In [1]:

```python
#This jupyter notebook is prepared by Jason Saini
```

In [2]:

```python
# import libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import sklearn
from scipy import stats
import missingno as msno
```

In [3]:

```python
#import the data to a dataframe and show how many rows and columns it has
df = pd.read_csv('hrdata.csv')
print("Number of rows = " + str(df.shape[0]))
print("Number of columns = " + str(df.shape[1]))
```

```
Number of rows = 21287
Number of columns = 18
```

In [4]:

```python
#call the describe method of dataframe to see some summary statistics of the numerical columns
df.describe()
```

Out[4]:

	Unnamed: 0	rec_num	enrollee_id	city_development_index	training_hours	target	city_development_matrics
count	21287.000000	21287.000000	21287.000000	21287.000000	21287.000000	19158.000000	21287.000000
mean	10643.000000	10644.000000	16873.983652	0.828462	65.328510	0.249348	8.284615
std	6145.171926	6145.171926	9612.131237	0.123537	60.075201	0.432647	1.235365
min	0.000000	1.000000	1.000000	0.448000	1.000000	0.000000	4.480000
25%	5321.500000	5322.500000	8554.500000	0.739000	23.000000	0.000000	7.390000
50%	10643.000000	10644.000000	16967.000000	0.903000	47.000000	0.000000	9.030000
75%	15964.500000	15965.500000	25161.500000	0.920000	88.000000	0.000000	9.200000
max	21286.000000	21287.000000	33380.000000	0.949000	336.000000	1.000000	9.490000

In [5]:

```python
df.dtypes
```

Out[5]:

```
Unnamed: 0                   int64
rec_num                      int64
enrollee_id                  int64
city                        object
city_development_index     float64
gender                      object
relevent_experience         object
enrolled_university         object
education_level             object
major_discipline            object
experience                  object
company_size                object
company_type                object
last_new_job                object
training_hours               int64
target                     float64
state                       object
city_development_matrics   float64
dtype: object
```

Interesting and good to know statistics:

- All counts besides target (19158) are exactly the same (21287)
- Max value == count for rec_num
- city_development_matrics == city_development_index * 10

In [6]:

```python
# show top 5 rows of dataframe
df.head()
```

Out[6]:

	Unnamed: 0	rec_num	enrollee_id	city	city_development_index	gender	relevent_experience	enrolled_university	education_level	major_discipline	experience	company_s
0	0	1	8949	city_103	0.920	Male	Has relevent experience	no_enrollment	Graduate	STEM	>20	N
1	1	2	29725	city_40	0.776	Male	No relevent experience	no_enrollment	Graduate	STEM	15	50
2	2	3	11561	city_21	0.624	NaN	No relevent experience	Full time course	Graduate	STEM	5	N
3	3	4	33241	city_115	0.789	NaN	No relevent experience	NaN	Graduate	Business Degree	<1	N

Unnamed: 0	rec_num	enrollee_id	city	city_development_index	gender	relevent_experience	enrolled_university	education_level	major_discipline	experience	company_s

In [7]:
```
# Show last 5 rows of dataframe
df.tail()
```

Out[7]:

	Unnamed: 0	rec_num	enrollee_id	city	city_development_index	gender	relevent_experience	enrolled_university	education_level	major_discipline	experience	comp
21282	21282	21283	1289	city_103	0.920	Male	No relevent experience	no_enrollment	Graduate	Humanities	16	
21283	21283	21284	195	city_136	0.897	Male	Has relevent experience	no_enrollment	Masters	STEM	18	
21284	21284	21285	31762	city_100	0.887	Male	No relevent experience	no_enrollment	Primary School	NaN	3	
21285	21285	21286	7873	city_102	0.804	Male	Has relevent experience	Full time course	High School	NaN	7	
21286	21286	21287	12215	city_102	0.804	Male	Has relevent experience	no_enrollment	Masters	STEM	15	

In [8]:
```
# list all numerical columns
numerical_features = df.select_dtypes(include = np.number)
numerical_features.columns
```

Out[8]:
```
Index(['Unnamed: 0', 'rec_num', 'enrollee_id', 'city_development_index',
       'training_hours', 'target', 'city_development_matrics'],
      dtype='object')
```

In [9]:
```
#list all categorical columns
categorical_features = df.select_dtypes(exclude = np.number)
categorical_features.columns
```

Out[9]:
```
Index(['city', 'gender', 'relevent_experience', 'enrolled_university',
       'education_level', 'major_discipline', 'experience', 'company_size',
       'company_type', 'last_new_job', 'state'],
      dtype='object')
```

Examine Missing Values

In [10]:
```
#Show a list with column wise count of missing values and display the list in count wise descending order
df.isnull().sum().sort_values(ascending = False)
```

Out[10]:
```
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
dtype: int64
```

In [11]:

```
# Show a list with column wise percentage of missing values and display the list in percentage wise descending order'
df.isna().sum().sort_values(ascending = False) * 100 / len(df)
```

Out[11]:

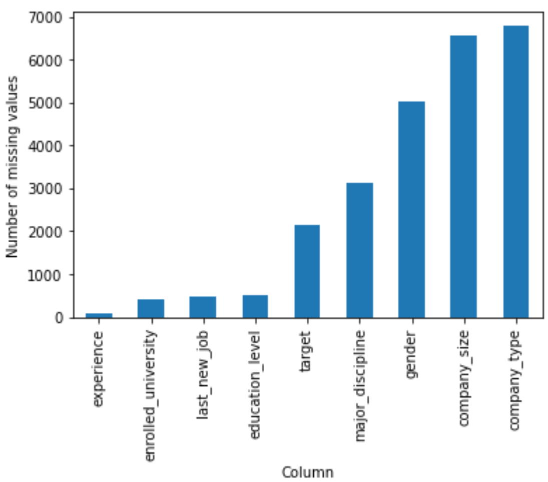
```
company_type                31.822239
company_size                30.816931
gender                      23.563677
major_discipline            14.680321
target                      10.001409
education_level              2.405224
last_new_job                 2.175036
enrolled_university          1.958942
experience                   0.328839
state                        0.000000
training_hours               0.000000
Unnamed: 0                   0.000000
rec_num                      0.000000
relevent_experience          0.000000
city_development_index       0.000000
city                         0.000000
enrollee_id                  0.000000
city_development_matrics     0.000000
dtype: float64
```

