.67042e+04, 3.00421e+04,
```

```
       3.33800e+04]),
 <BarContainer object of 10 artists>)
```



[58]:
```python
plt.hist(df['city_development_index'], density = True)
plt.figure(figsize = (10, 10))
```

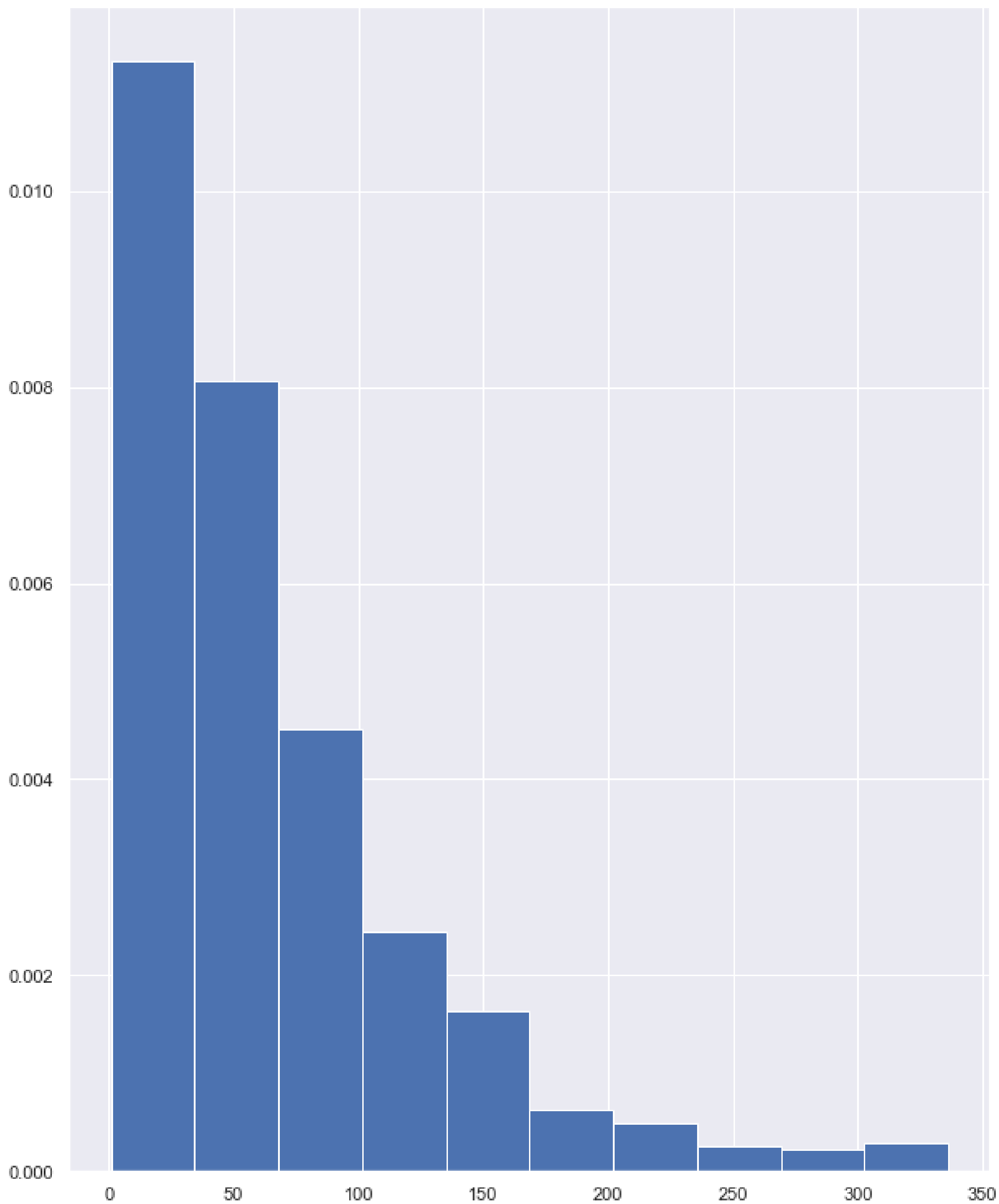
[58]:
```
<Figure size 720x720 with 0 Axes>
```



<Figure size 720x720 with 0 Axes>

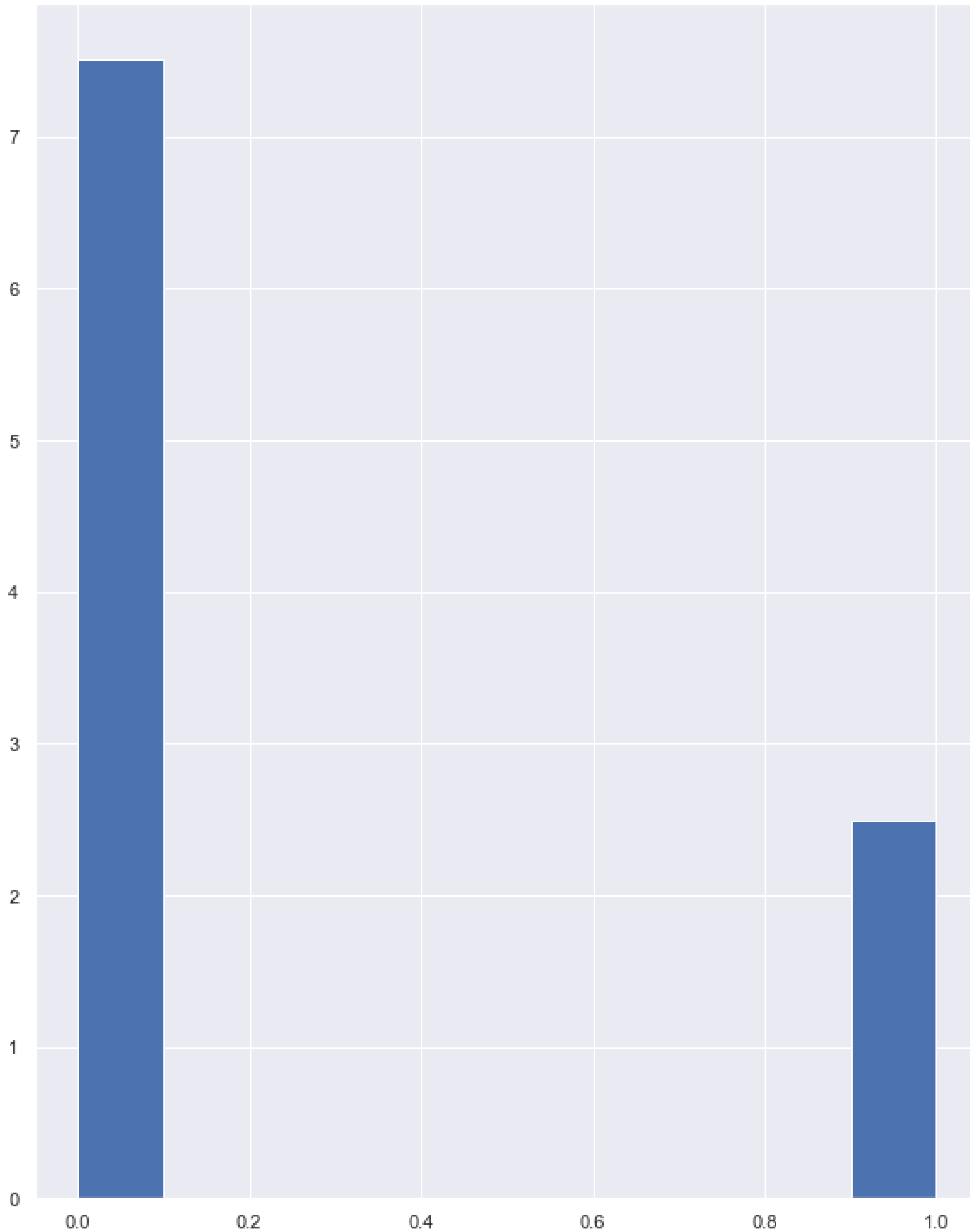
[59]:
```
plt.hist(df['training_hours'], density = True)
```

