

EDA: Visa Dataset

Dataset Link: <https://drive.google.com/file/d/1Fzzbf8Rj1NheQ-zfwFQHYY-T8FxB8ouT/view>

1. EDA

- Data Profiling
- Stastical analysis
- Graphical Analysis

```
In [1]: #importing necessary libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import statistics as stat
%matplotlib inline
# To display maximum columns of dataframe on screen
pd.pandas.set_option('display.max_columns', None)
```

load the dataset and display basic info like shape, data types, basic statistical info like mean median mode etc

```
In [3]: visa=pd.read_csv('Visadataset.csv')
visa.head()
```

```
Out[3]:
```

	case_id	continent	education_of_employee	has_job_experience	requires_job_training	no_of_employees	yr_c
0	EZYV01	Asia	High School	N	N	14513	
1	EZYV02	Asia	Master's	Y	N	2412	
2	EZYV03	Asia	Bachelor's	N	Y	44444	
3	EZYV04	Asia	Bachelor's	N	N	98	
4	EZYV05	Africa	Master's	Y	N	1082	

```
In [4]: #data types
visa.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 25480 entries, 0 to 25479
Data columns (total 12 columns):
#   Column                                Non-Null Count  Dtype
---  -
0   case_id                              25480 non-null  object
1   continent                            25480 non-null  object
2   education_of_employee                25480 non-null  object
3   has_job_experience                   25480 non-null  object
4   requires_job_training                25480 non-null  object
5   no_of_employees                     25480 non-null  int64
6   yr_of_estab                         25480 non-null  int64
7   region_of_employment                25480 non-null  object
8   prevailing_wage                     25480 non-null  float64
9   unit_of_wage                        25480 non-null  object
10  full_time_position                  25480 non-null  object
11  case_status                         25480 non-null  object
dtypes: float64(1), int64(2), object(9)
memory usage: 2.3+ MB
```

```
In [6]: #shape to display number of rows and columns
visa.shape
```

```
Out[6]: (25480, 12)
```

Observation

- there are 25480 rows and 12 columns
- no_of_employees, yr_of_estab are numerical, prevailing_wage is float and rest are categorical features

Separating Numerical and Categorical features

```
In [13]: numeric_feat=[feats for feats in visa.columns if visa[feats].dtype!='O' and feats!='case',
categorical_feat=[feats for feats in visa.columns if visa[feats].dtype=='O' and feats!='case']
```

```
In [14]: numeric_feat
```

```
Out[14]: ['no_of_employees', 'yr_of_estab', 'prevailing_wage']
```

```
In [15]: categorical_feat
```

```
Out[15]: ['continent',
'education_of_employee',
'has_job_experience',
'requires_job_training',
'region_of_employment',
'unit_of_wage',
'full_time_position',
'case_status']
```

```
In [16]: visa[numeric_feat].head()
```

Out[16]:

	no_of_employees	yr_of_estab	prevailing_wage
0	14513	2007	592.2029
1	2412	2002	83425.6500
2	44444	2008	122996.8600
3	98	1897	83434.0300
4	1082	2005	149907.3900

Numerical Features

Discrete Numerical features

In [19]:

```
discrete_numeric_feats=[feat for feat in numeric_feat if len(visa[feat].unique())<25]
```

In [20]:

```
discrete_numeric_feats
```

Out[20]: []

Continuous Numerical Features

In [23]:

```
continuous_numeric_feats=[feat for feat in numeric_feat if len(visa[feat].unique())>25]  
continuous_numeric_feats
```

Out[23]: ['no_of_employees', 'yr_of_estab', 'prevailing_wage']

Categorical Features

In [25]:

```
visa[categorical_feat]
```

Out[25]:

	continent	education_of_employee	has_job_experience	requires_job_training	region_of_employment	uni
0	Asia	High School	N	N	West	
1	Asia	Master's	Y	N	Northeast	
2	Asia	Bachelor's	N	Y	West	
3	Asia	Bachelor's	N	N	West	
4	Africa	Master's	Y	N	South	
...
25475	Asia	Bachelor's	Y	Y	South	
25476	Asia	High School	Y	N	Northeast	
25477	Asia	Master's	Y	N	South	
25478	Asia	Master's	Y	Y	West	
25479	Asia	Bachelor's	Y	N	Midwest	

25480 rows × 8 columns

Missing Values

In [26]:

```
missing_val=[feat for feat in visa.columns if visa[feat].isnull().sum()>1]
```

```
In [27]: missing_val
```

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

Observation

- There is no missing value in the dataset

Statistical Analysis

Mean, Median, Mode of the numerical dataset

```
In [28]: #Mean of the numeric features  
visa[numeric_feat].mean()
```

```
Out[28]: no_of_employees    5667.043210  
yr_of_estab      1979.409929  
prevailing_wage  74455.814592  
dtype: float64
```

```
In [30]: #Median of the numeric features  
visa[numeric_feat].median()
```

```
Out[30]: no_of_employees    2109.00  
yr_of_estab      1997.00  
prevailing_wage  70308.21  
dtype: float64
```

```
In [33]: #Mode of the numeric features  
visa[numeric_feat].mode().loc[0]
```

```
Out[33]: no_of_employees    183.00  
yr_of_estab      1998.00  
prevailing_wage    100.66  
Name: 0, dtype: float64
```

Variance and Standard Deviation of the numerical dataset

```
In [35]: #Variance  
round(visa[numeric_feat].var(),2)
```

```
Out[35]: no_of_employees    5.233996e+08  
yr_of_estab      1.794960e+03  
prevailing_wage  2.789524e+09  
dtype: float64
```

```
In [37]: # Standard Deviation  
visa[numeric_feat].std()
```

```
Out[37]: no_of_employees    22877.928848  
yr_of_estab      42.366929  
prevailing_wage  52815.942327  
dtype: float64
```

Covariance of numeric dataset

```
In [38]: visa[numeric_feat].cov()
```

```
Out[38]:
```

	no_of_employees	yr_of_estab	prevailing_wage
no_of_employees	5.233996e+08	-17224.155003	-1.150624e+07
yr_of_estab	-1.722416e+04	1794.956681	2.761653e+04
prevailing_wage	-1.150624e+07	27616.530171	2.789524e+09

Correlation of numeric dataset

```
In [41]: #Pearson correlation coefficient
visa[numeric_feat].corr()
```

```
Out[41]:
```

	no_of_employees	yr_of_estab	prevailing_wage
no_of_employees	1.000000	-0.017770	-0.009523
yr_of_estab	-0.017770	1.000000	0.012342
prevailing_wage	-0.009523	0.012342	1.000000

```
In [42]: # 2. Spearman's rank correlation coefficient
visa[numeric_feat].corr(method='spearman')
```

```
Out[42]:
```

	no_of_employees	yr_of_estab	prevailing_wage
no_of_employees	1.000000	-0.006214	-0.015197
yr_of_estab	-0.006214	1.000000	0.019566
prevailing_wage	-0.015197	0.019566	1.000000

```
In [43]: # 3. kendall rank correlation coefficient
visa[numeric_feat].corr(method='kendall')
```

```
Out[43]:
```

	no_of_employees	yr_of_estab	prevailing_wage
no_of_employees	1.000000	-0.004180	-0.010159
yr_of_estab	-0.004180	1.000000	0.013151
prevailing_wage	-0.010159	0.013151	1.000000

Five point summary for outliers

```
In [46]: for feat in numeric_feat:
    print("Five Point Summary for {}".format(feat))
    print("1. Minimum value is: {}".format(visa[feat].min()))
    print("2. 1st quartile is: {}".format(np.percentile(visa[feat], 25)))
    print("3. Median is: {}".format(np.percentile(visa[feat], 50)))
    print("4. 3rd quartile is: {}".format(np.percentile(visa[feat], 75)))
    print("5. Maximum value is: {}".format(visa[feat].max()))
    print(" ")
```

Five Point Summary for no_of_employees

1. Minimum value is: -26
2. 1st quartile is: 1022.0
3. Median is: 2109.0
4. 3rd quartile is: 3504.0
5. Maximum value is: 602069

Five Point Summary for yr_of_estab

1. Minimum value is: 1800
2. 1st quartile is: 1976.0
3. Median is: 1997.0
4. 3rd quartile is: 2005.0
5. Maximum value is: 2016

Five Point Summary for prevailing_wage

1. Minimum value is: 2.1367
2. 1st quartile is: 34015.479999999996
3. Median is: 70308.20999999999
4. 3rd quartile is: 107735.51250000001
5. Maximum value is: 319210.27

Mode of Categorical Features

```
In [50]: visa[categorical_feat].mode()
```

```
Out[50]:
```

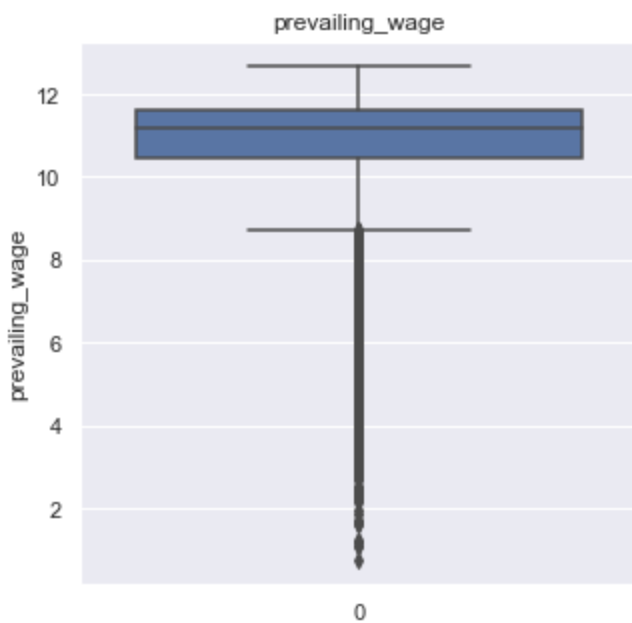
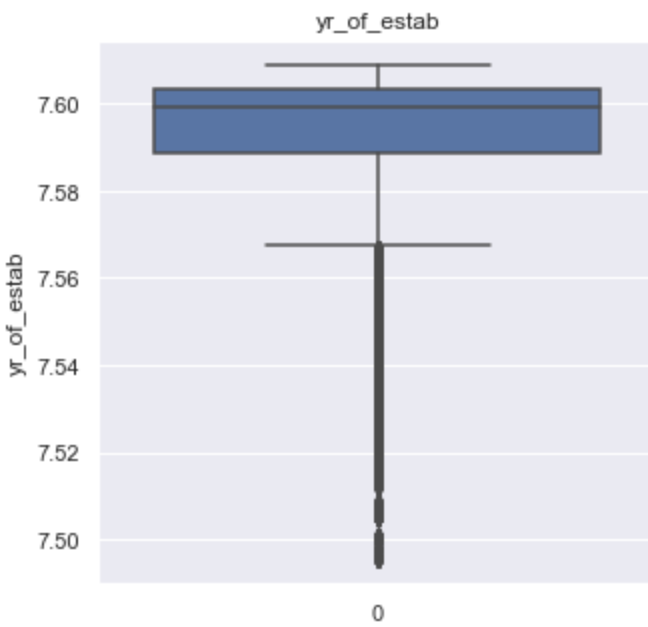
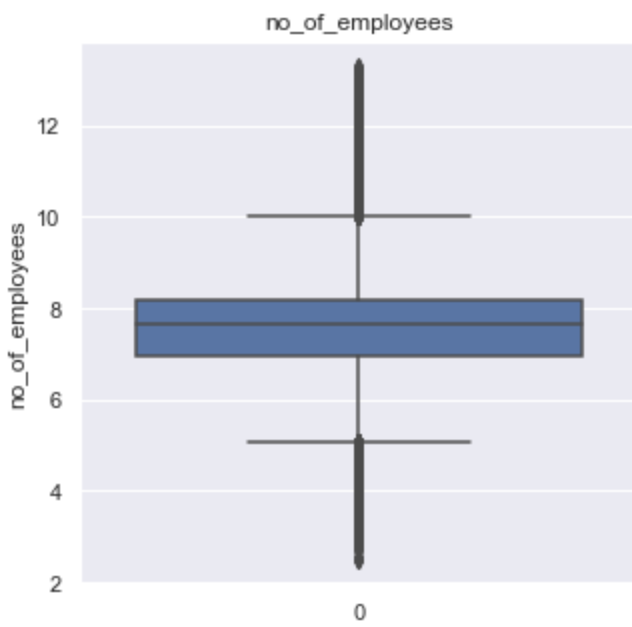
	continent	education_of_employee	has_job_experience	requires_job_training	region_of_employment	unit_of_
0	Asia	Bachelor's	Y	N	Northeast	