In [12]:

```
# Display a bar plot to visualize only the columns with missing values and their count
null_df = df.isnull().sum()
null_df = null_df[null_df > 0]
null_df.sort_values(inplace = True)
plt.xlabel("Column")
plt.ylabel("Number of missing values")
null_df.plot.bar()
```

Out[12]:

```
<AxesSubplot:xlabel='Column', ylabel='Number of missing values'>
```

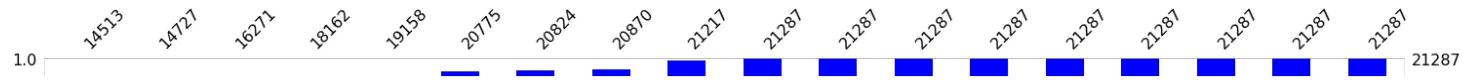


In [13]:

```
#Use missingno's bar plot
msno.bar(df, color = 'blue', sort = "ascending" )
```

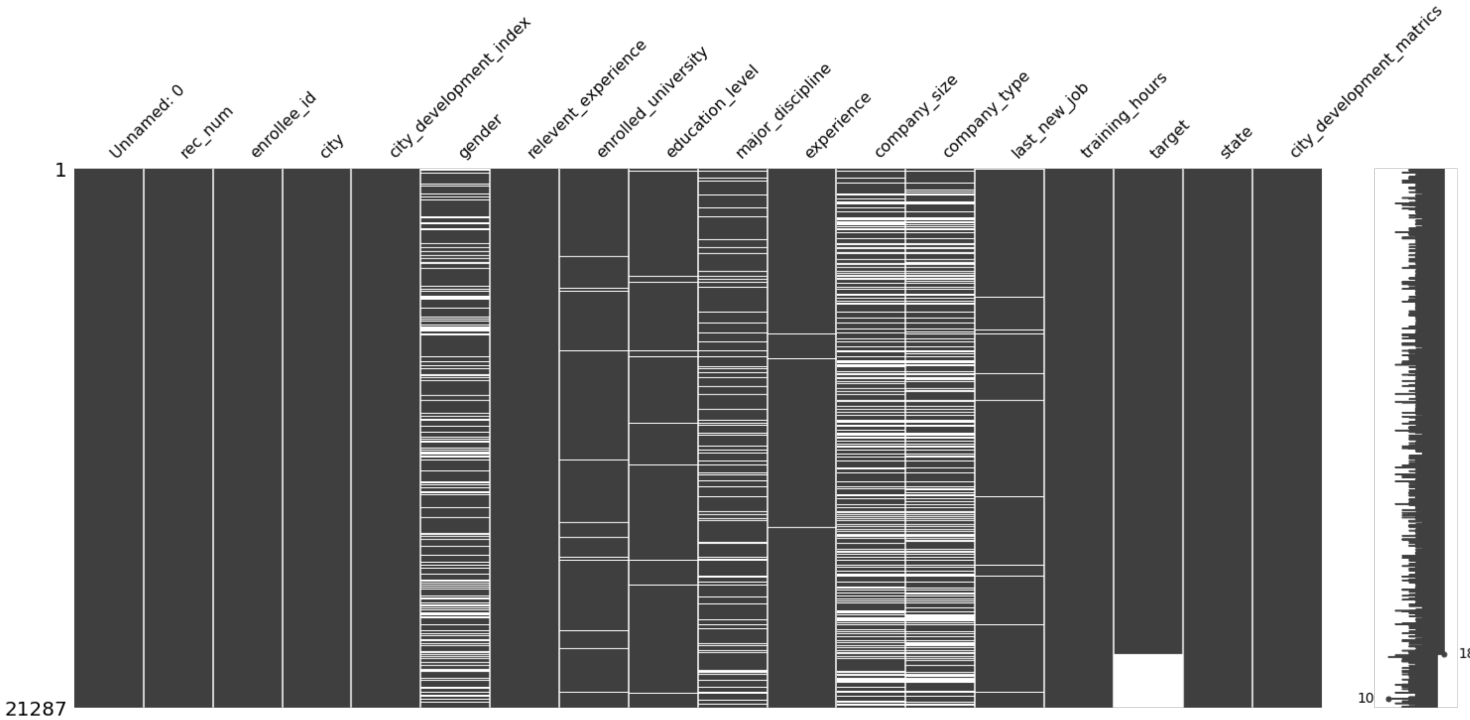
Out[13]:

```
<AxesSubplot:>
```



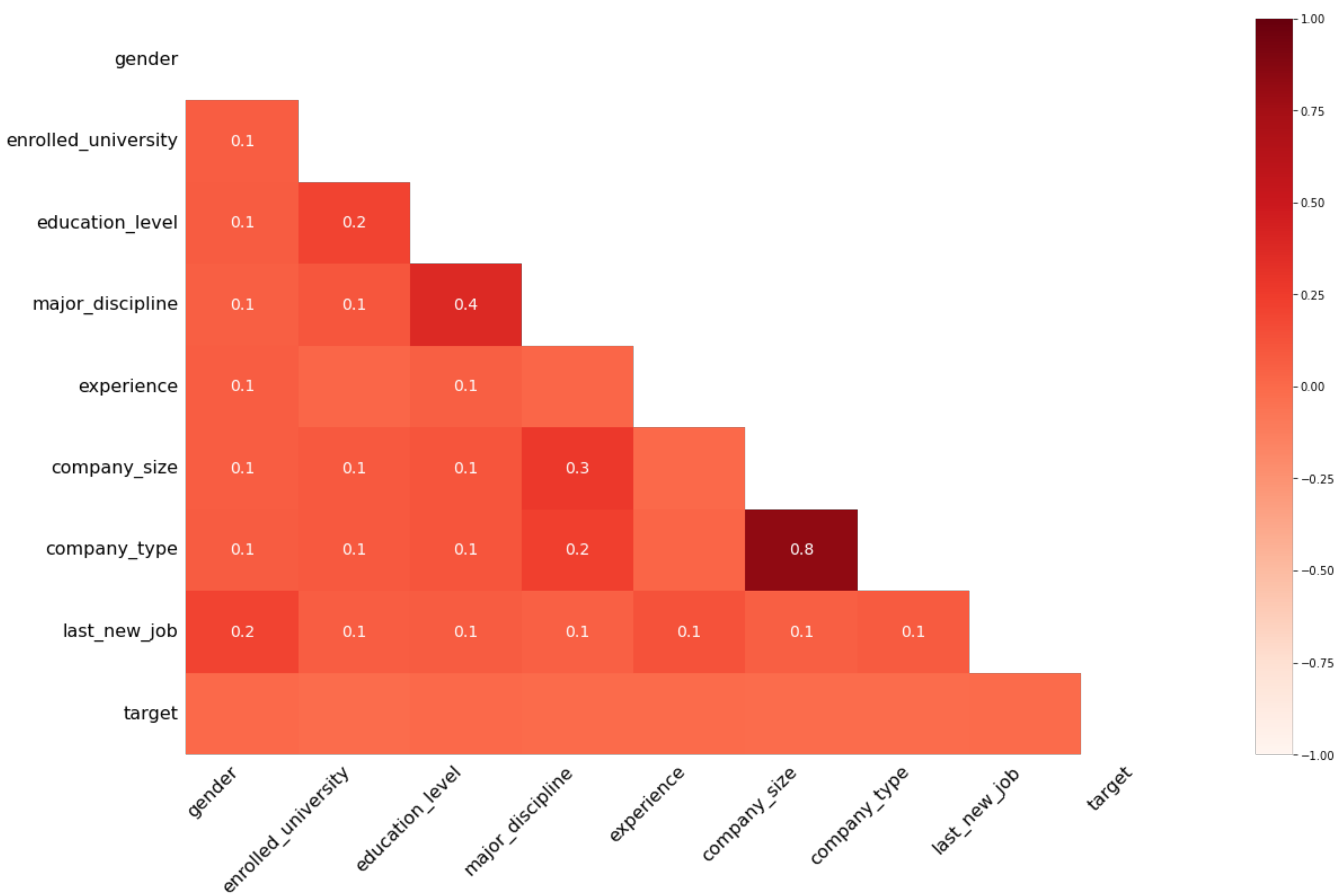
In [14]:
```
#Use missingno's matrix plot w/ 200 sample
msno.matrix(df)
```

Out[14]: <AxesSubplot:>



In [15]:
```