```
[59]: (array([0.01131796, 0.00806743, 0.0045154 , 0.00243579, 0.00163929,
         0.00062402, 0.0004852 , 0.00025802, 0.00021595, 0.00029168]),
 array([  1. ,  34.5,  68. , 101.5, 135. , 168.5, 202. , 235.5, 269. ,
        302.5, 336. ]),
 <BarContainer object of 10 artists>)
```



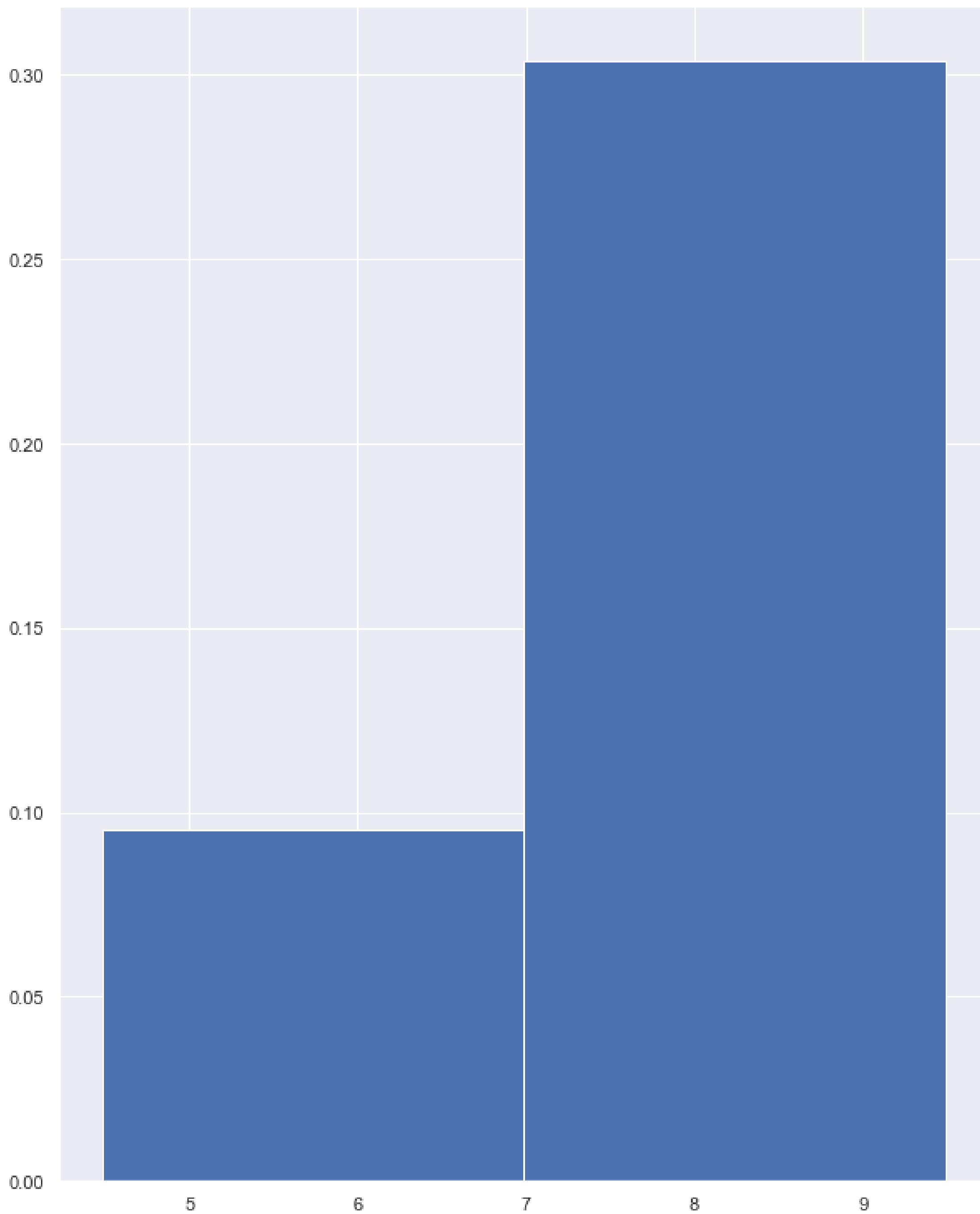
[60]:
```
plt.hist(df['target'], density = True)
```

[60]:
```
(array([7.50652469, 0.        , 0.        , 0.        , 0.        ,
        0.        , 0.        , 0.        , 0.        , 2.49347531]),
 array([0. , 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1. ]),
 <BarContainer object of 10 artists>)
```



[61]:
```python
plt.hist(df['city_development_matrics'], density = True, bins = 2)
```

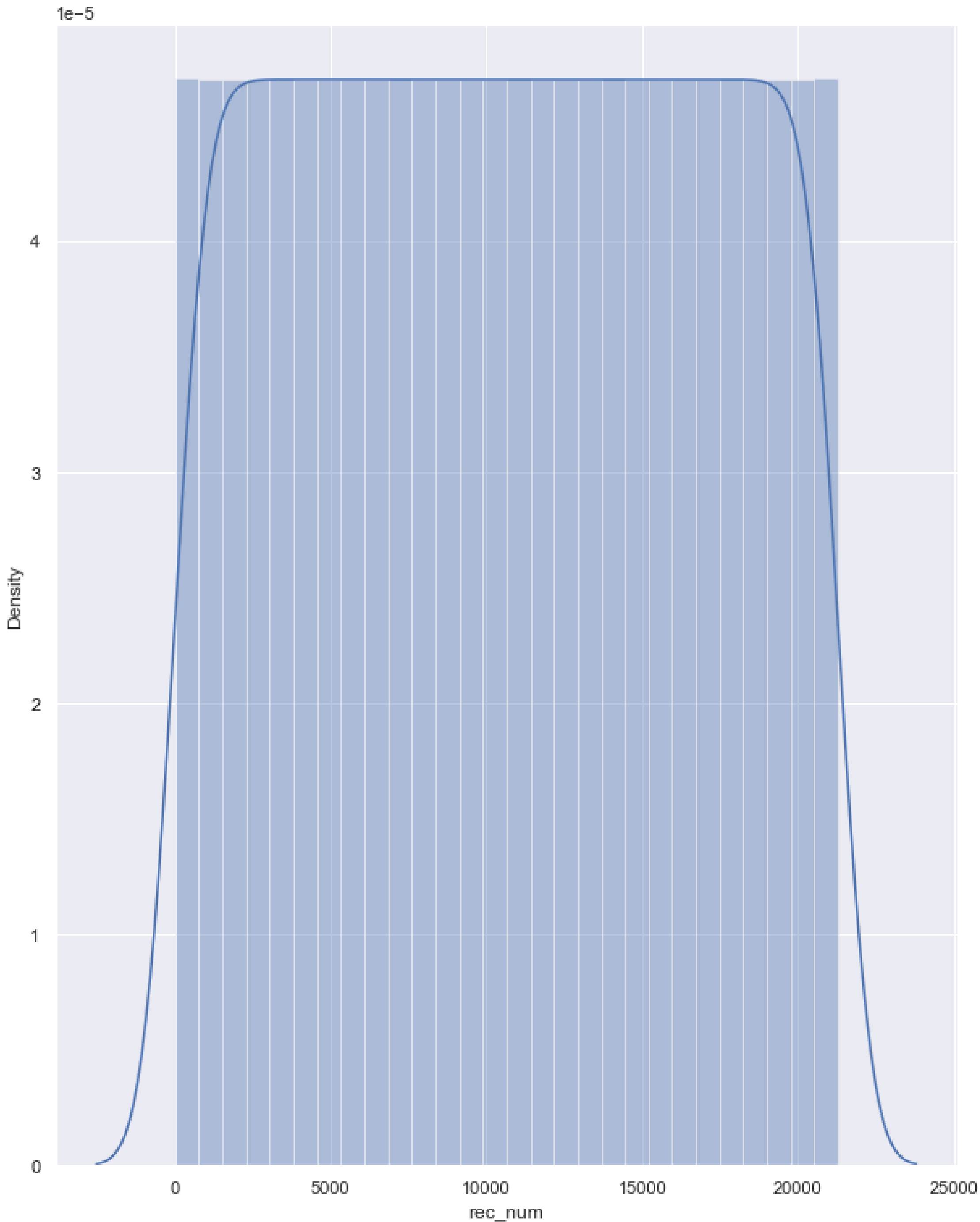
[61]:
```
(array([0.09551058, 0.30369102]),
 array([4.48 , 6.985, 9.49 ]),
 <BarContainer object of 2 artists>)
```



[62]:
```python
#Plot the distribution using seaborn distplot
sns.distplot(df['rec_num'])
```

```
/Users/gabby/opt/anaconda3/lib/python3.9/site-
packages/seaborn/distributions.py:2619: FutureWarning: `distplot` is a
deprecated function and will be removed in a future version. Please adapt your
code to use either `displot` (a figure-level function with similar flexibility)
or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