Graphical Analysis

Box Plot for outliers

```
In [51]: sns.set(rc={'figure.figsize':(5,5)})
for feat in continuous_numeric_feats:
    visa_copy=visa.copy()
    # here we are ignoring all zero values,since log(0) is undefined
    if 0 in visa_copy[feat].unique():
        pass
    else:
        visa_copy[feat]=np.log(visa_copy[feat])
        sns.boxplot(data=visa_copy[feat])
        plt.ylabel(feat)
        plt.title(feat)
        plt.show()
```

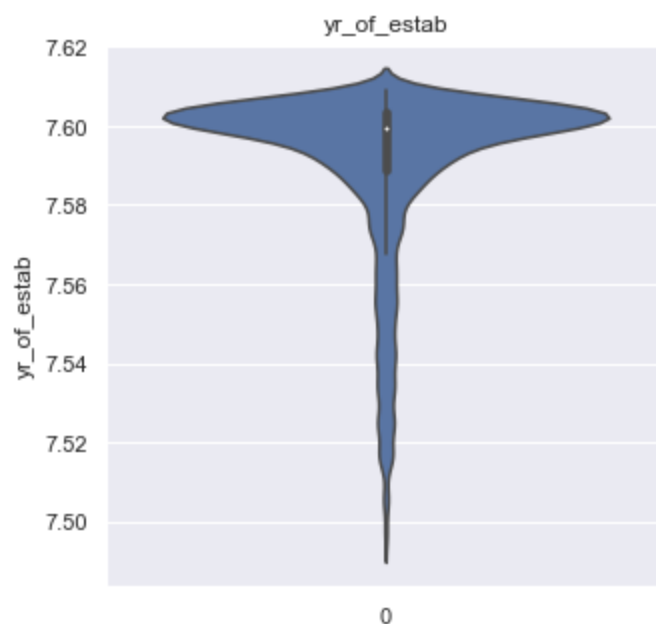
```
C:\Users\subho\anaconda3\lib\site-packages\pandas\core\arraylike.py:397: RuntimeWarning:
invalid value encountered in log
  result = getattr(ufunc, method)(*inputs, **kwargs)
```



Observation

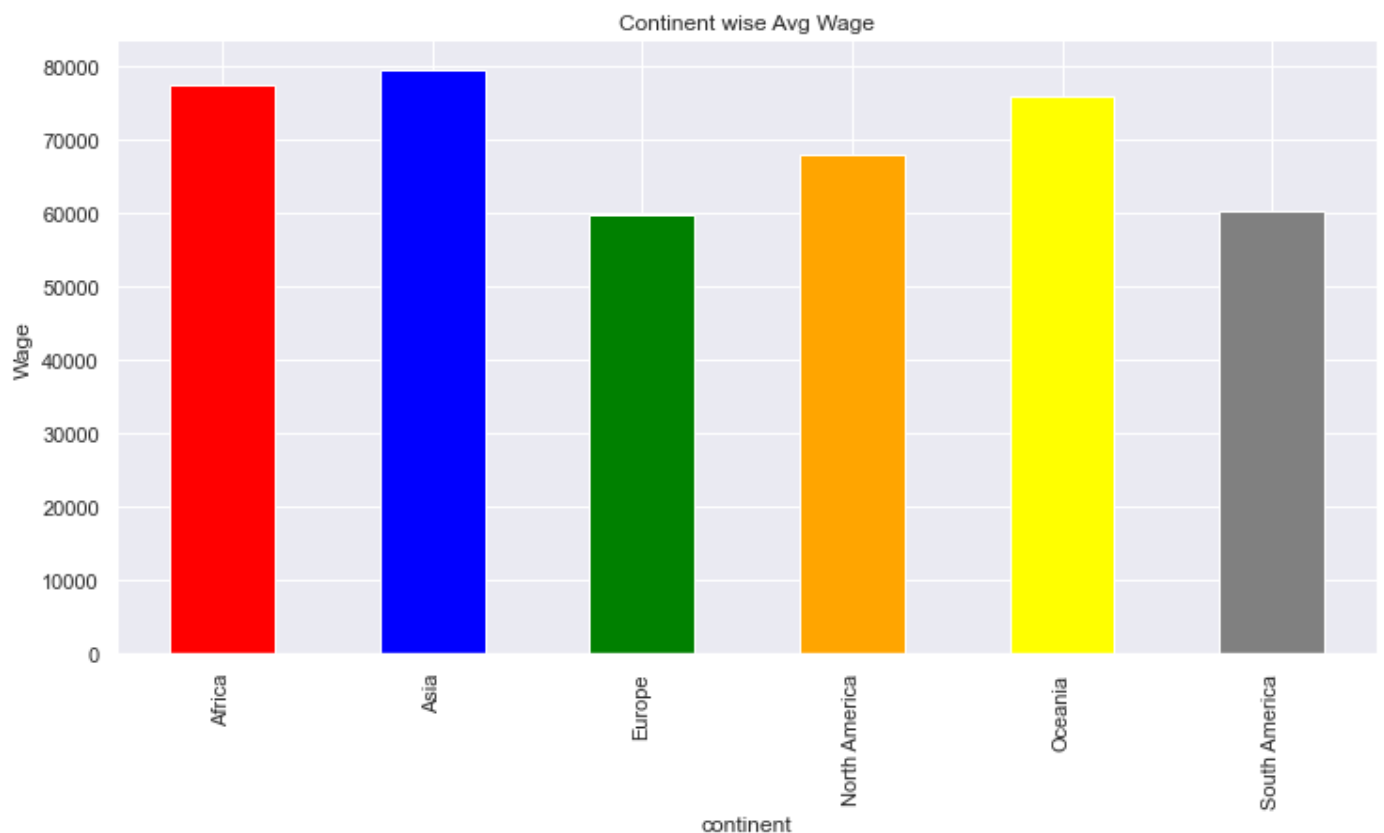
```
In [53]: # violin plot for checking outliers
sns.set(rc={'figure.figsize':(5,5)})
for feat in continuous_numeric_feats:
    visa_copy=visa.copy()
    # here we are ignoring all zero values, since log(0) is undefined
    if 0 in visa_copy[feat].unique():
        pass
    else:
        visa_copy[feat]=np.log(visa_copy[feat])
        sns.violinplot(data=visa_copy[feat])
        plt.ylabel(feat)
        plt.title(feat)
        plt.show()
```

C:\Users\subho\anaconda3\lib\site-packages\pandas\core\arraylike.py:397: RuntimeWarning: invalid value encountered in log
 result = getattr(ufunc, method)(*inputs, **kwargs)





```
In [59]: #continent wise mean salary
visa_copy=visa.copy()
visa_copy.groupby(by='continent')['prevailing_wage'].mean().plot.bar(figsize=(12,6),color
plt.xlabel('continent')
plt.ylabel('Wage')
plt.title('Continent wise Avg Wage')
plt.show()
```

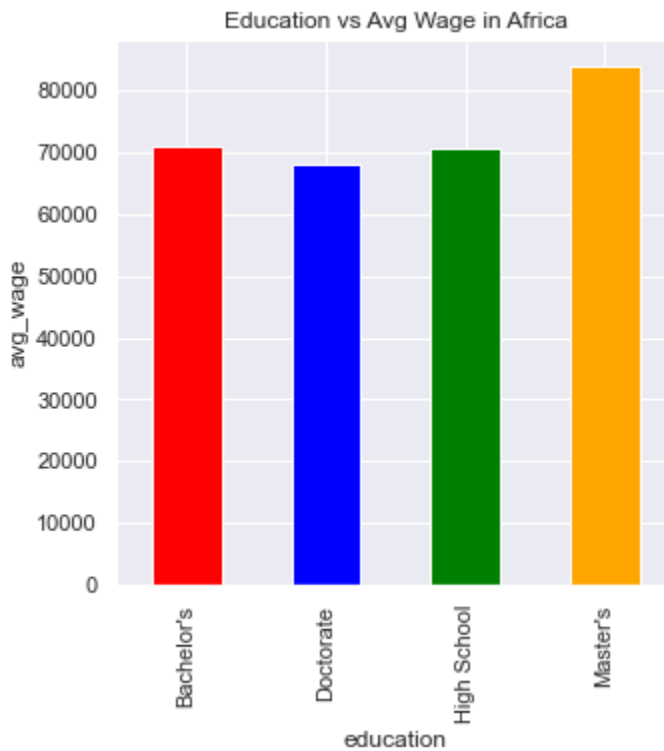
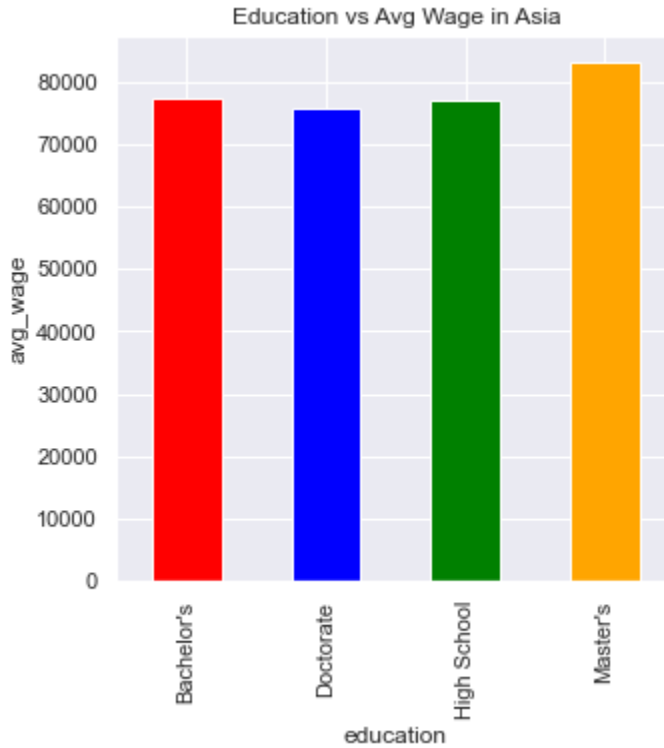


Observation

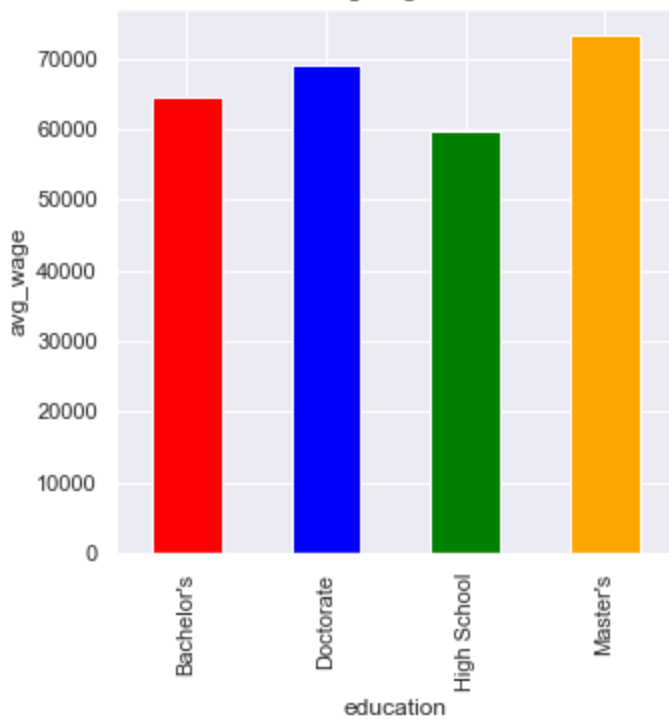
- Asia has highest average wage followed by africa

```
In [67]: #education wise mean salary in each continents
visa_copy=visa.copy()
for continents in visa_copy['continent'].unique():
```