# Use missingno's heatmap
msno.heatmap(df, cmap = "Reds")
```

Out[15]: <AxesSubplot:>



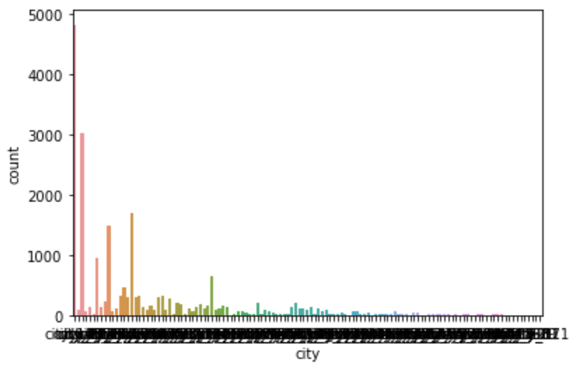
Interpret any interesting information you found in the heatmap and any one plot:

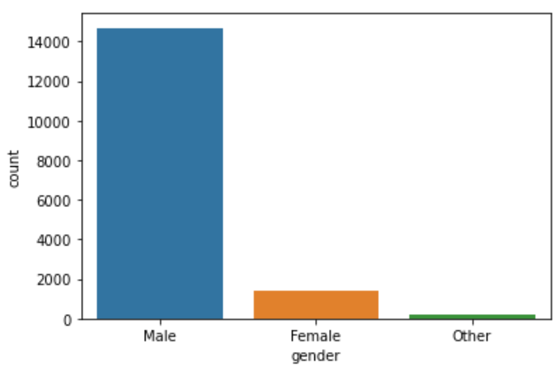
- matrix plot shows us that company_size & company_type are the two columns with highest missing values
- heatmap shows us that there is a strong positive correlation between company size and company type (might need to find a way to substitute missing values for higher accuracy before engineering a new feature)

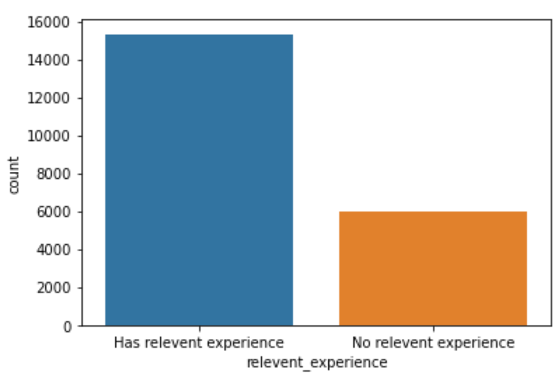
Understanding Categorical attributes

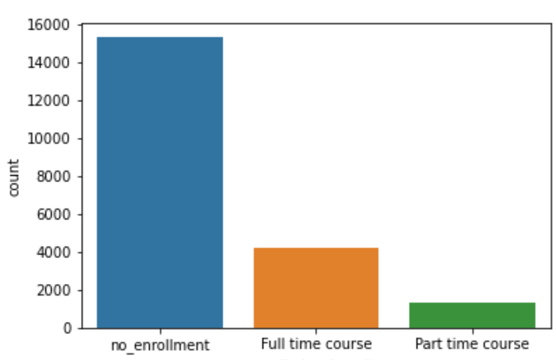
In [16]:
```
categorical_columns = df.select_dtypes(exclude = np.number)
```