[62]:
```
<AxesSubplot:xlabel='rec_num', ylabel='Density'>
```

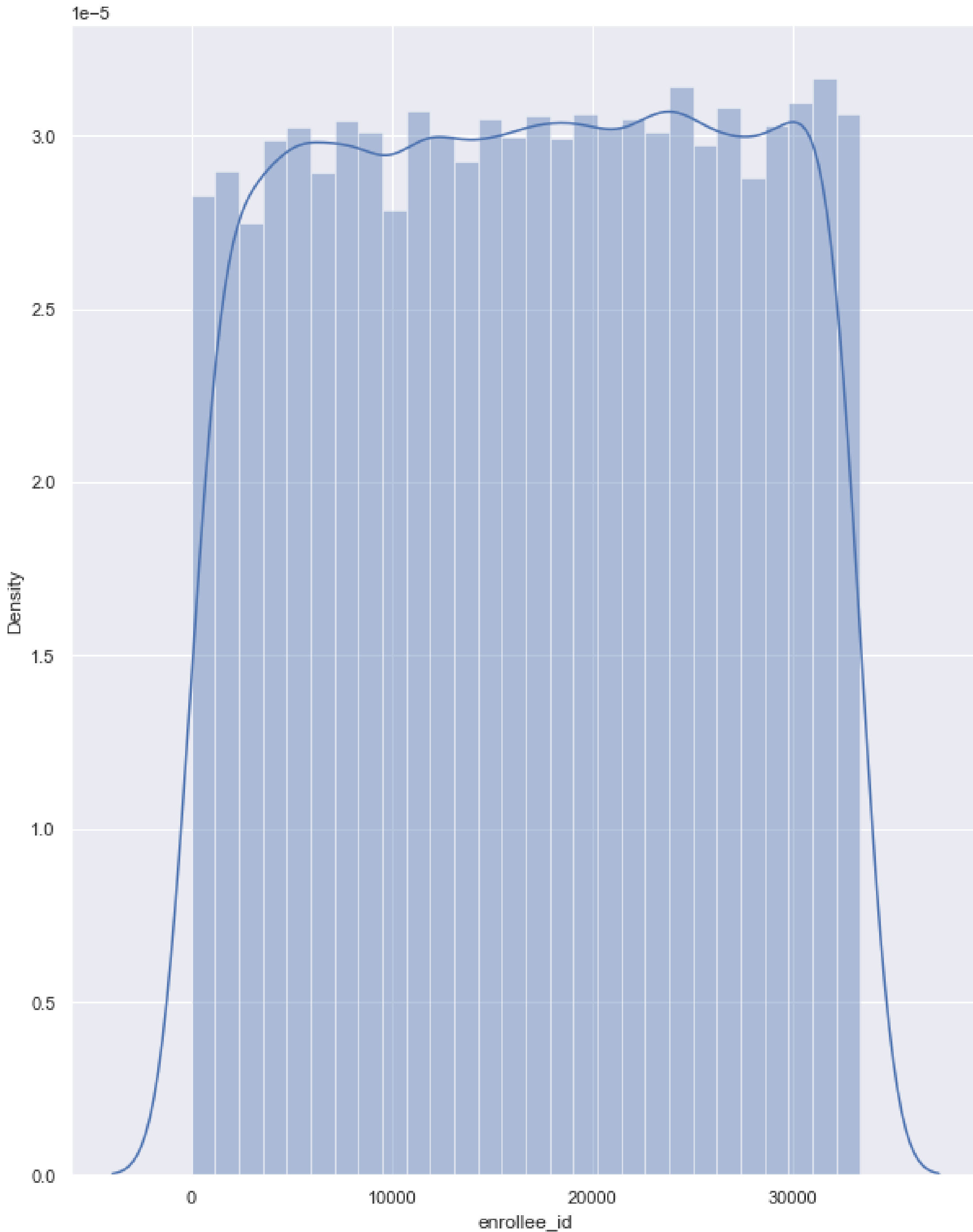


[63]:
```
sns.distplot(df['enrollee_id'])
```

/Users/gabby/opt/anaconda3/lib/python3.9/site-packages/seaborn/distributions.py:2619: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility)

```
or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

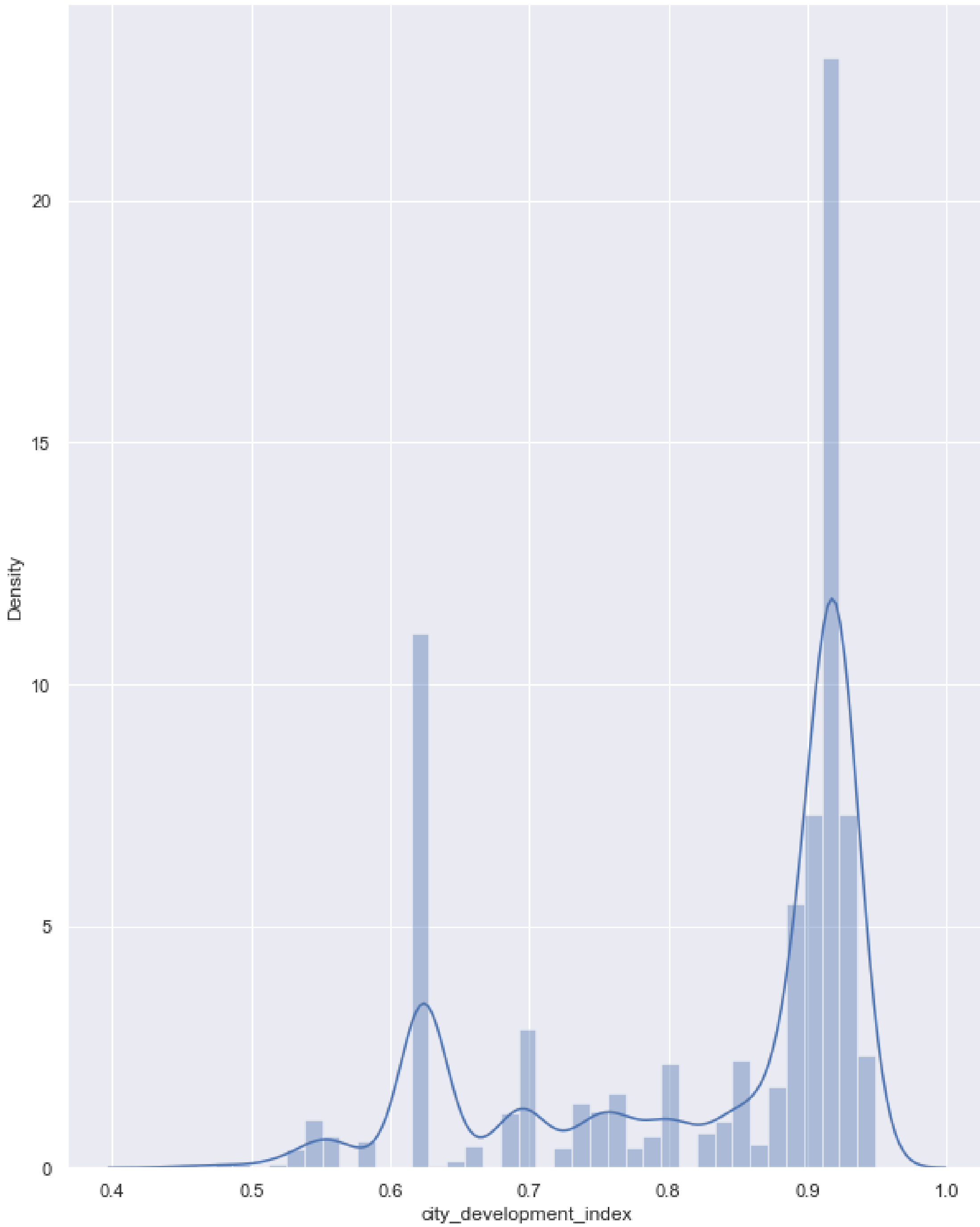
[63]: <AxesSubplot:xlabel='enrollee_id', ylabel='Density'>



[64]:
```python
sns.distplot(df['city_development_index'])
```

```
/Users/gabby/opt/anaconda3/lib/python3.9/site-
packages/seaborn/distributions.py:2619: FutureWarning: `distplot` is a
deprecated function and will be removed in a future version. Please adapt your
code to use either `displot` (a figure-level function with similar flexibility)
or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