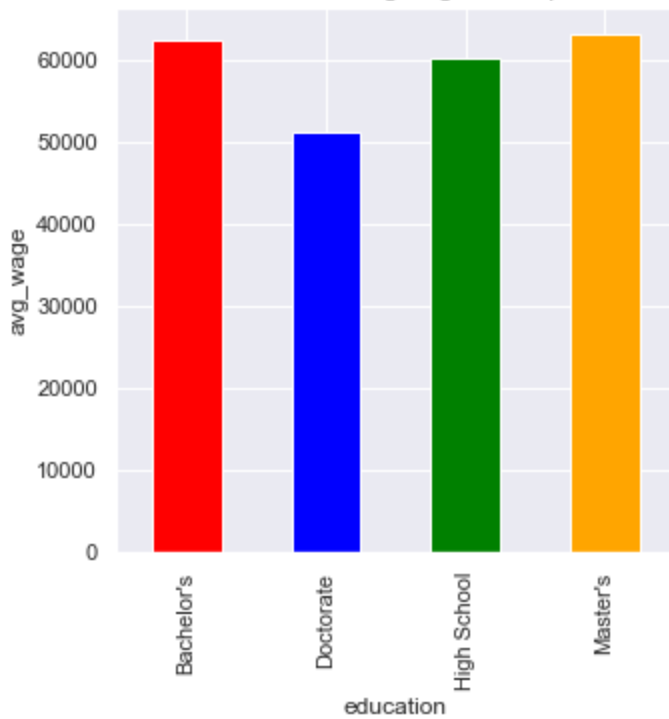
```
visa_copy[visa_copy['continent']=='continents'].groupby(by='education_of_employee')['p  
plt.xlabel('education')  
plt.ylabel('avg_wage')  
plt.title('Education vs Avg Wage in {}'.format(continents))  
plt.show()
```

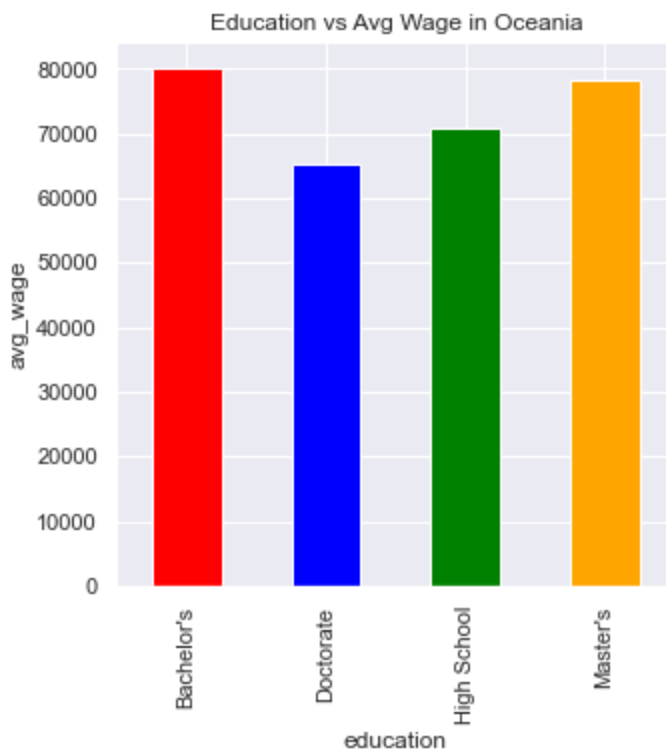
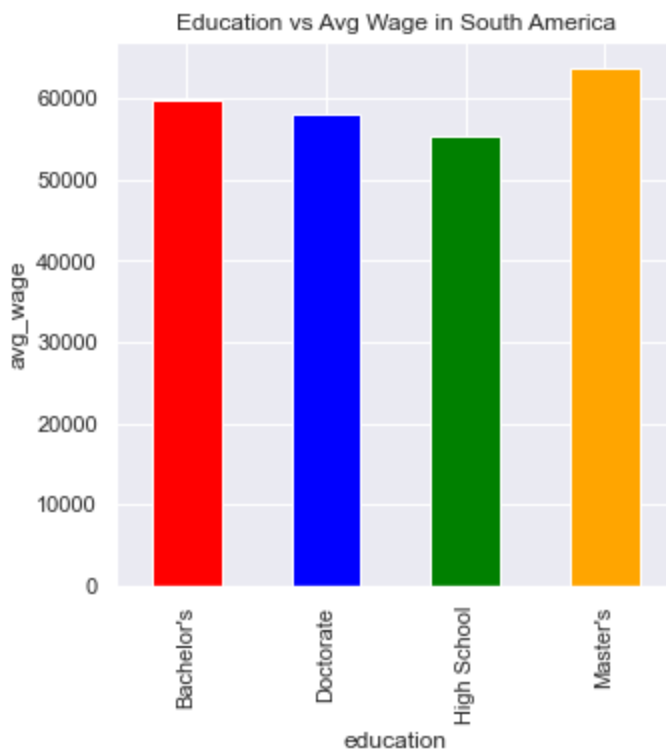


Education vs Avg Wage in North America

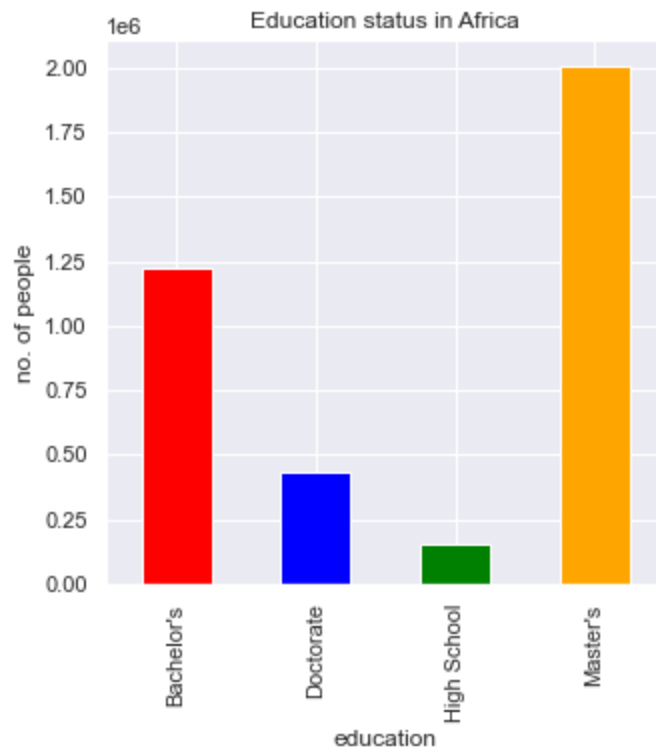
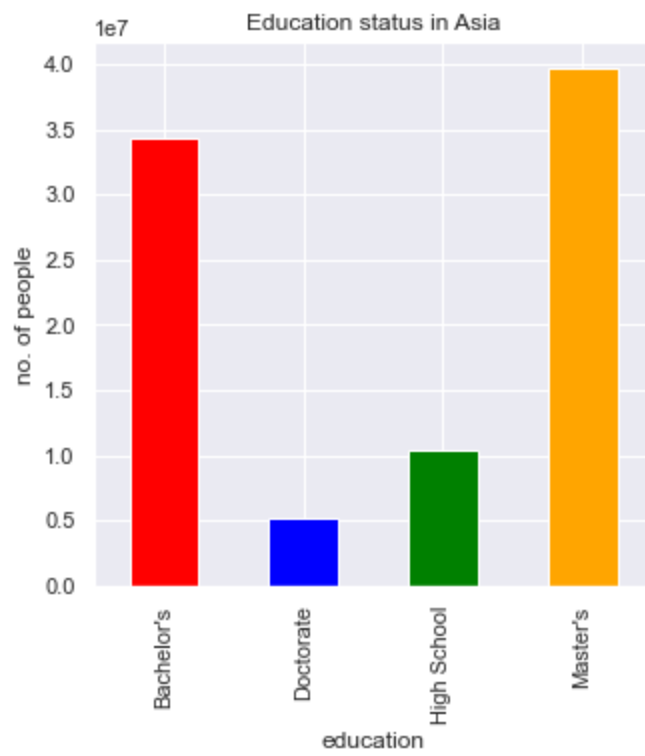


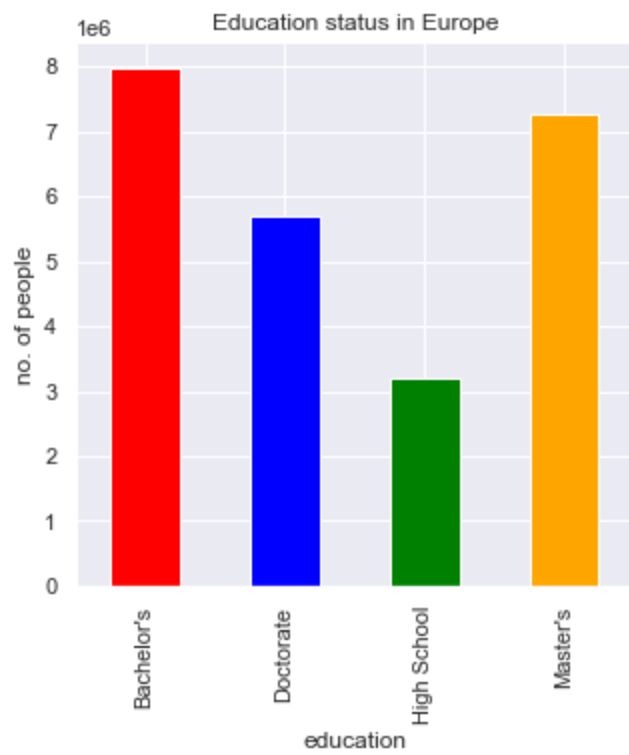
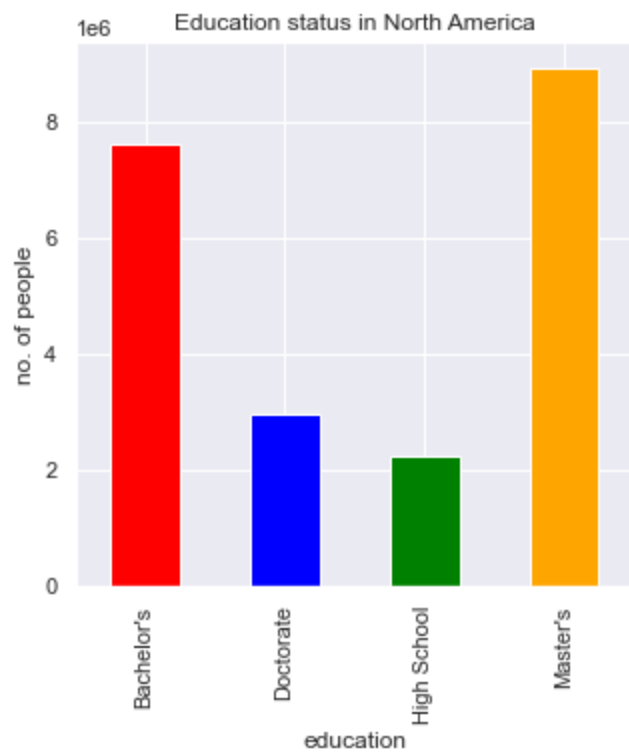
Education vs Avg Wage in Europe