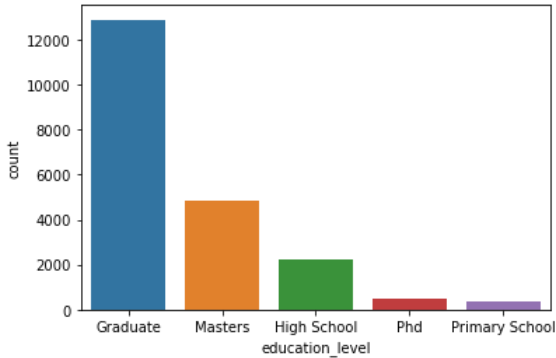
In [18]:
```
    #Use seaborn bar plot for the categorical feature to see different values and count
    for cat in categorical_columns:
        sns.countplot(x = cat, data = df)
        plt.show()
```

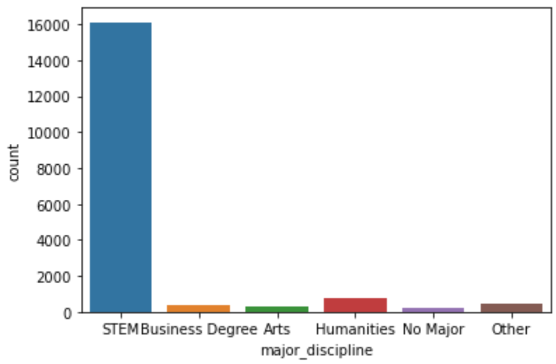


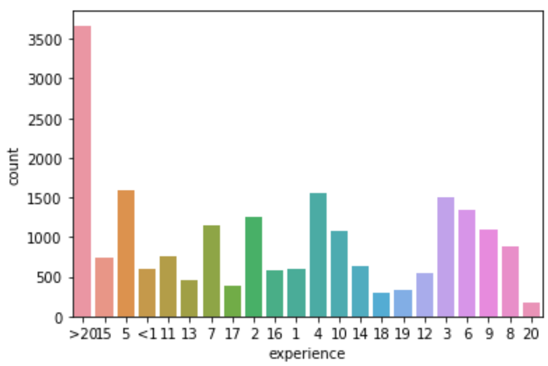


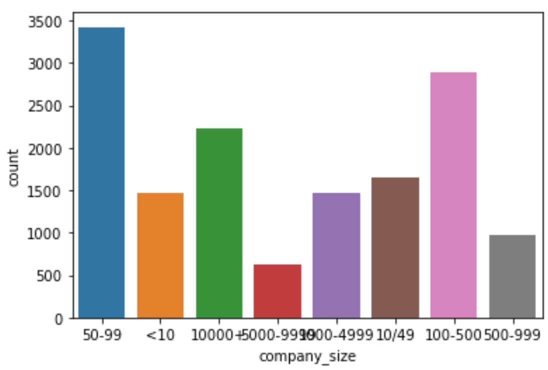


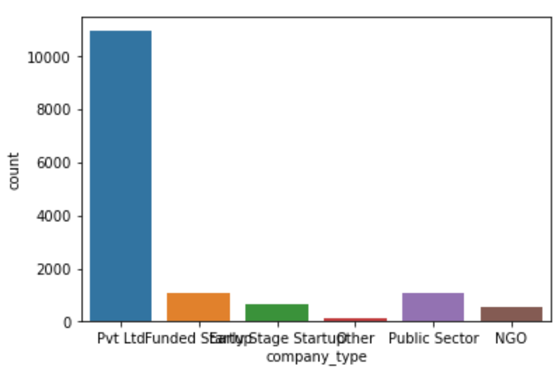


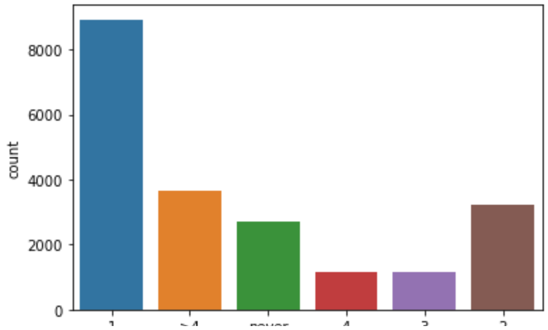

count
0
2000
4000
6000
8000
10000
12000
Graduate
Masters
High School
Phd
Primary School
education_level


count
0
2000
4000
6000
8000
10000
12000
14000
16000
STEM
Business Degree
Arts
Humanities
No Major
Other
major_discipline


count
0
500
1000
1500
2000
2500
3000
3500
>20
15
5
<1
11
13
7
17
2
16
1
4
10
14
18
19
12
3
6
9
8
20
experience

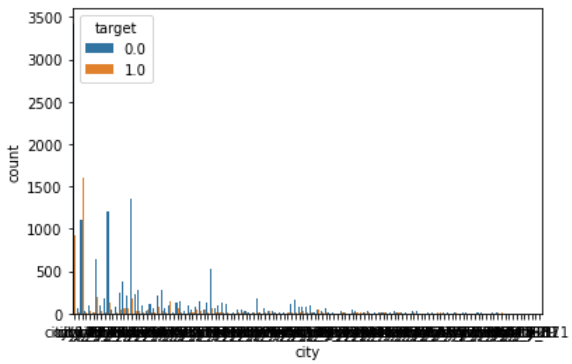

count
0
500
1000
1500
2000
2500
3000
3500
50-99
<10
10000+
5000-9999
1000-4999
10/49
100-500
500-999
company_size

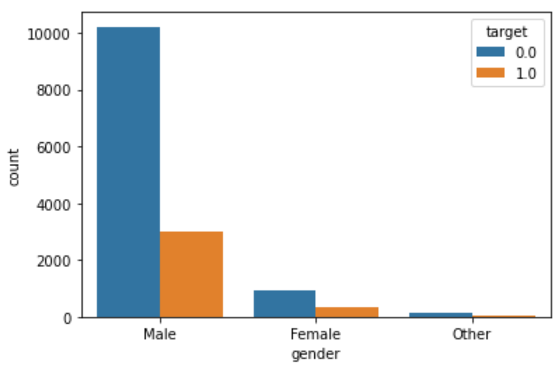

count
0
2000
4000
6000
8000
10000
Pvt Ltd
Funded Startup
Early Stage Startup
Other
Public Sector
NGO
company_type