[64]:
```
<AxesSubplot:xlabel='city_development_index', ylabel='Density'>
```

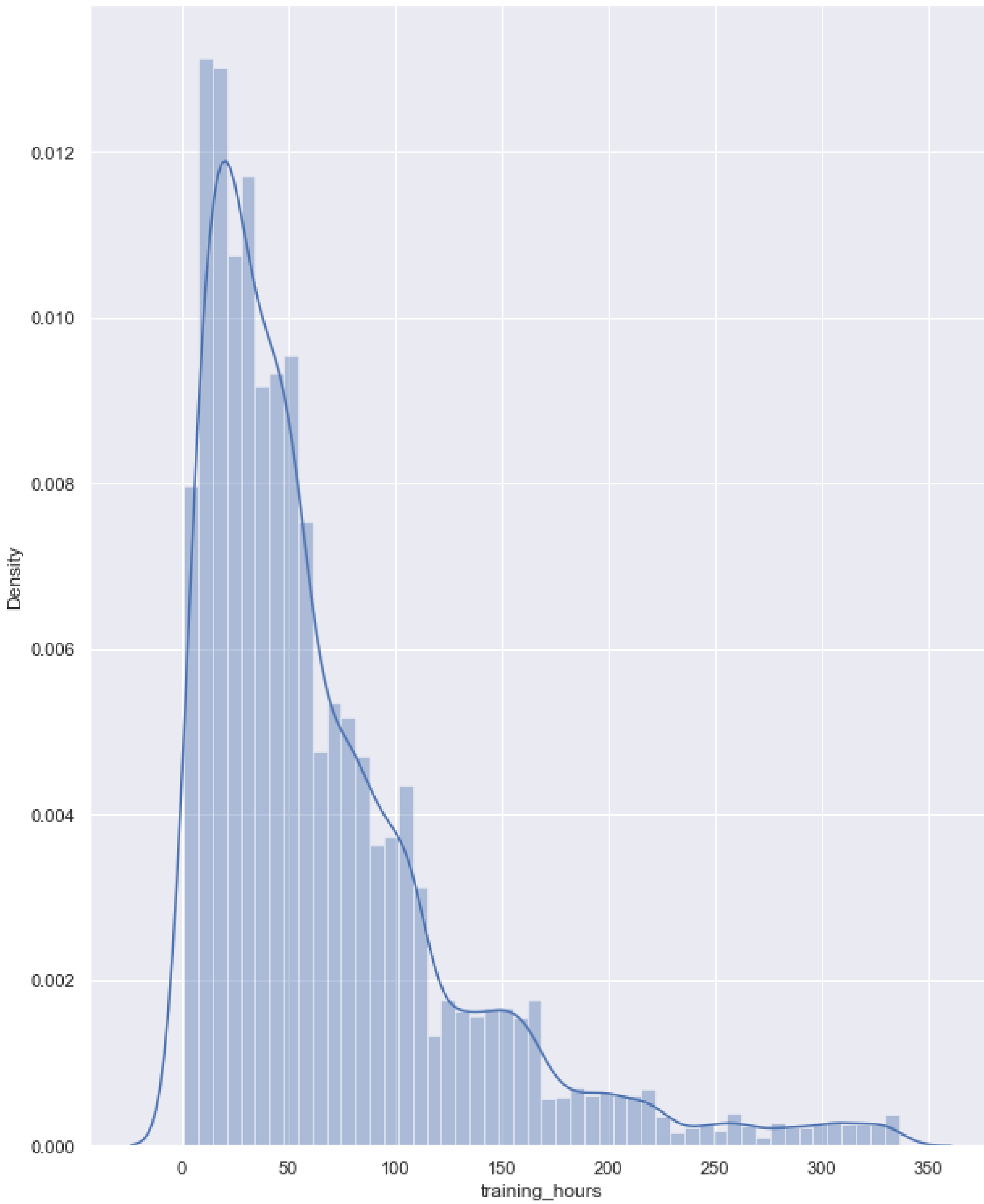


[65]:
```
sns.distplot(df['training_hours'])
```

```
/Users/gabby/opt/anaconda3/lib/python3.9/site-
packages/seaborn/distributions.py:2619: FutureWarning: `distplot` is a
deprecated function and will be removed in a future version. Please adapt your
code to use either `displot` (a figure-level function with similar flexibility)
```

```
or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

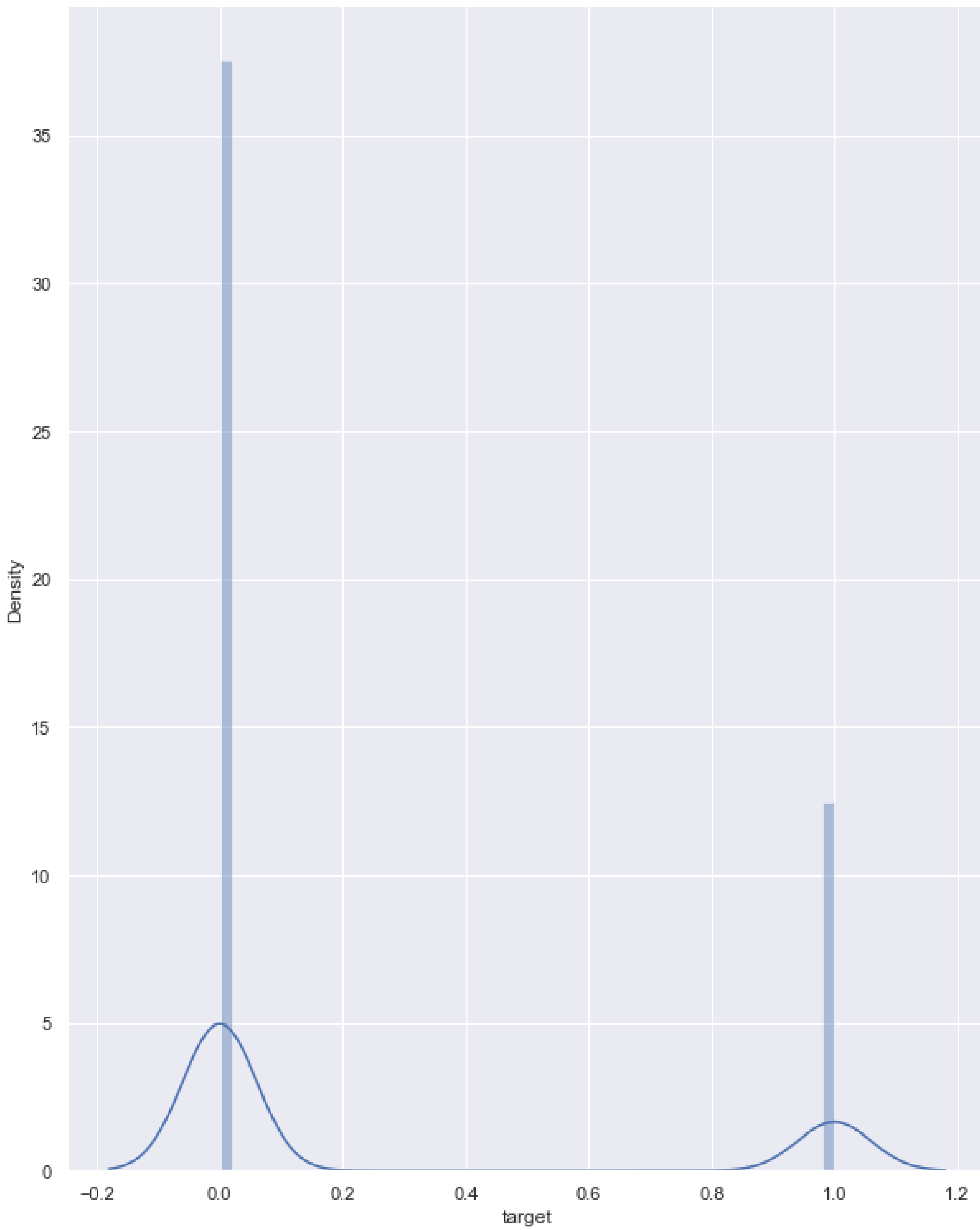
[65]: <AxesSubplot:xlabel='training_hours', ylabel='Density'>



[66]:
```
sns.distplot(df['target'])
```

```
/Users/gabby/opt/anaconda3/lib/python3.9/site-
packages/seaborn/distributions.py:2619: FutureWarning: `distplot` is a
deprecated function and will be removed in a future version. Please adapt your
code to use either `displot` (a figure-level function with similar flexibility)
or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

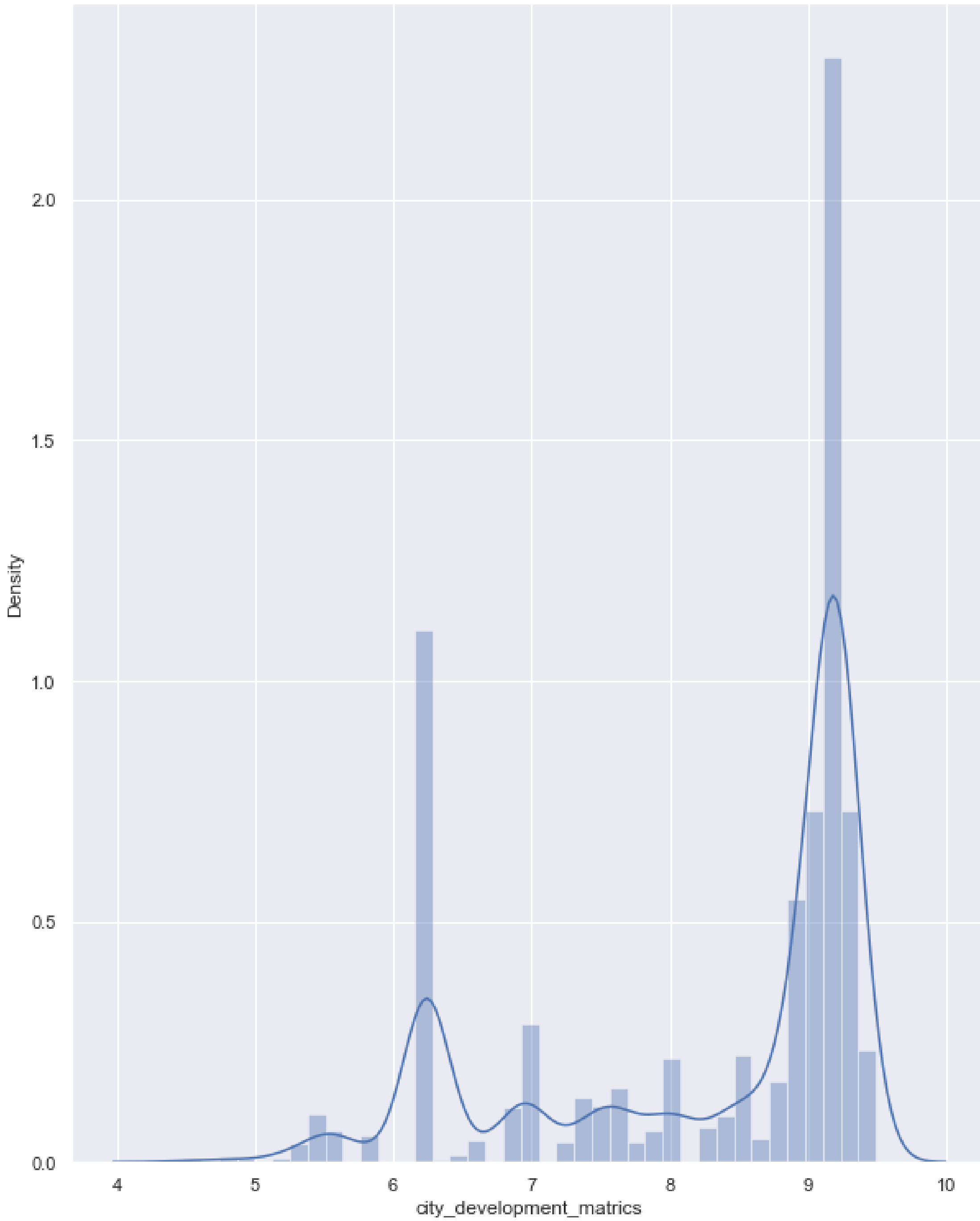
[66]: <AxesSubplot:xlabel='target', ylabel='Density'>