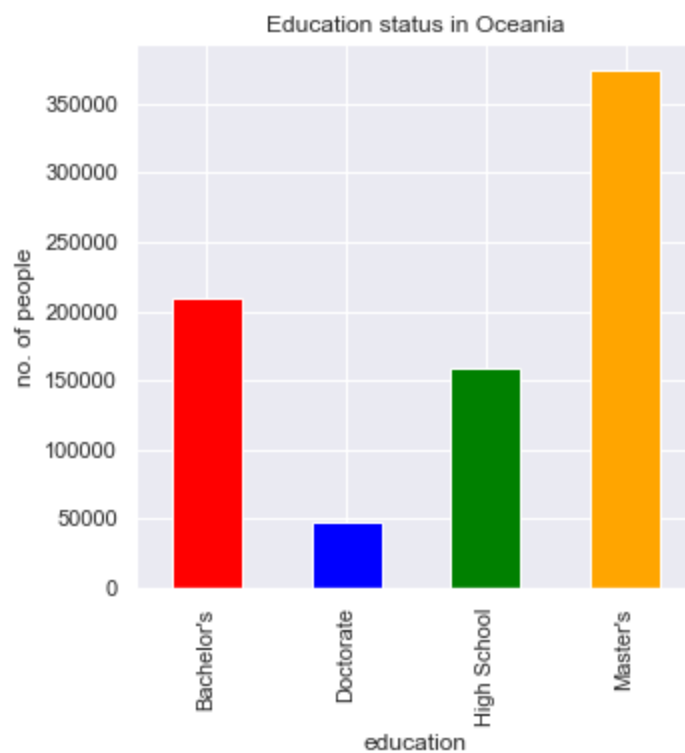
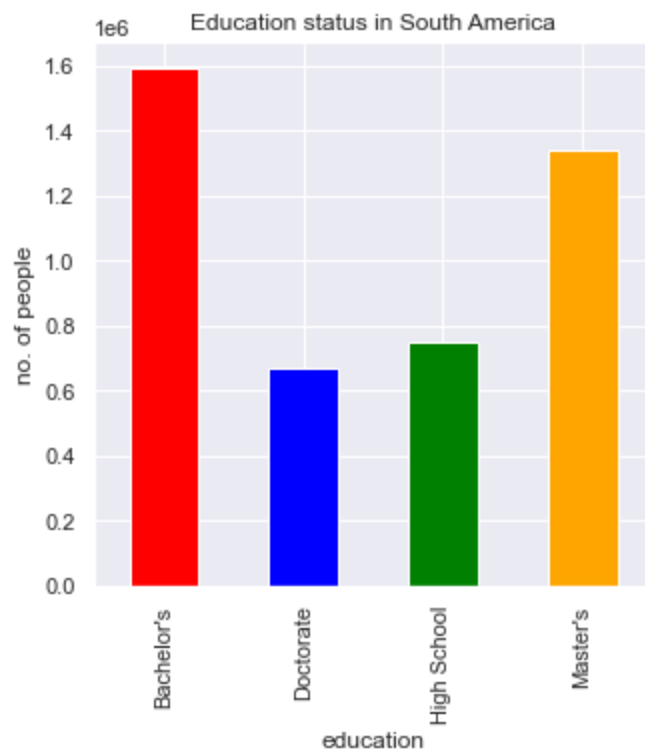




```
In [79]: #Continent wise education of people
visa_copy=visa.copy()
for continents in visa_copy['continent'].unique():
    visa_copy[visa_copy['continent']==continents].groupby(by='education_of_employee').su
    plt.xlabel('education')
    plt.ylabel('no. of people')
    plt.title('Education status in {}'.format(continents))
    plt.show()
```





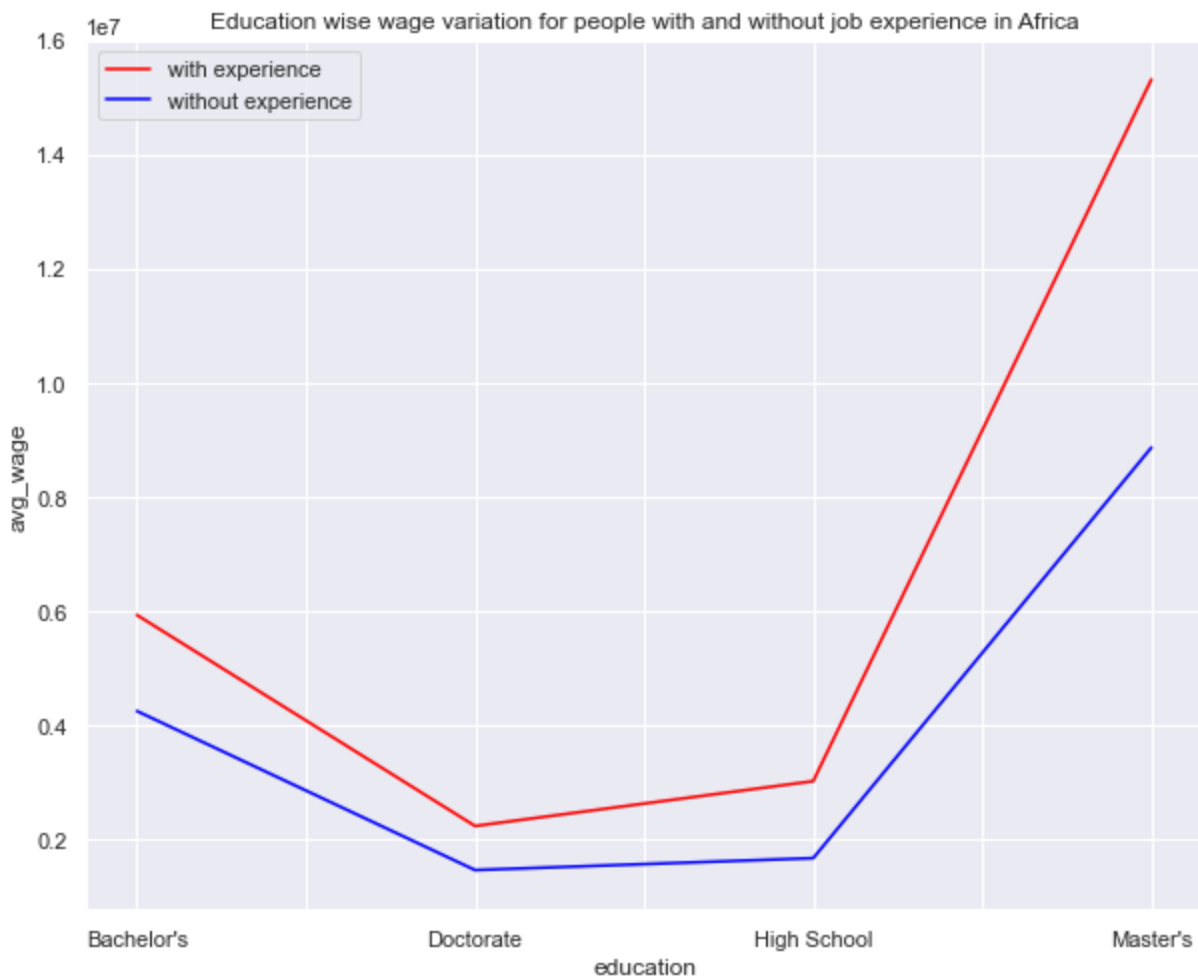
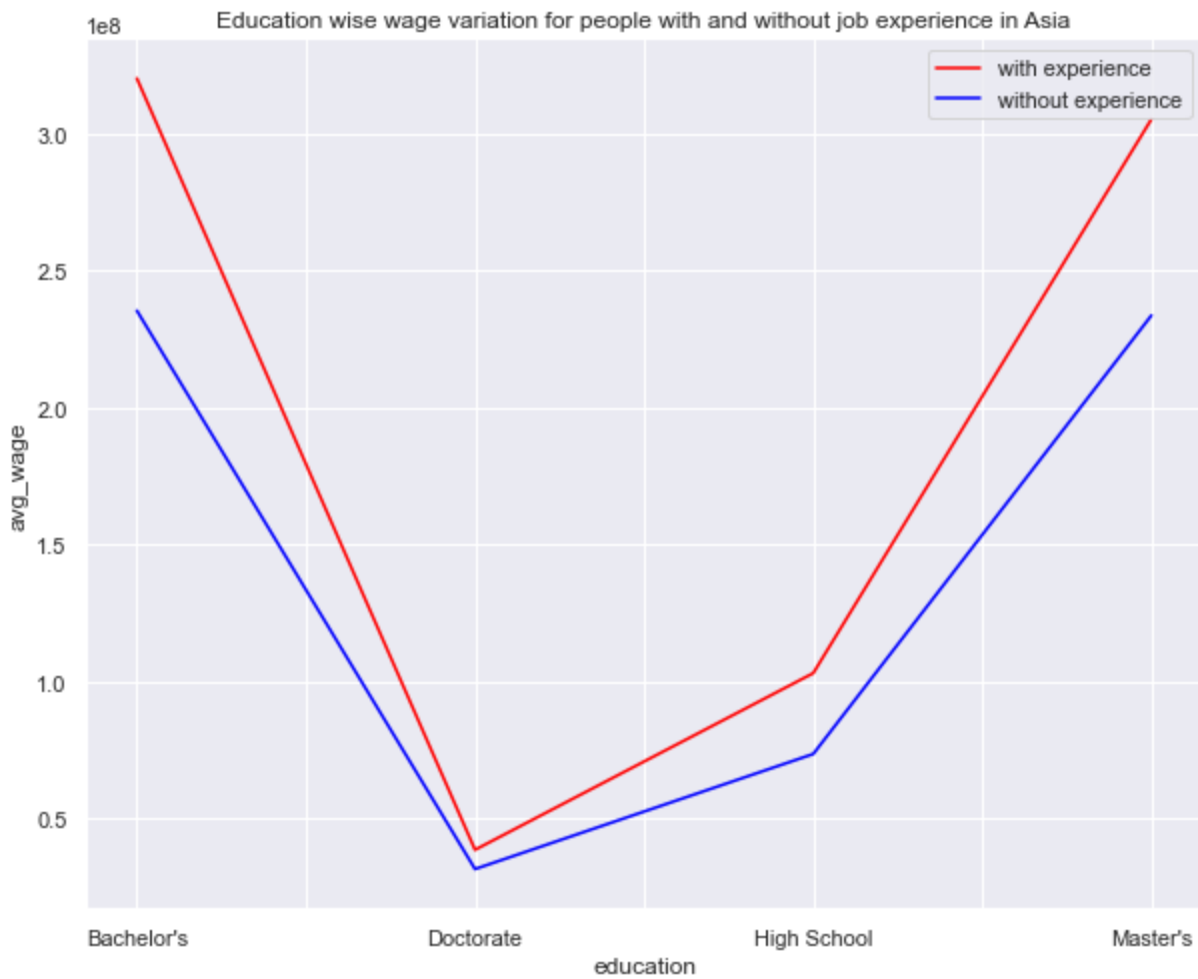