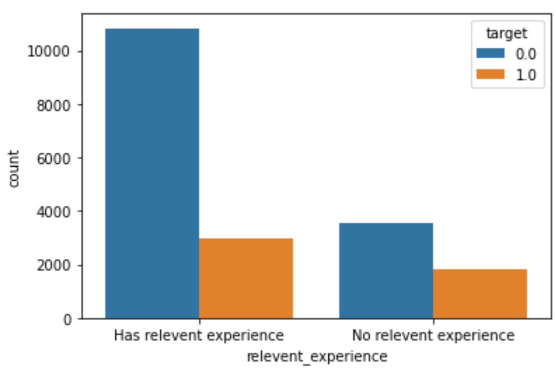


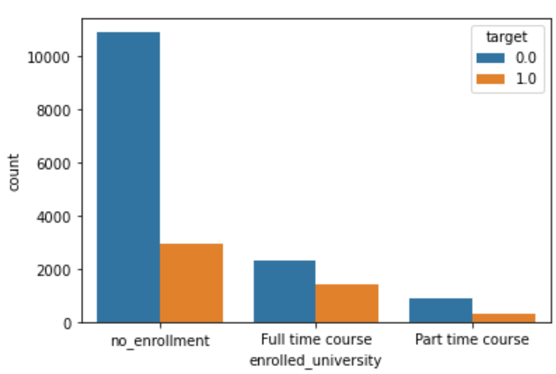
Note: countplot is a type of barplot that shows counts of each category, and its implementation is much cleaner

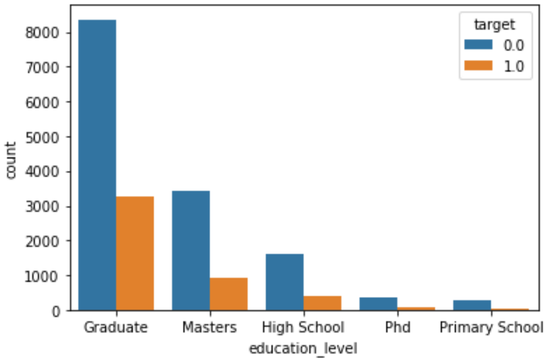
In [17]:
```
#Use seaborn countplot for the categorical feature against the values of the target
for cat in categorical_columns:
    sns.countplot(x = cat, hue = df["target"],data = df)
    plt.show()
```

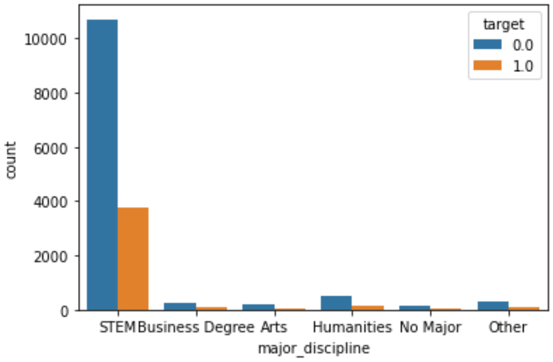


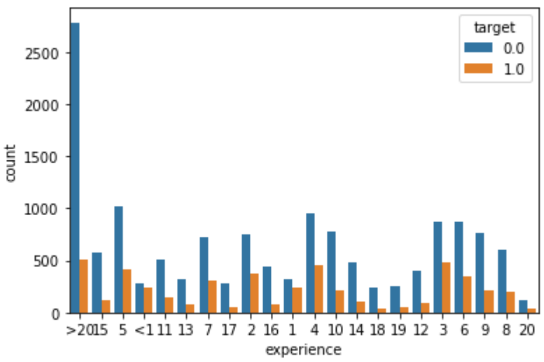


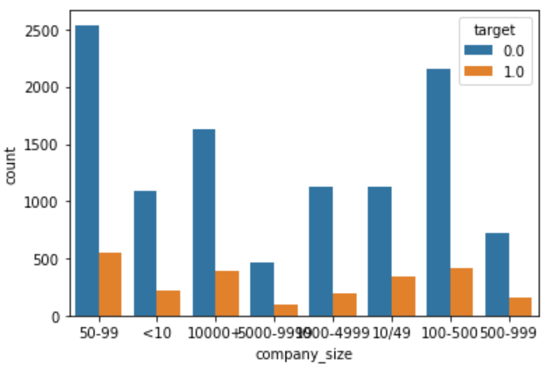


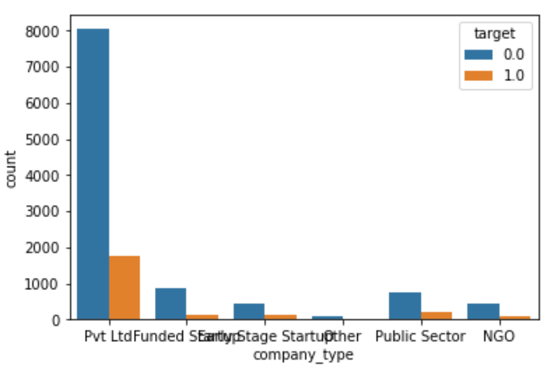


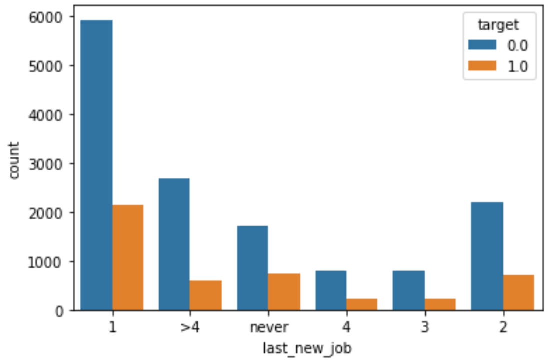

target
0.0
1.0
count
0
1000
2000
3000
4000
5000
6000
7000
8000
Graduate
Masters
High School
Phd
Primary School
education_level


target
0.0
1.0
count
0
2000
4000
6000
8000
10000
STEM
Business Degree
Arts
Humanities
No Major
Other
major_discipline


target
0.0
1.0
count
0
500
1000
1500
2000
2500
>20 15 5 <1 11 13 7 17 2 16 1 4 10 14 18 19 12 3 6 9 8 20
experience


target
0.0
1.0
count
0
500
1000
1500
2000
2500
50-99
<10
10000+
5000-9999
1000-4999
10/49
100-500
500-999
company_size


target
0.0
1.0
count
0
1000
2000
3000
4000
5000
6000
7000
8000
Pvt Ltd
Funded Startup
Early Stage Startup
Other
Public Sector
NGO
company_type