[67]:
```python
sns.distplot(df['city_development_matrics'])
```

```
/Users/gabby/opt/anaconda3/lib/python3.9/site-
packages/seaborn/distributions.py:2619: FutureWarning: `distplot` is a
deprecated function and will be removed in a future version. Please adapt your
code to use either `displot` (a figure-level function with similar flexibility)
or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

[67]:
```
<AxesSubplot:xlabel='city_development_matrics', ylabel='Density'>
```

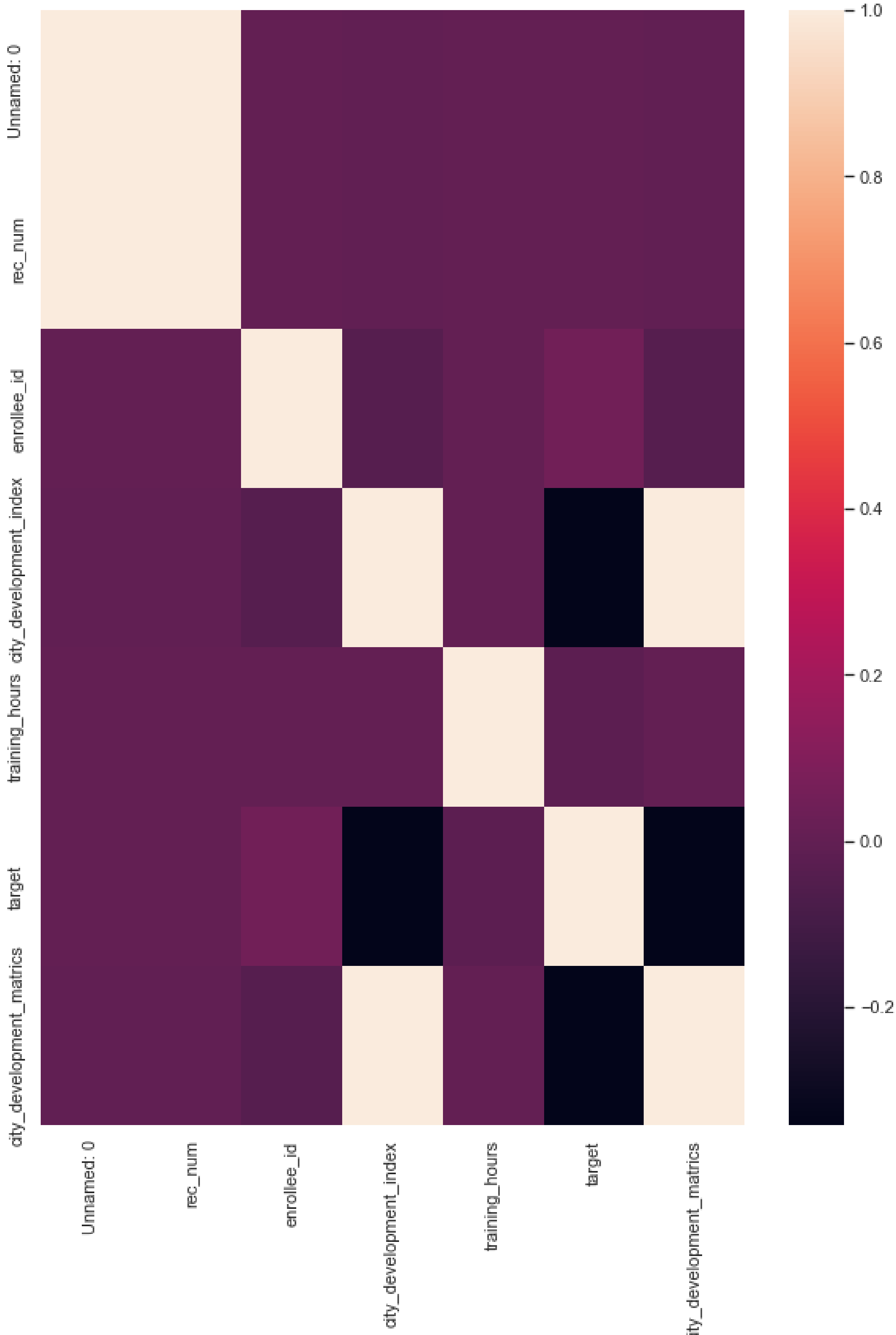



```
[68]: #Interpret any interesting information
```

```
#These plots don't work well with things like IDs because there is one for each␣
↪person, but it's good for making observations with values like␣
↪'training_hours' where you can observe that the majority of people have␣
↪between 0 and around 70 hours of training under their belt, and there are␣
↪some with as many as 300 training hours
```

[69]:
```
#For the numerical attributes, use heatmap to show the correlation
correlation = numerical.corr()
sns.heatmap(correlation)
```

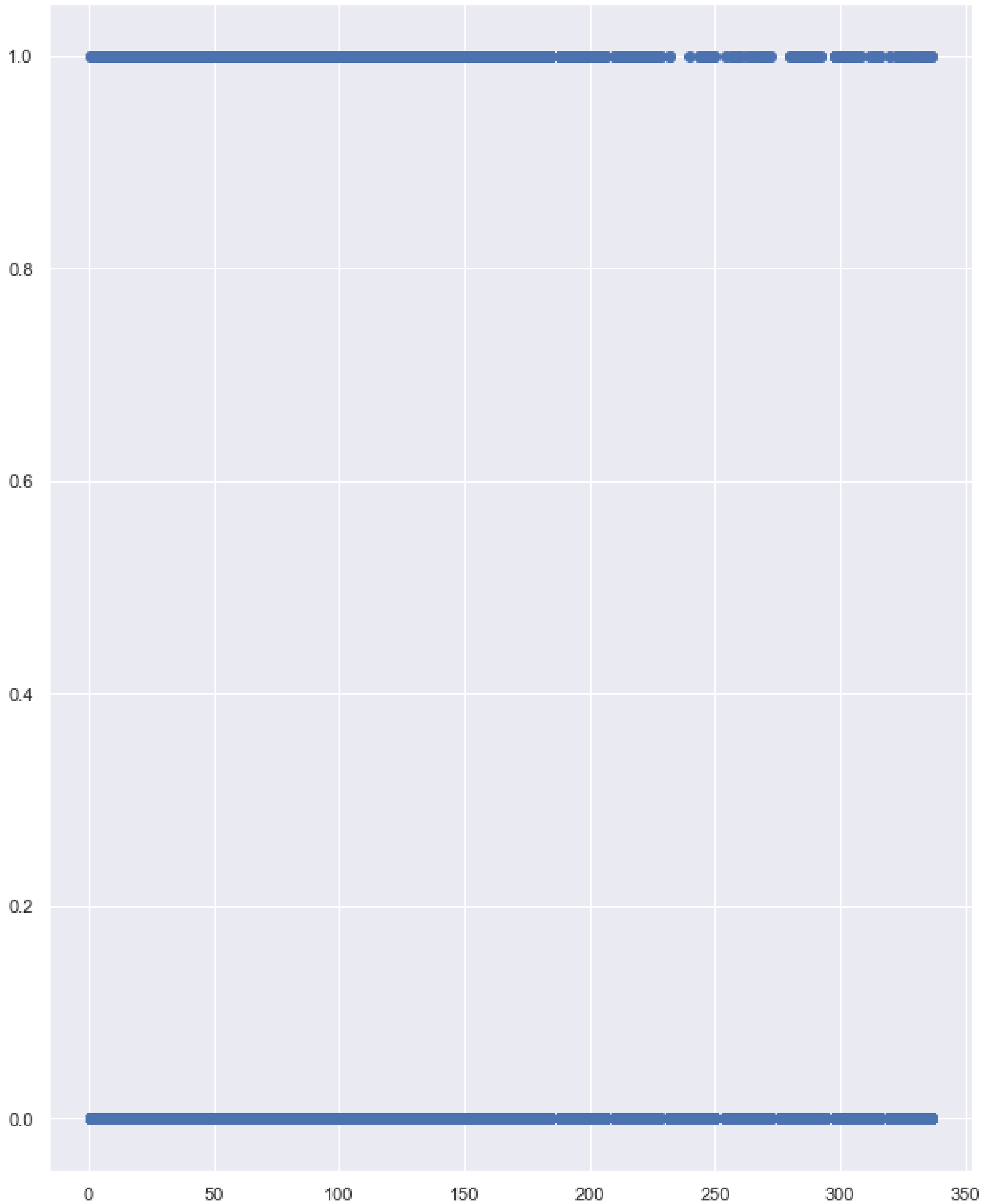
[69]: <AxesSubplot:>


Unnamed: 0
rec_num
enrollee_id
city_development_index
training_hours
target
city_development_matrics
1.0
0.8
0.6
0.4
0.2
0.0
−0.2

[70]:
```
#If you find any interesting short list of columns, create another heatmap with␣
↪them and show the correlations inside the heaptmap as well
#Nothing interesting I hadn't already explained from the above heatmap
```

[71]:
```
#Show scatter plots between columns to show the relationships with the target
plt.scatter(data = df, x = 'training_hours', y = 'target')
```

[71]:
```
<matplotlib.collections.PathCollection at 0x7fd25238df70>
```



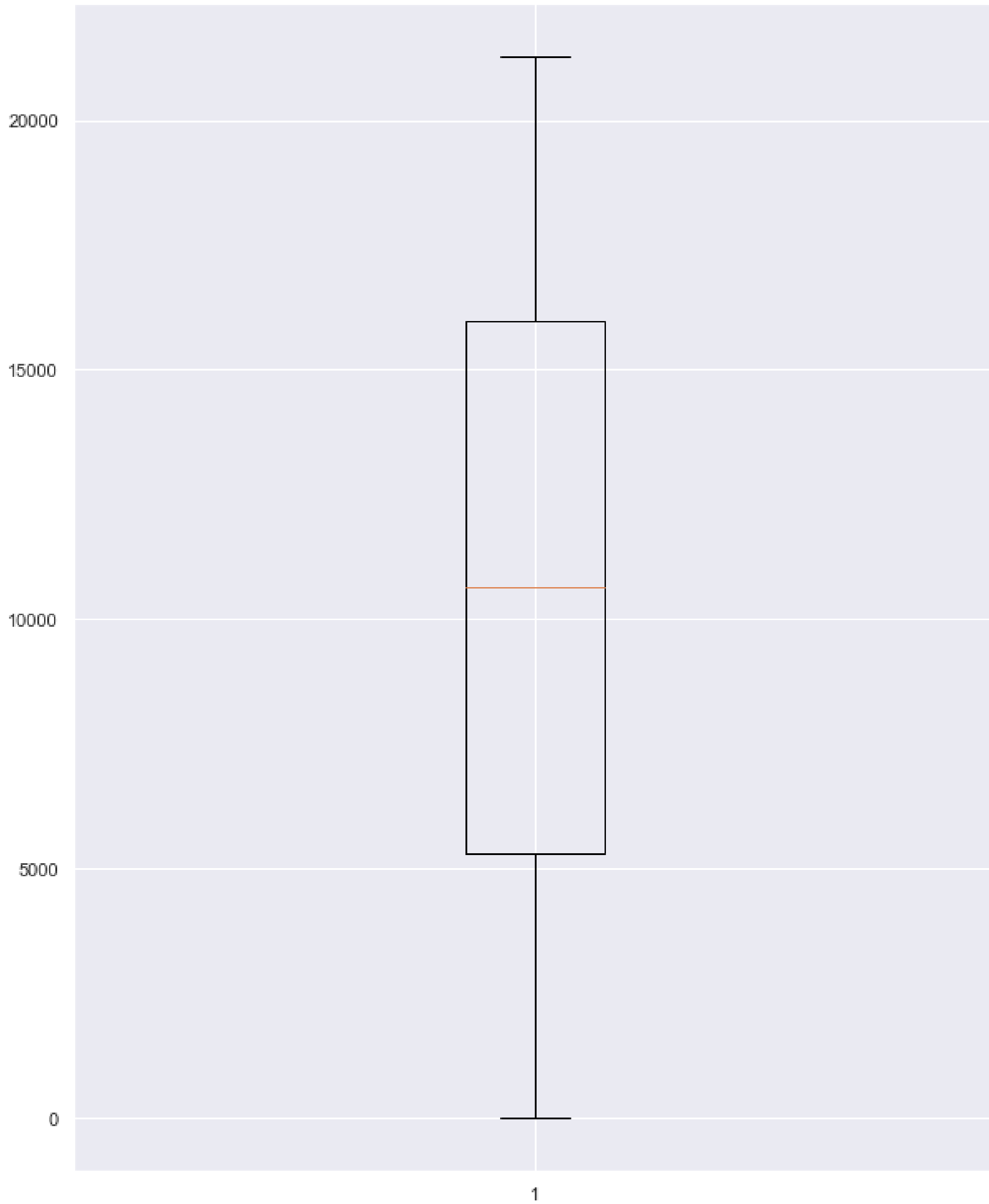
[72]:
```
#As you can see, a scatterplot in these situations wouldn't be very useful for
↪analysis as the values of target are either 1 or 0
```

[73]:
```
#Interpret and explain any finding and next course of action from there
```