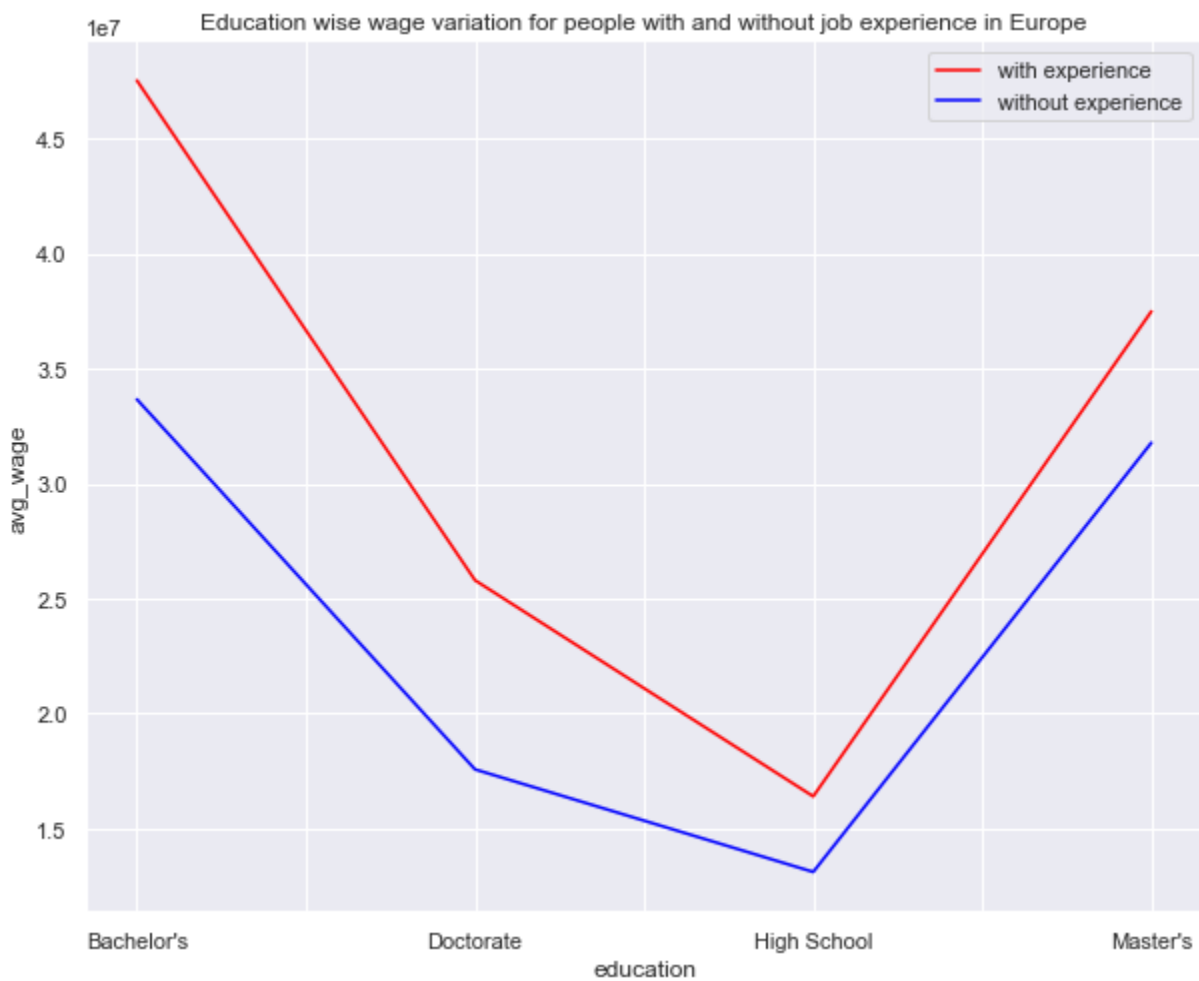
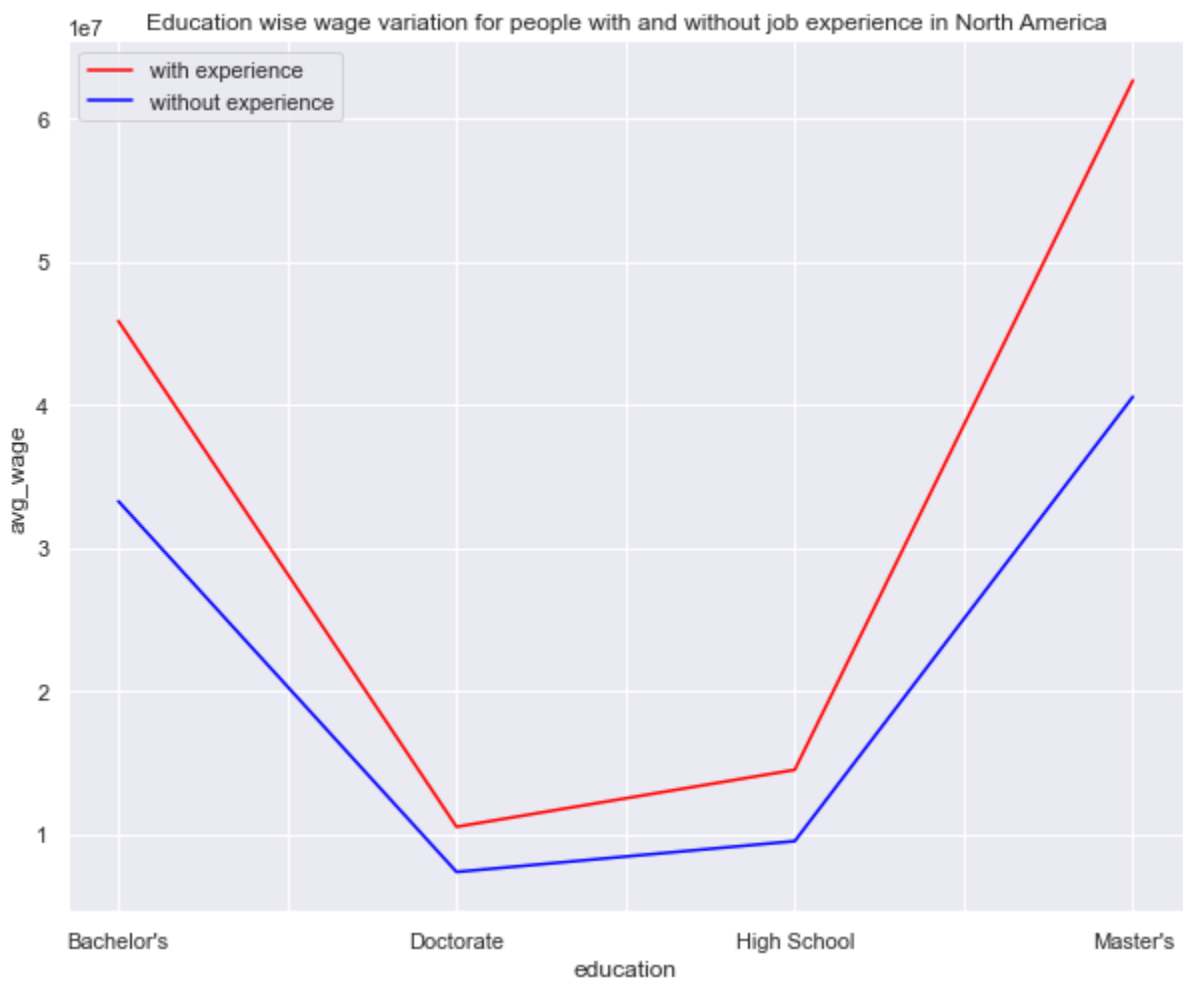
Observation

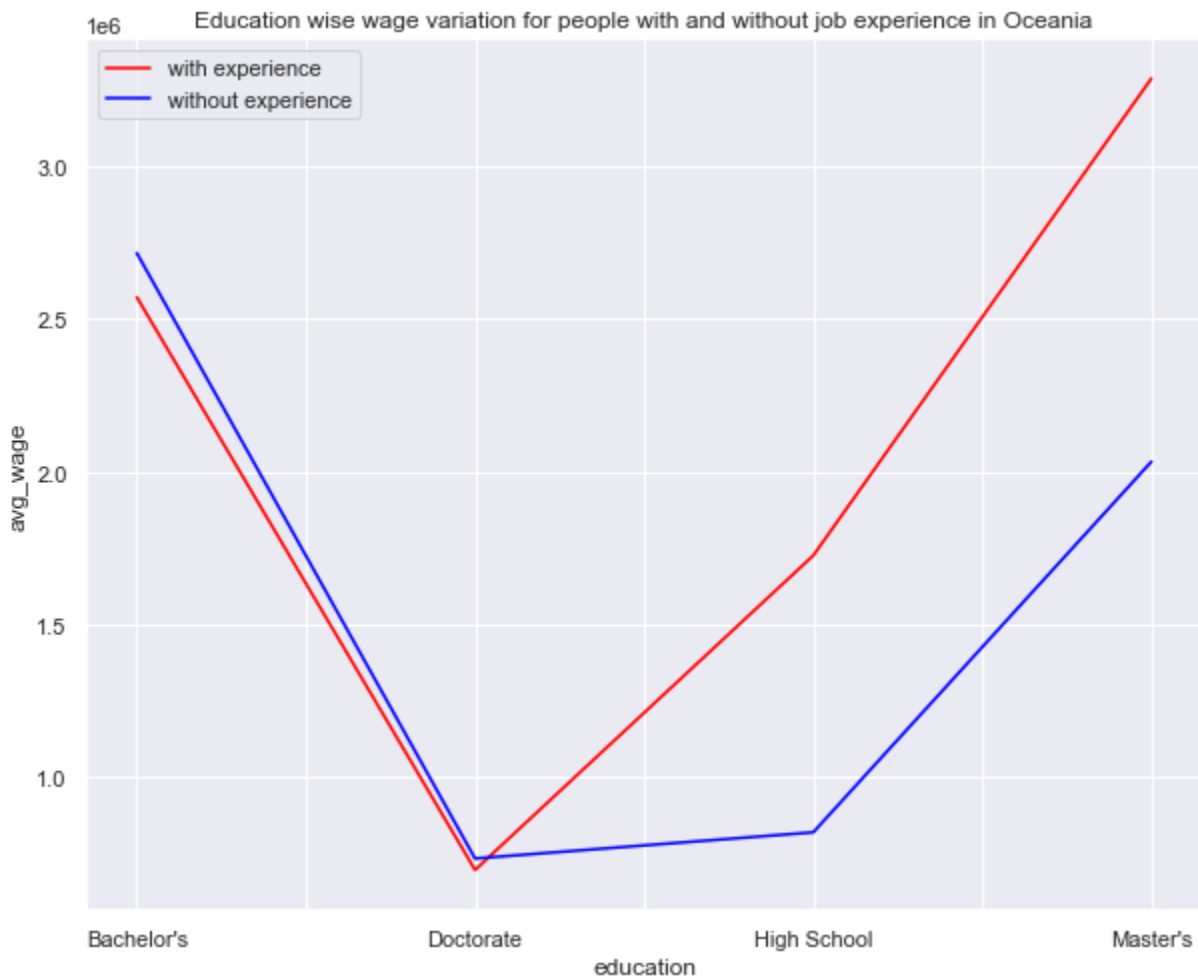
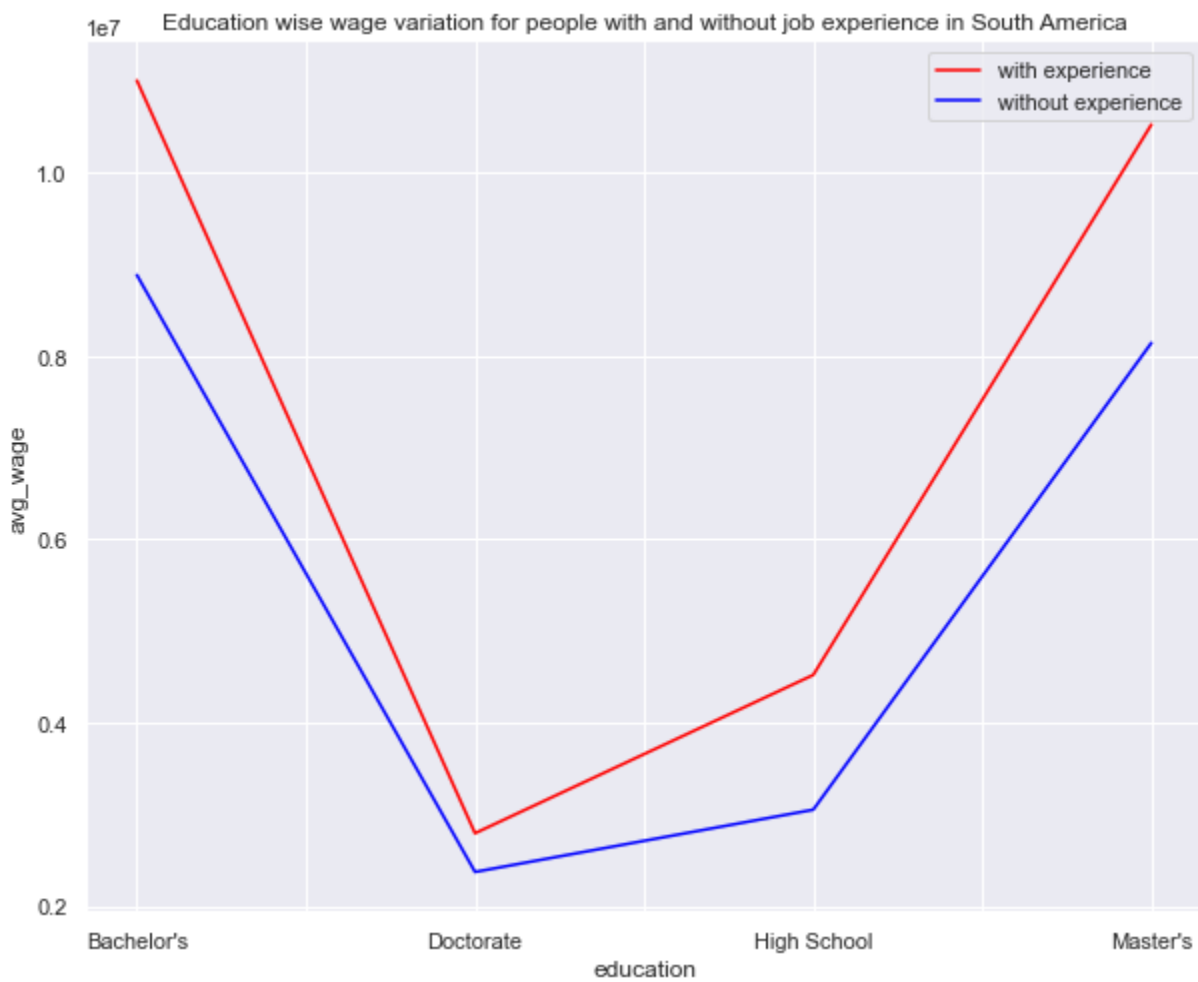
- It seems Masters' is the most popular education across all continents in terms of salary

```
In [110]: #Continent wise job experience vs Salary
#People having job experience
visa_copy=visa.copy()
for continents in visa_copy['continent'].unique():
    plt.figure(figsize=(10,8))
    visa_copy.loc[np.where((visa_copy['continent']==continents) & (visa_copy['has_job_ex
    visa_copy.loc[np.where((visa_copy['continent']==continents) & (visa_copy['has_job_ex
    plt.legend()
    plt.xlabel('education')
    plt.ylabel('avg_wage')
```

```
plt.title('Education wise wage variation for people with and without job experience')
plt.show()
```