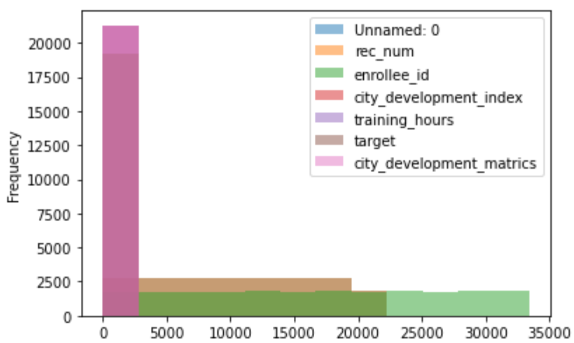
Interpret any interesting information and any information that might help you to make any decision on combining, removing, or adding features based on that, or any resampling maybe needed.

- We clearly need to resample for states as there is only one (CA)
- A lot of data is skewed to the left so we there might be a bias
- Might need to resample majors as there is a clear bias towards STEM

Understanding Numerical Attributes

In [19]:
```
#Plot their distributions using histogram
numerical_features.plot.hist(bins = 12,alpha = .5)
```

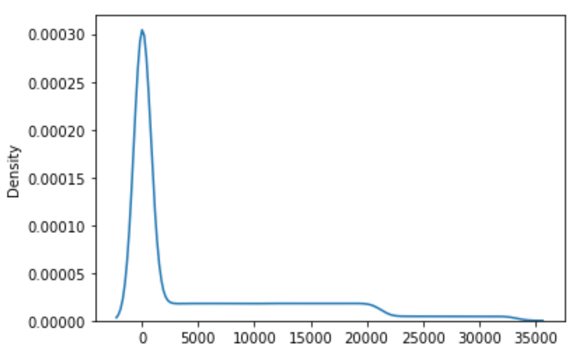
Out[19]: <AxesSubplot:ylabel='Frequency'>



In [20]:
```
#Plot the distribution using seaborn distplot
sns.distplot(numerical_features, hist = False)
```

```
C:\Users\Admin\anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWarning: `distplot` is a deprecated function and will b
e removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `kd
eplot` (an axes-level function for kernel density plots).
  warnings.warn(msg, FutureWarning)
```

Out[20]: <AxesSubplot:ylabel='Density'>



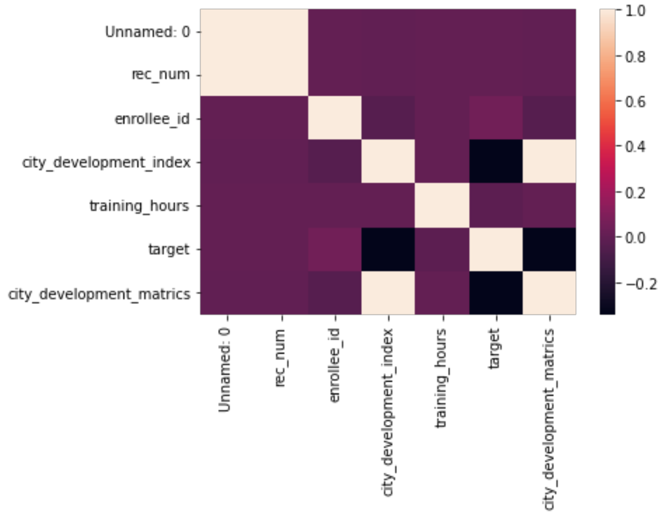
Interpret any interesting information:

- training_hours and city_development_index have much higher frequencies than the rest of the features

Correlation

In [21]:
```
#For the numerical attributes, use heatmap to show the correlation
sns.heatmap(numerical_features.corr())
```

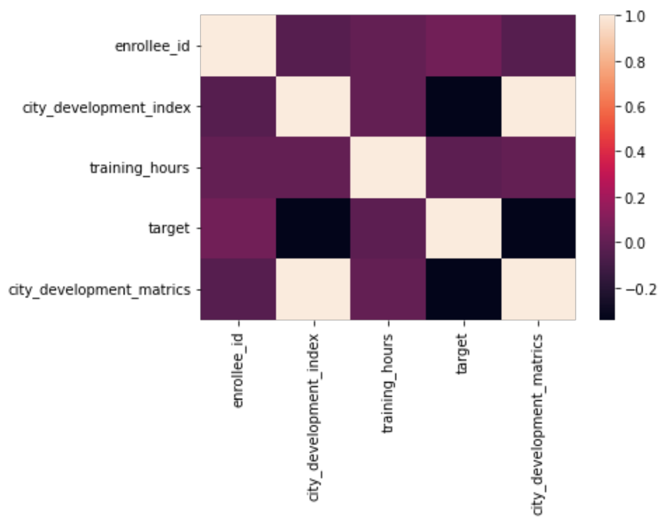
Out[21]: <AxesSubplot:>



In [30]:

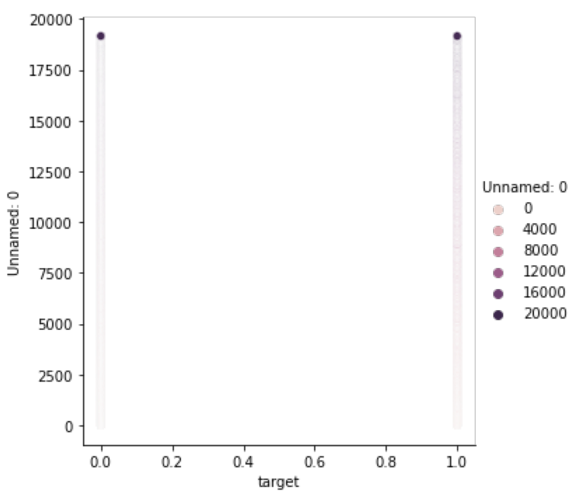
```python
# Heatmap with shortlisted columns
sns.heatmap(numerical_features.drop(labels = ["Unnamed: 0","rec_num"], axis = 1).corr())
```