```
#Since the city_development_index and the city_development_matrix have no␣
↪correlation to the target, there's no real reason to use it in a predictive␣
↪model. I'd remove them both
```

[74]:
```
#Use boxplot or any other strategies to find outliers
plt.boxplot(data = df, x = 'rec_num')
```

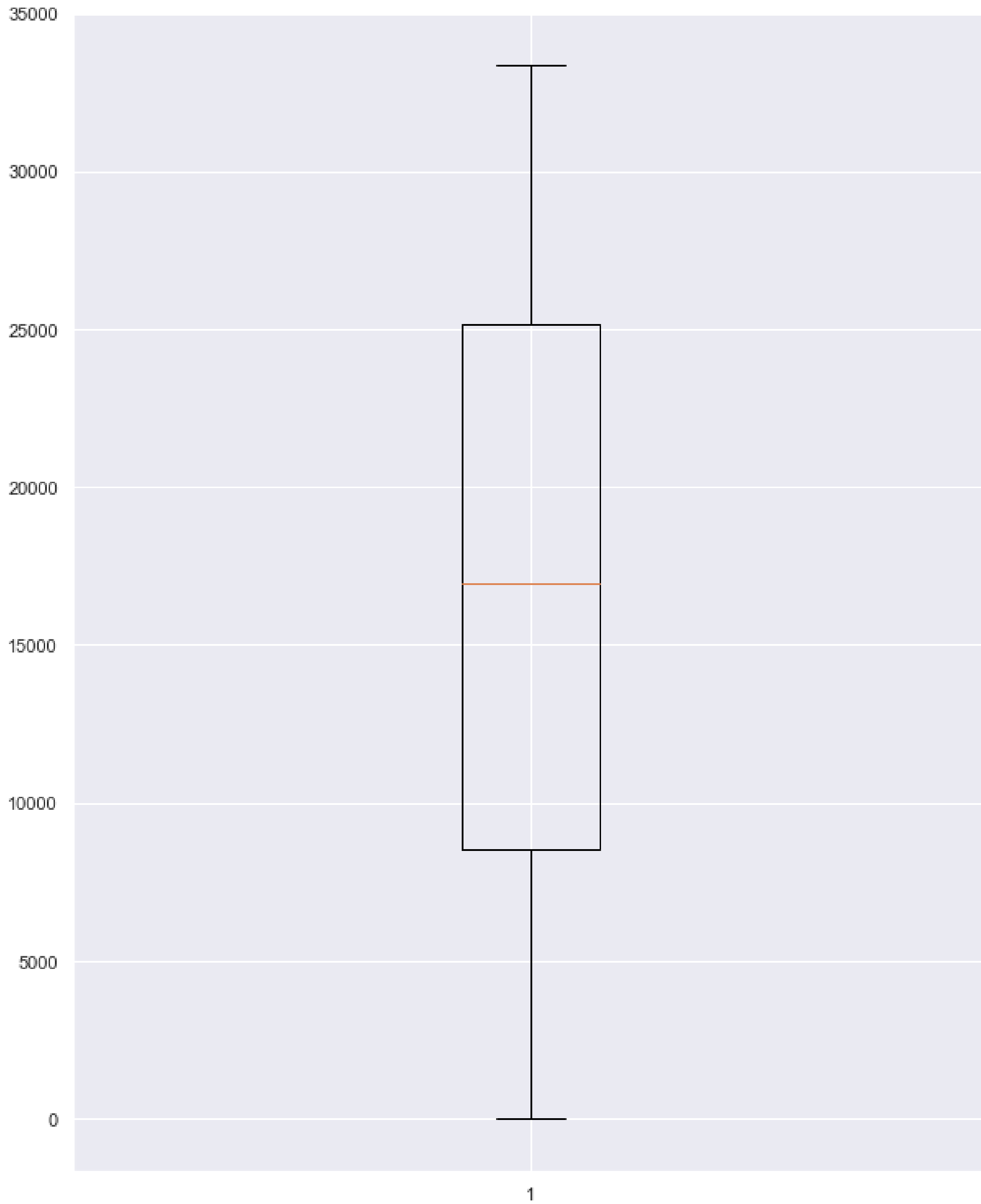
[74]:
```
{'whiskers': [<matplotlib.lines.Line2D at 0x7fd25240df40>,
  <matplotlib.lines.Line2D at 0x7fd25241f310>],
 'caps': [<matplotlib.lines.Line2D at 0x7fd25241f6a0>,
  <matplotlib.lines.Line2D at 0x7fd25241fa30>],
 'boxes': [<matplotlib.lines.Line2D at 0x7fd25240dbb0>],
 'medians': [<matplotlib.lines.Line2D at 0x7fd25241fdc0>],
 'fliers': [<matplotlib.lines.Line2D at 0x7fd25242c190>],
 'means': []}
```



[75]:
```
plt.boxplot(data = df, x = 'enrollee_id')
```

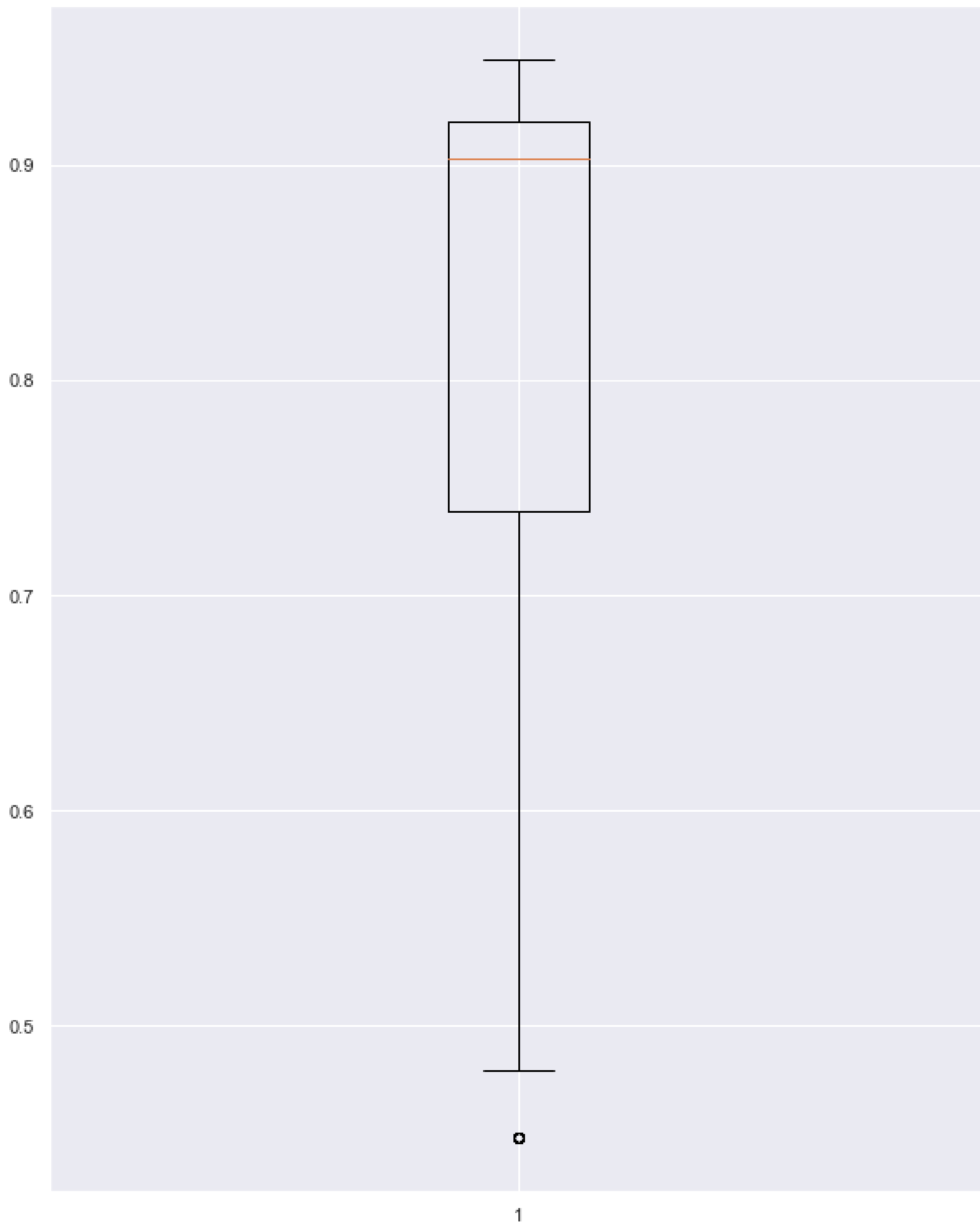
[75]:
```
{'whiskers': [<matplotlib.lines.Line2D at 0x7fd269b27dc0>,
  <matplotlib.lines.Line2D at 0x7fd269b9a160>],
 'caps': [<matplotlib.lines.Line2D at 0x7fd269b9afd0>,
  <matplotlib.lines.Line2D at 0x7fd269b9a8b0>],
```