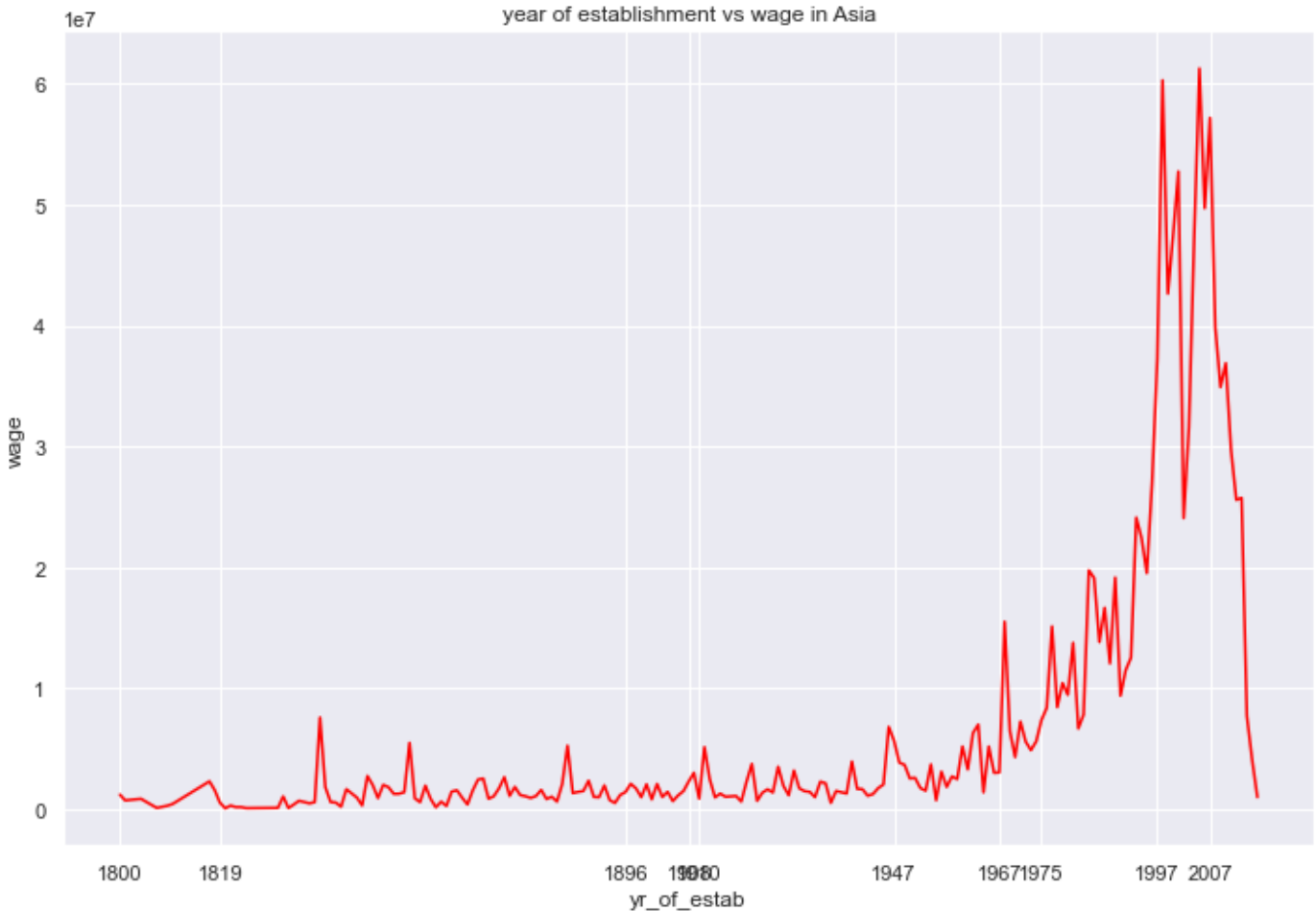


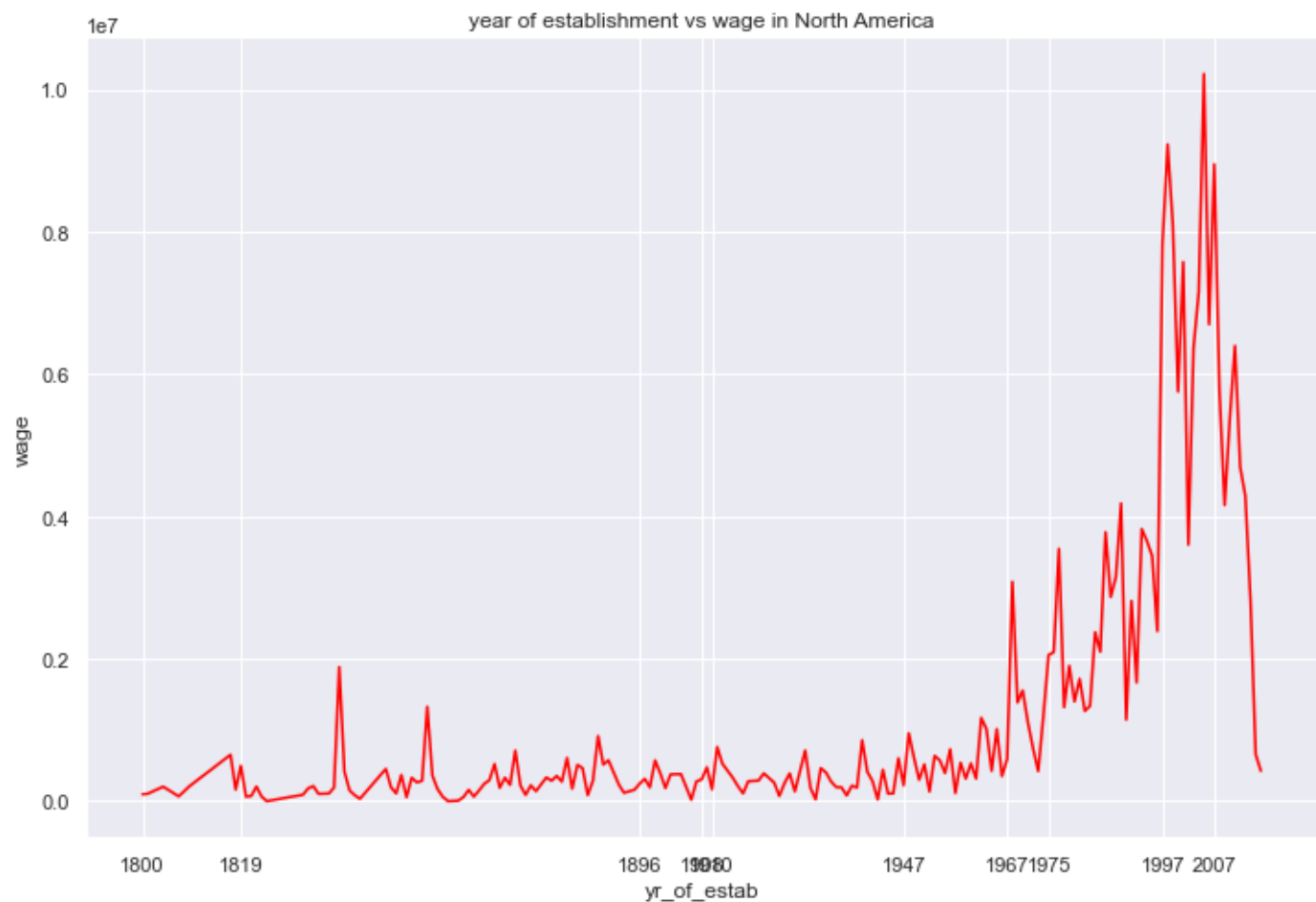
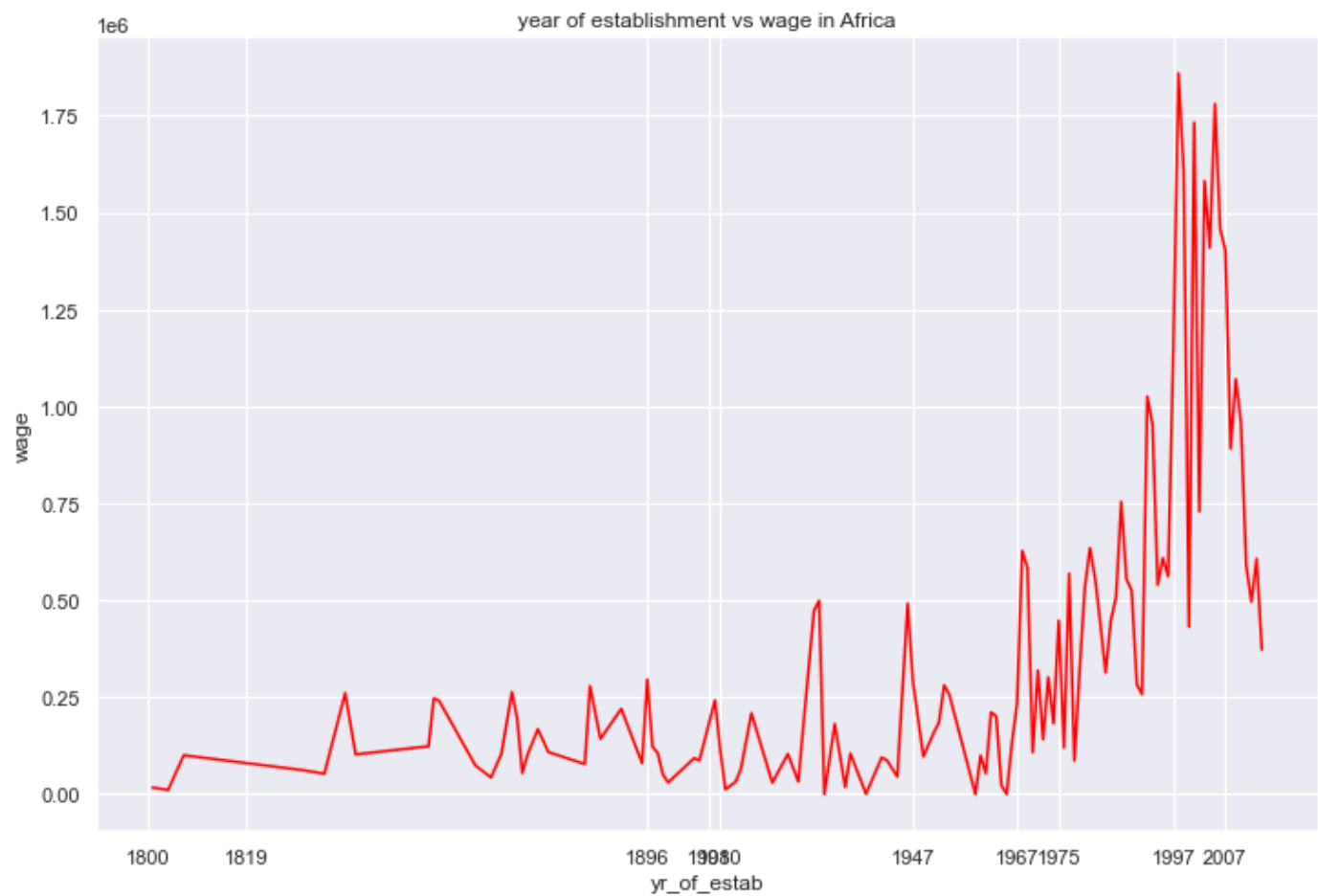