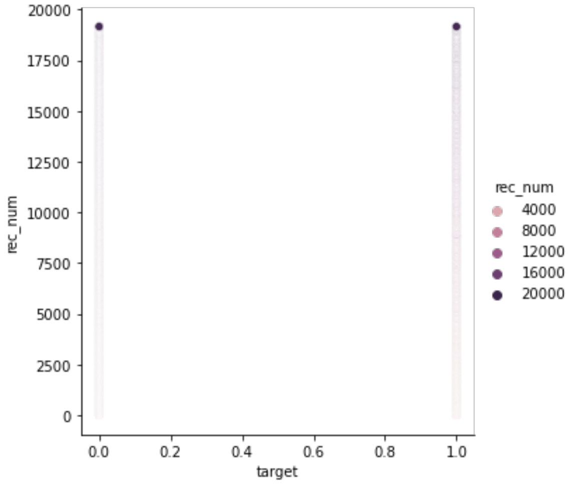
Out[30]: <AxesSubplot:>

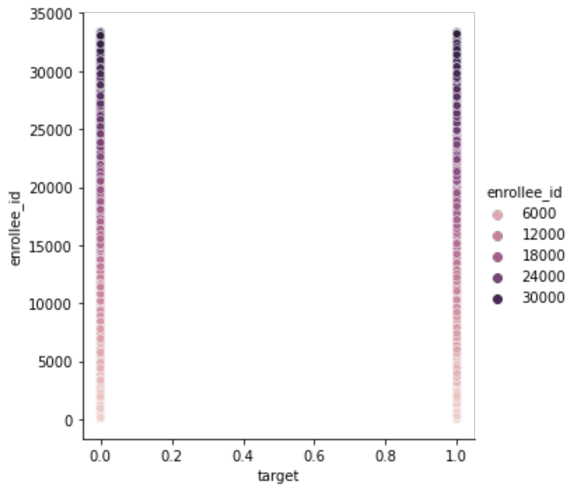


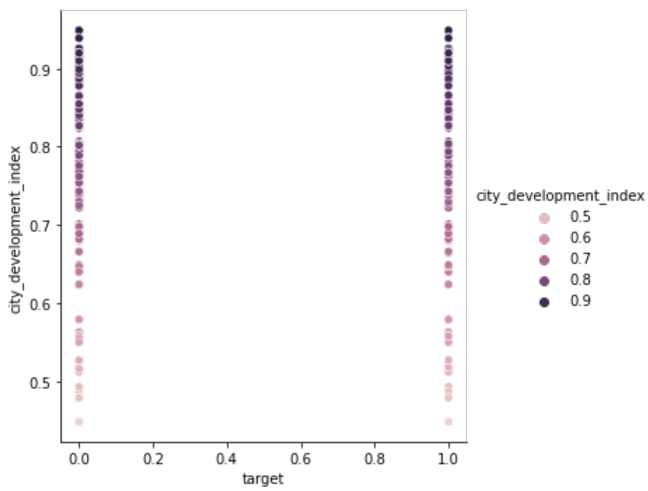
In [23]:

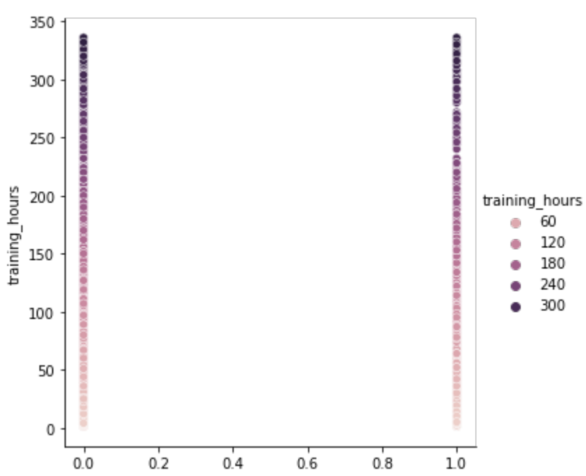
```python
#Show scatter plots between columns to show the relationships with the target
for numerical_col in numerical_features:
    sns.relplot(data = numerical_features, y = numerical_col, x = "target", hue = numerical_col)
    plt.show()
```

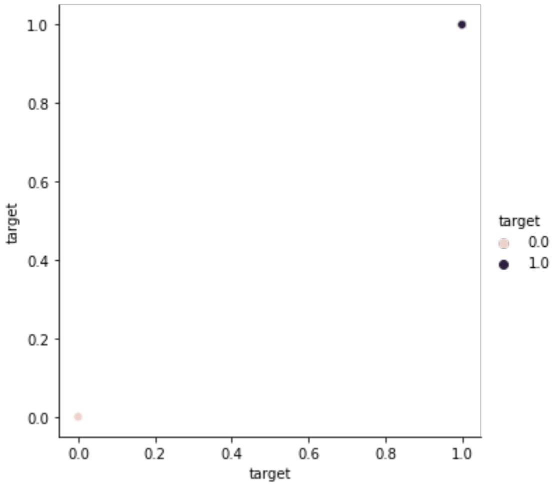


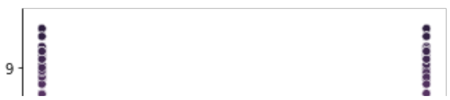

rec_num
target
rec_num
4000
8000
12000
16000
20000


enrollee_id
target
enrollee_id
6000
12000
18000
24000
30000


city_development_index
target
city_development_index
0.5
0.6
0.7
0.8
0.9


training_hours
target
training_hours
60
120
180
240
300





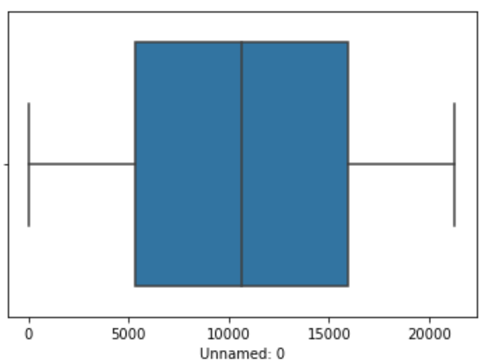
Interpret and explain any finding and next course of action:

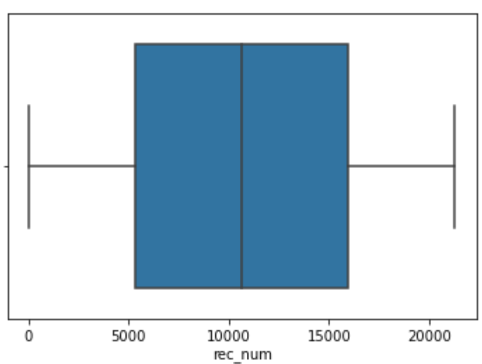
- We should re-evaluate the range for our target it is hard to distinguish when there is only 0 and 1
- We can remove rec_num feature as it has no correlation with our target value

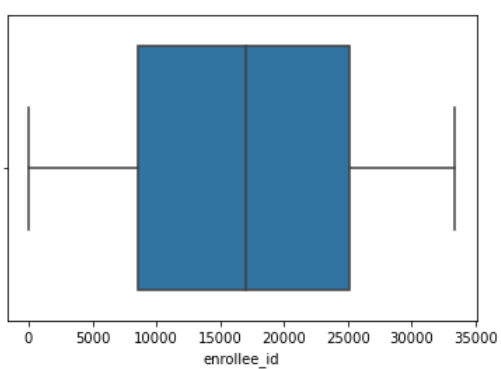
Outliers

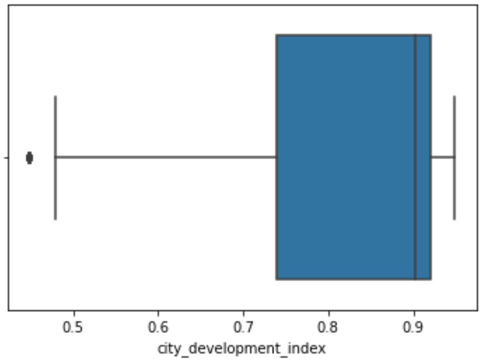
In [24]:

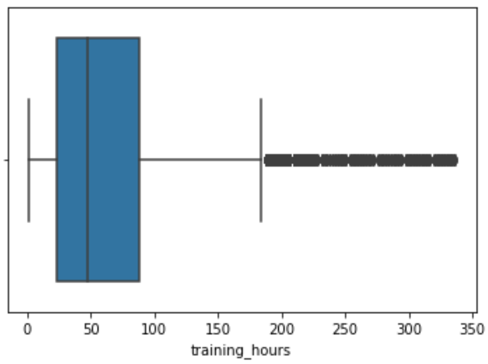
```
#Use boxplot or any other strategies to find outliers
for numerical_col in numerical_features:
    sns.boxplot(data = numerical_features,x = numerical_col)
    plt.show()
```

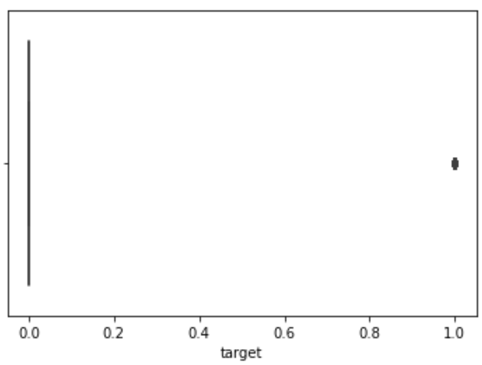


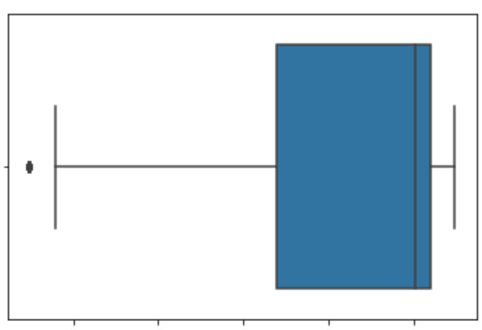








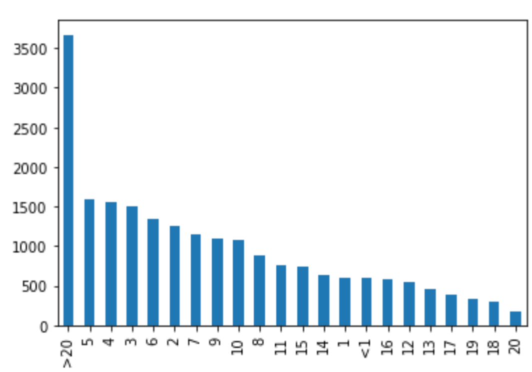




In [26]:

```
categorical_features["experience"].value_counts().plot(kind='bar')
```

Out[26]: <AxesSubplot:>



What are the different values of experience, can you categorize them in to 0, 1, and 2?

- There are too many different values of experience to categorize in to 0,1 and 2 unless we utilize data ranges.

Summary and discussion: 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.

- One part of our feature engineering should be to combine city_development_metrics and city_development_index (or we can remove one of them for simplicity)
- We should resample company_size & company_type as there are a lot of missing values
- Company_size & company_type can possible be engineered into a single feature(or one can be droppped) but we cannot be sure until we resample the missing values (or fill them in with mean,median, etc).
- We need to resample states because our data is biased to CA (we only have data from one state)
- We might also have to resample our data for majors as there is a clear skew to STEM majors which may result in bias
- We should re-evaluate the range for our target it is hard to distinguish when there is only 0 and 1
- We can remove rec_num feature as it has no correlation with our target value