```
'boxes': [<matplotlib.lines.Line2D at 0x7fd26bf8d250>],
'medians': [<matplotlib.lines.Line2D at 0x7fd26a0c26a0>],
'fliers': [<matplotlib.lines.Line2D at 0x7fd26994a070>],
'means': []}
```



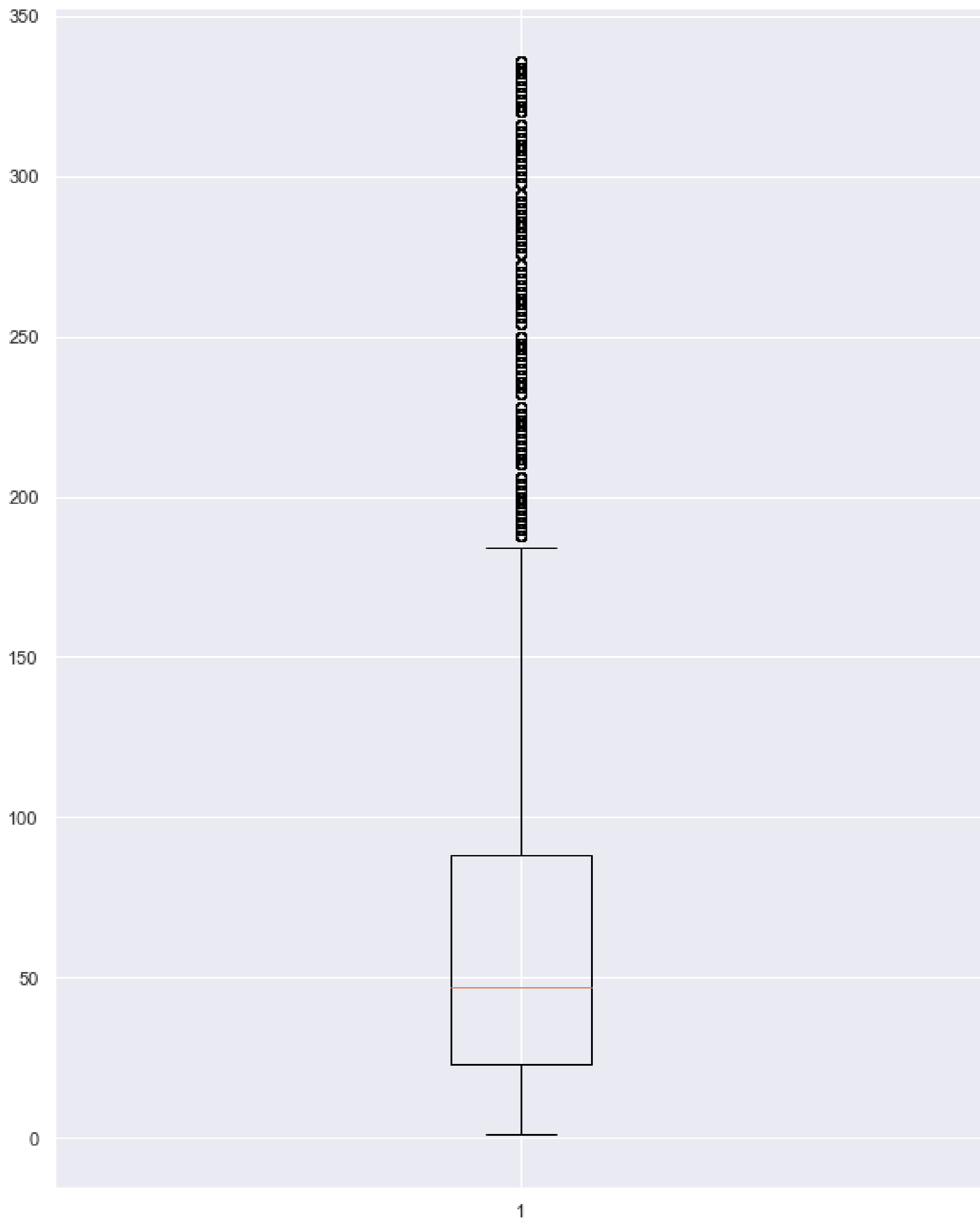