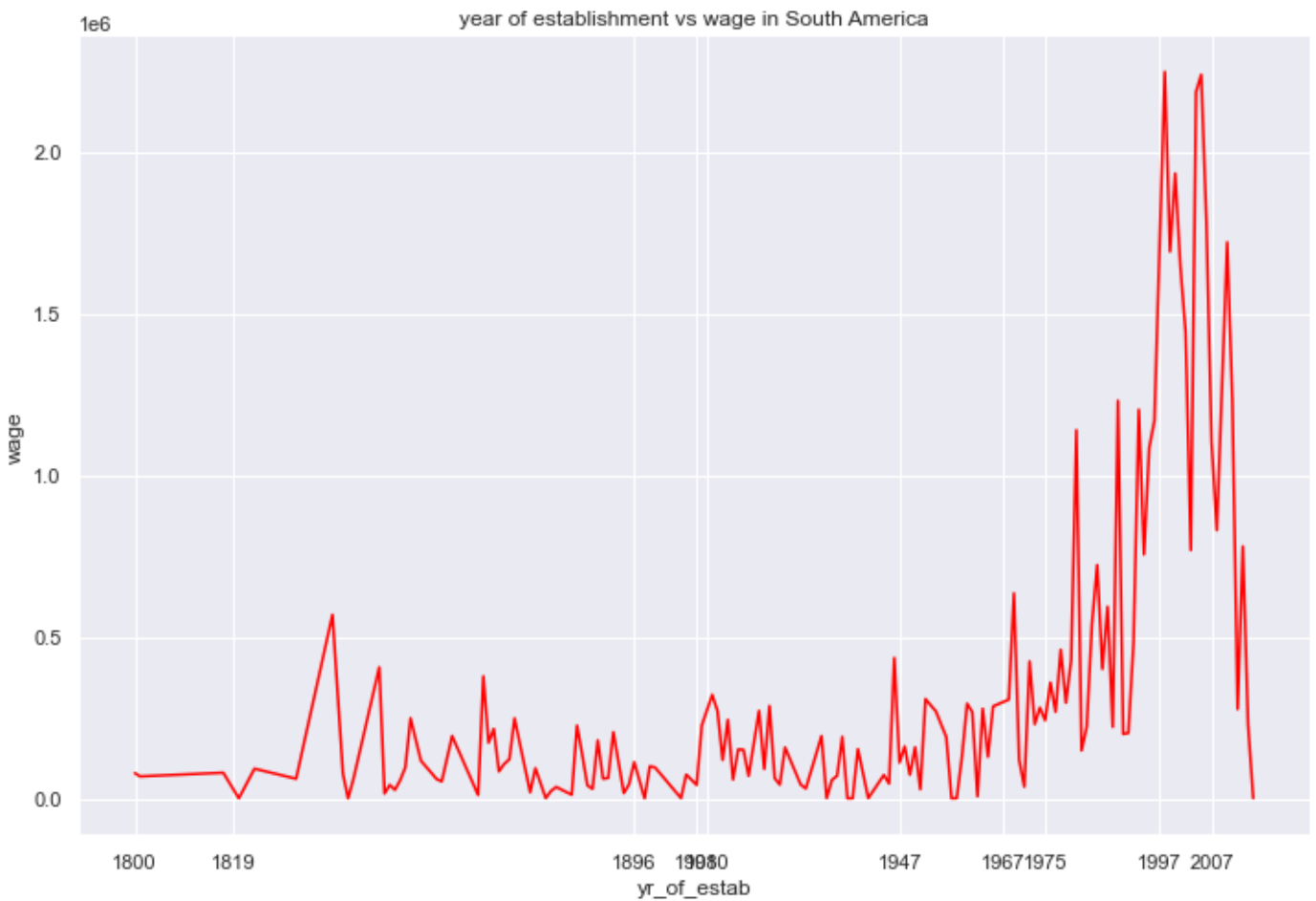
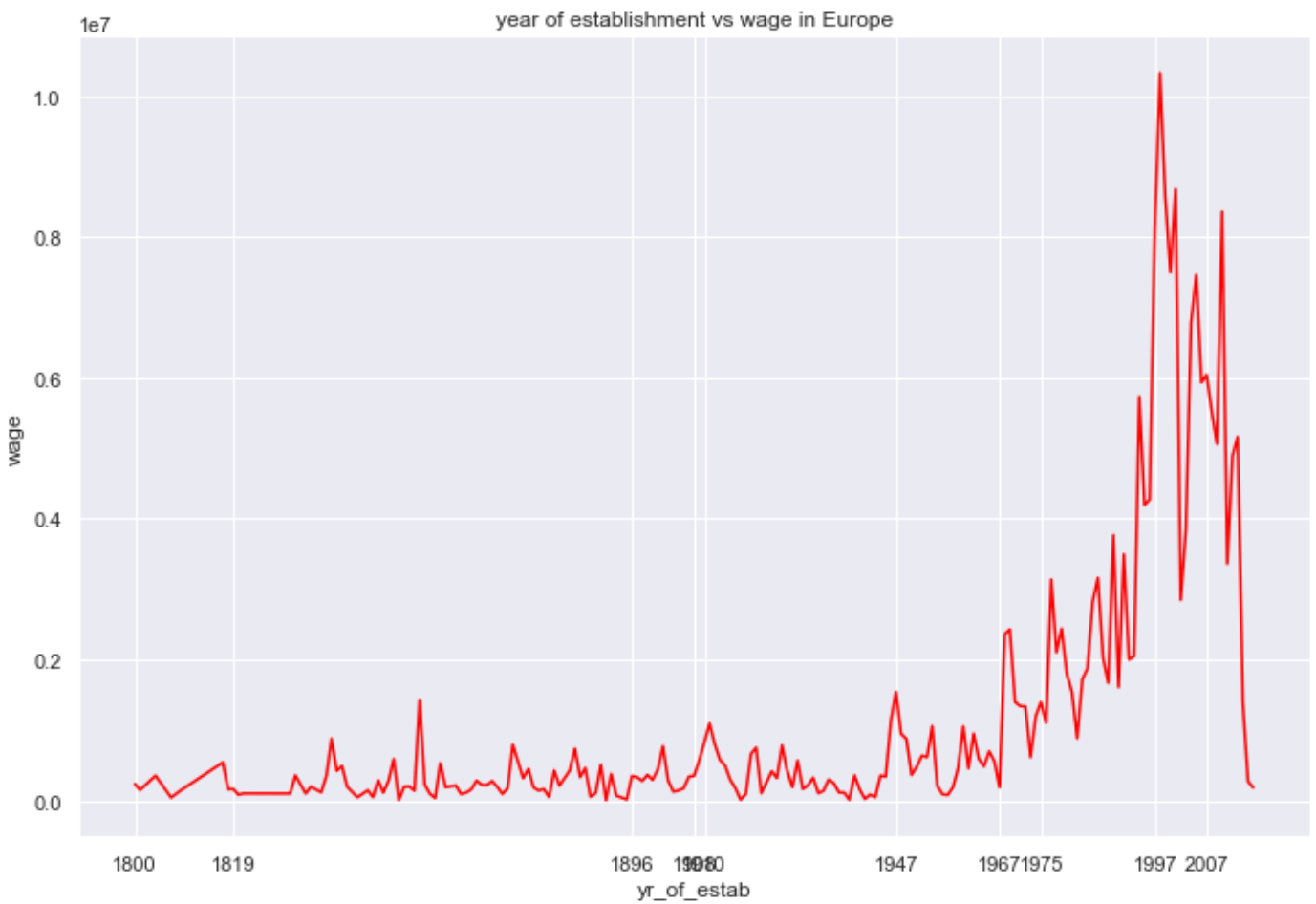
Observation

- from the above graphical analysis it is evident that people having job experience get more wage than those who don't.

```
In [122... #year of establishment vs wage continent wise
visa_copy=visa.copy()
for continents in visa_copy['continent'].unique():
    visa_copy[visa_copy['continent']==continents].groupby(by='yr_of_estab').sum()['preva
plt.xticks(visa_copy['yr_of_estab'].unique()[::20])
plt.xlabel('yr_of_estab')
plt.ylabel('wage')
plt.title('year of establishment vs wage in {}'.format(continents))
plt.show()
```





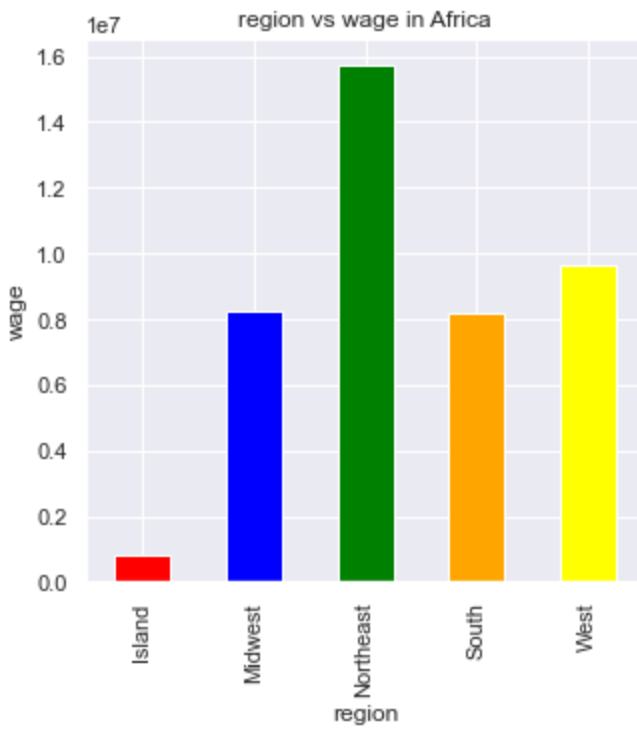
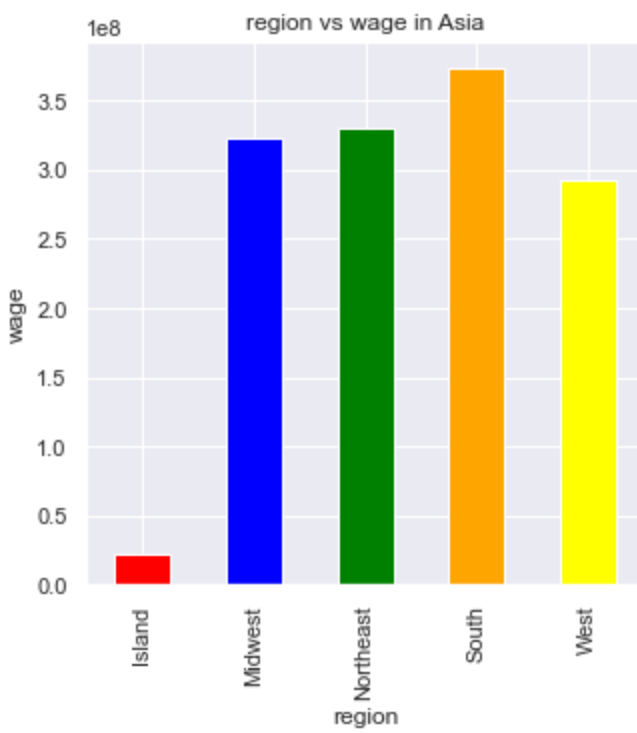