```
[76]: plt.boxplot(data = df, x = 'city_development_index')
```

```
[76]: {'whiskers': [<matplotlib.lines.Line2D at 0x7fd25293d2e0>,
        <matplotlib.lines.Line2D at 0x7fd25293d670>],
       'caps': [<matplotlib.lines.Line2D at 0x7fd25293da00>,
        <matplotlib.lines.Line2D at 0x7fd25293dd90>],
       'boxes': [<matplotlib.lines.Line2D at 0x7fd252933f10>],
       'medians': [<matplotlib.lines.Line2D at 0x7fd252949160>],
       'fliers': [<matplotlib.lines.Line2D at 0x7fd2529494f0>],
       'means': []}
```



[77]:
```
plt.boxplot(data = df, x = 'training_hours')
```

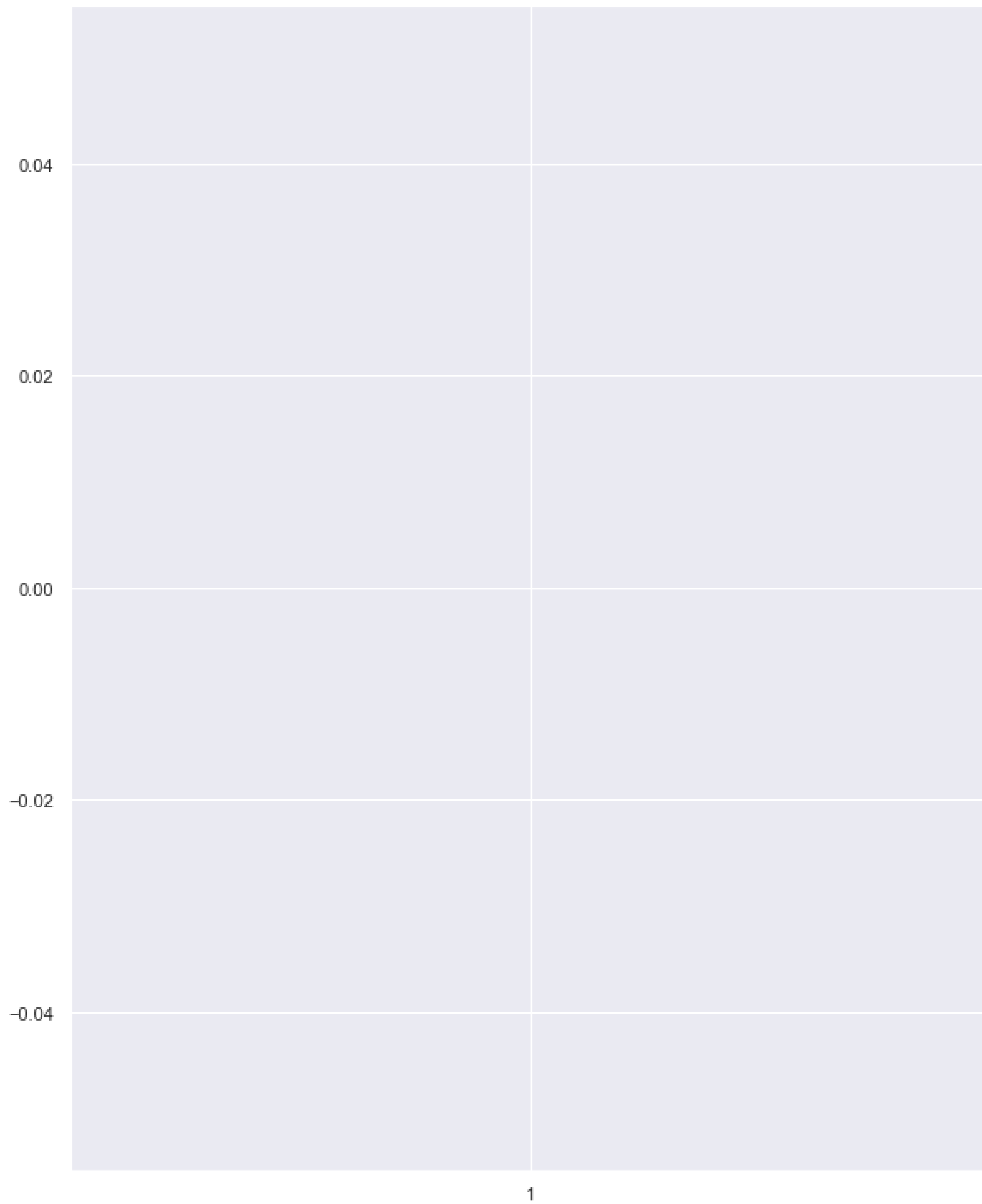
[77]:
```
{'whiskers': [<matplotlib.lines.Line2D at 0x7fd253495580>,
  <matplotlib.lines.Line2D at 0x7fd253495910>],
 'caps': [<matplotlib.lines.Line2D at 0x7fd253495ca0>,
  <matplotlib.lines.Line2D at 0x7fd2534a0070>],
 'boxes': [<matplotlib.lines.Line2D at 0x7fd2534951f0>],
 'medians': [<matplotlib.lines.Line2D at 0x7fd2534a0400>],
 'fliers': [<matplotlib.lines.Line2D at 0x7fd2534a0790>],
 'means': []}
```



[78]:
```
plt.boxplot(data = df, x = 'target')
```

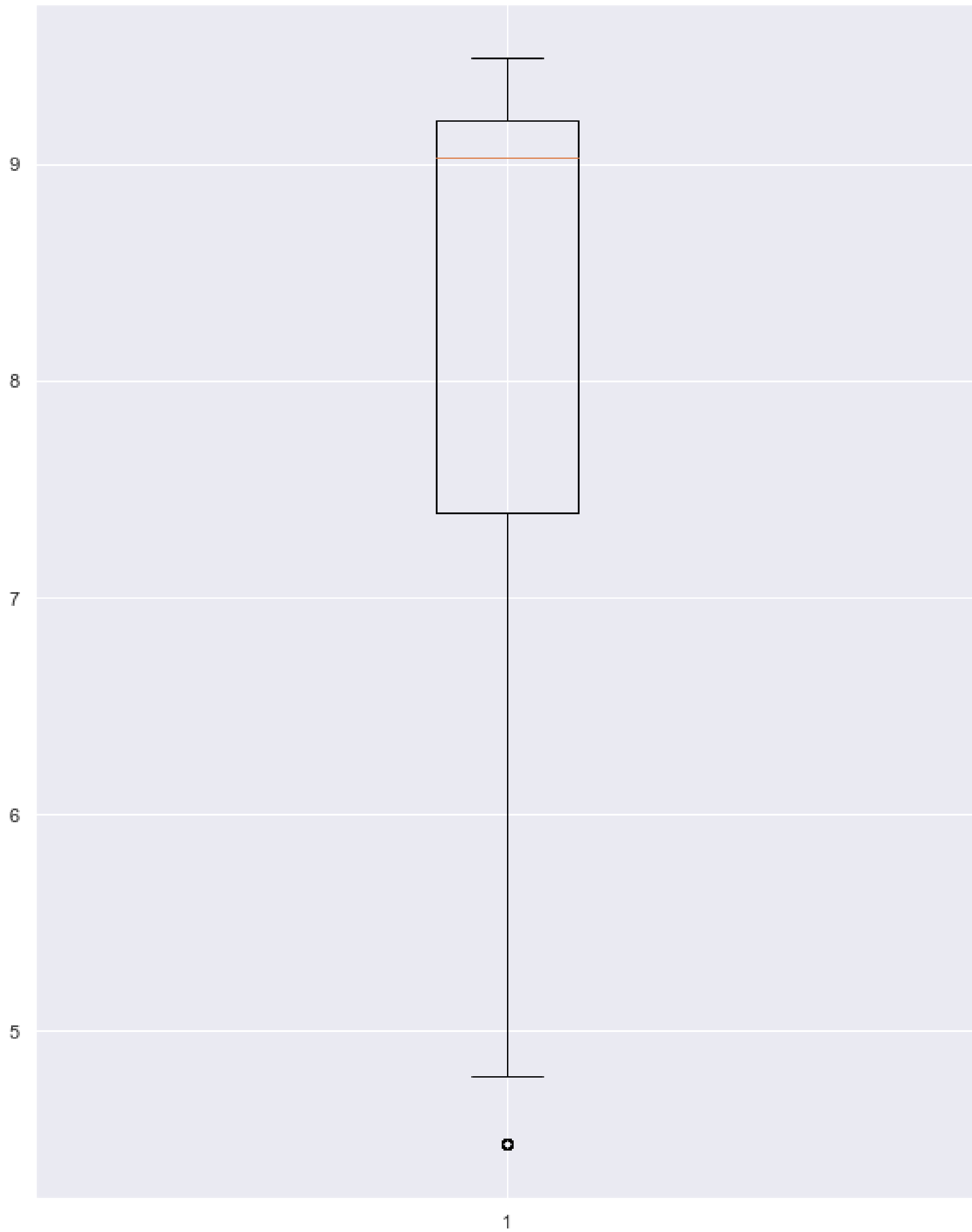
[78]:
```
{'whiskers': [<matplotlib.lines.Line2D at 0x7fd2536a58e0>,
  <matplotlib.lines.Line2D at 0x7fd2536a5c70>],
 'caps': [<matplotlib.lines.Line2D at 0x7fd2536b3040>,
```

```
 <matplotlib.lines.Line2D at 0x7fd2536b33d0>],
'boxes': [<matplotlib.lines.Line2D at 0x7fd2536a5550>],
'medians': [<matplotlib.lines.Line2D at 0x7fd2536b3760>],
'fliers': [<matplotlib.lines.Line2D at 0x7fd2536b3af0>],
'means': []}
```



[79]:
```
plt.boxplot(data = df, x = 'city_development_matrics')
```

[79]:
```
{'whiskers': [<matplotlib.lines.Line2D at 0x7fd253a78b20>,
  <matplotlib.lines.Line2D at 0x7fd253a78eb0>],
 'caps': [<matplotlib.lines.Line2D at 0x7fd253a86280>,
  <matplotlib.lines.Line2D at 0x7fd253a86610>],
 'boxes': [<matplotlib.lines.Line2D at 0x7fd253a78790>],
 'medians': [<matplotlib.lines.Line2D at 0x7fd253a869a0>],
 'fliers': [<matplotlib.lines.Line2D at 0x7fd253a86d30>],
 'means': []}
```



[80]:

```
#Lots of outliars in the 'training_hours' column, only 1 in the␣
↪'city_development_matrics' column, and 1 in the 'city_development_index'
```

[81]:
```
#What are the different values of experience, can you categorize them in to 0,␣
↪1, and 2?
#The years of experience in this data set are values that range from less than␣
↪one year of experience to more than 20 years.
#It woouldn't be too difficult to batch them into groups of 3, like 0 = years␣
↪ranging from <1 to 7, 1 = years from 8 to 14, and 2 = years from 15 to 20+
```

[82]:
```
#Finally after all the above EDA, summarize your finding, next course of action␣
↪such as we may need to transform distribution because of right skew etc,␣
↪need to remove a particular columns for any reasons, remove records for any␣
↪reasons, need to rebalance data and what are the rebalancing options (if␣
↪needed), and any other finding
#After the above EDA, values like rec_num, enrollee_id, and state are all␣
↪columns I'd remove from the data as they the first two are unique for each␣
↪person, thus no correlation can be found from that. Also, the state column␣
↪consists of only those from california, so it's not useful for predicting or␣
↪analysis at all.
#I would also consider not using any data that is missing a target value as it␣
↪wouldn't be very useful in predicting they they'd stay with the company or␣
↪not.
#It appears that men with relevant experience, are not currently enrolled in a␣
↪university, are university graduates from the STEM field with more than 20␣
↪years of experience are only a few categories that make up the majority of␣
↪those trained that wish to stay with the company. I believe the data␣
↪provided would be sufficient for creating and training a predictive model,␣
↪so long as the columns specified above are removed, as the model created␣
↪might have a bias against anyone in a state other than california.
```