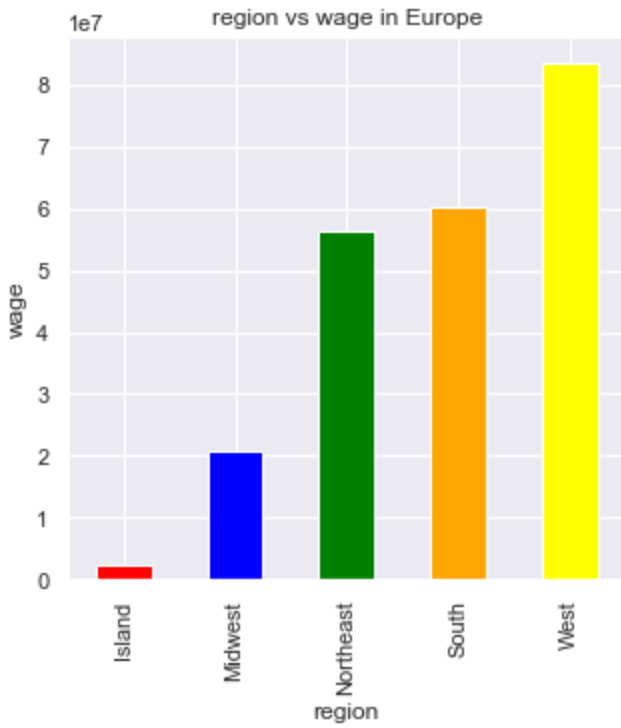
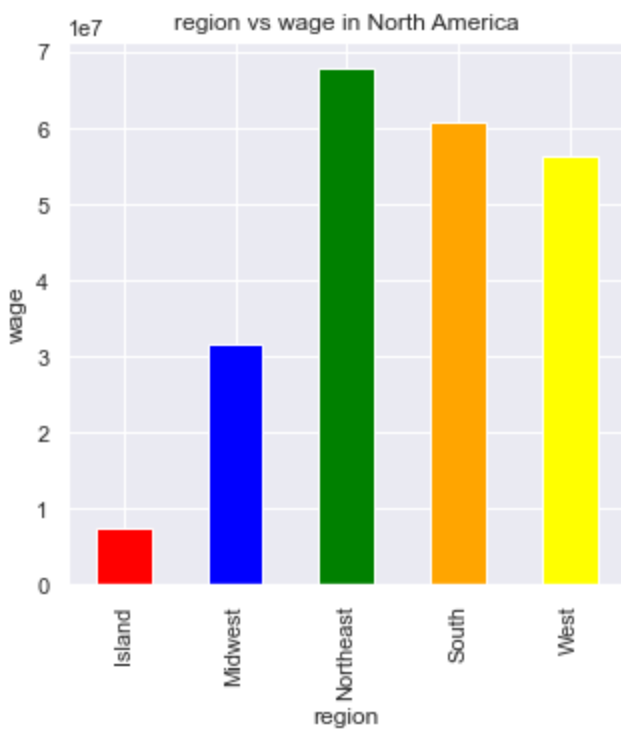


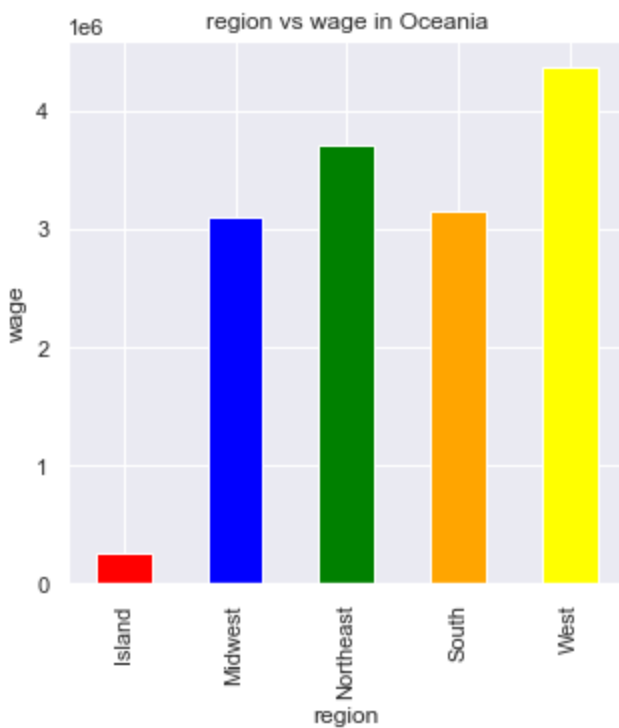
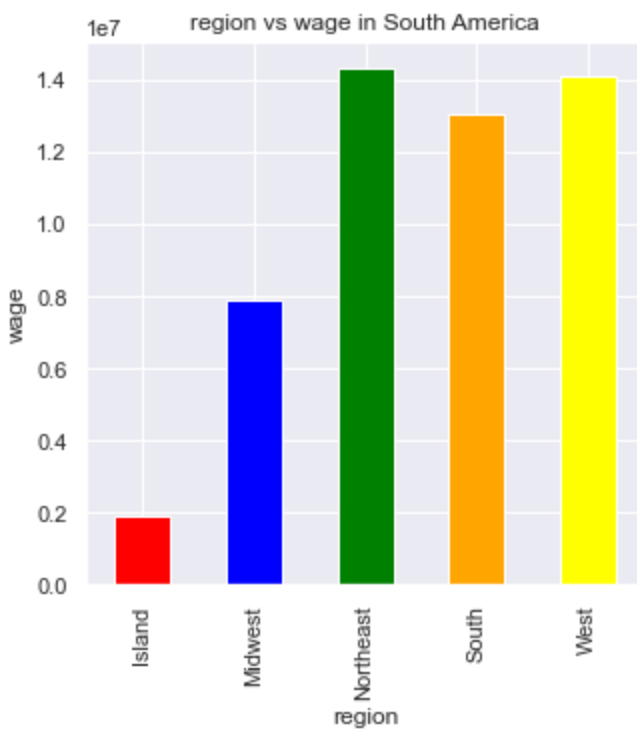
Observation

- From the above graphical analysis it is evident that wage was highest during around 2007 and then there is a decline

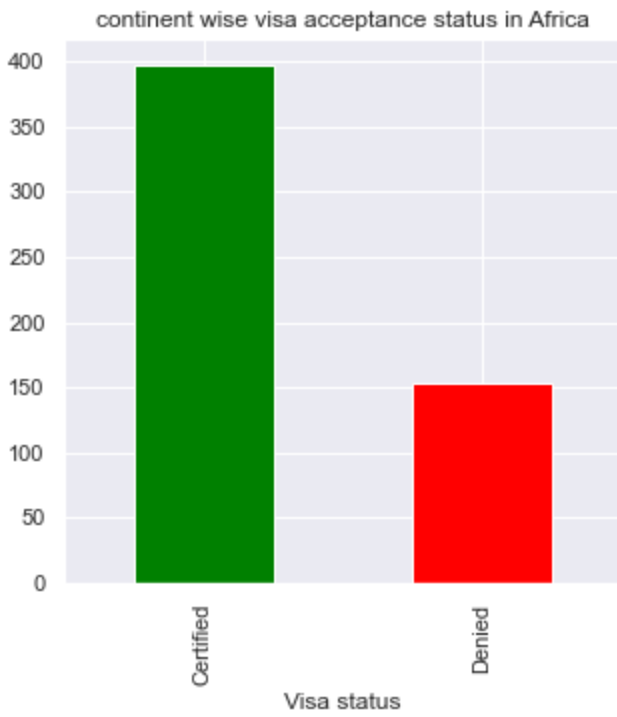
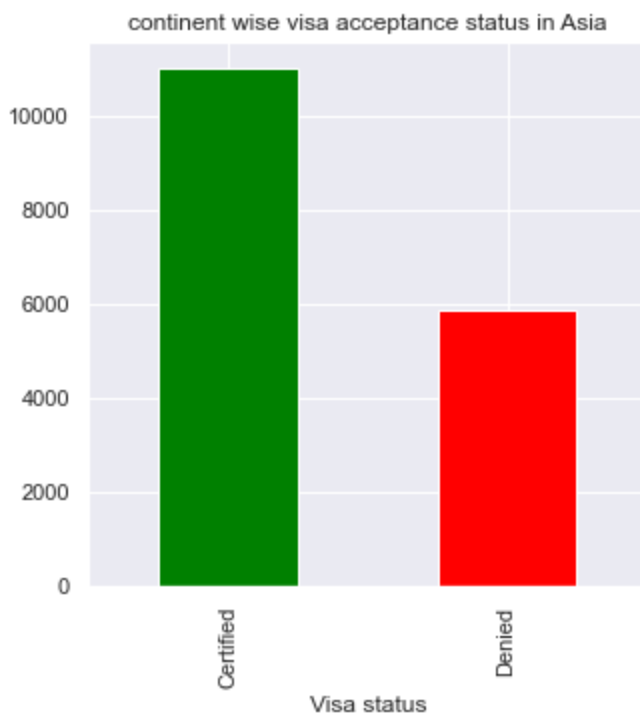
```
In [125... #region wise salary variation in each continents
visa_copy=visa.copy()
for continents in visa_copy['continent'].unique():
    visa_copy[visa_copy['continent']==continents].groupby(by='region_of_employment').sum
    plt.xlabel('region')
    plt.ylabel('wage')
    plt.title('region vs wage in {}'.format(continents))
    plt.show()
```



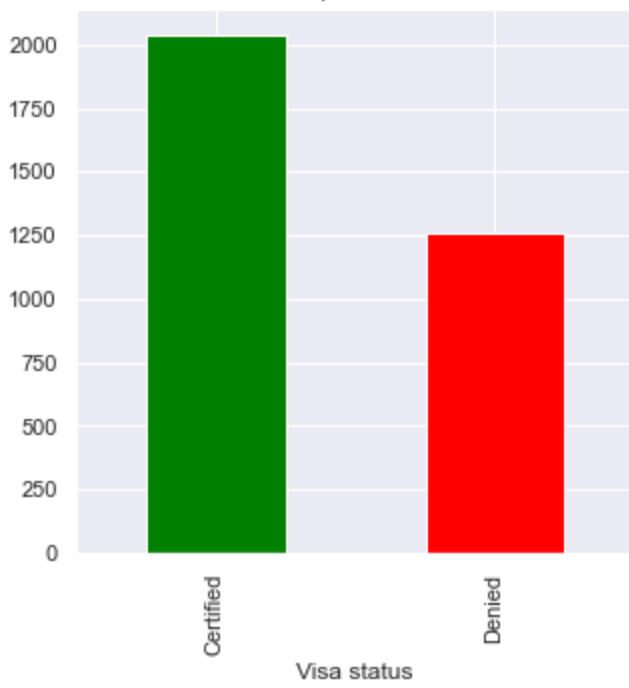




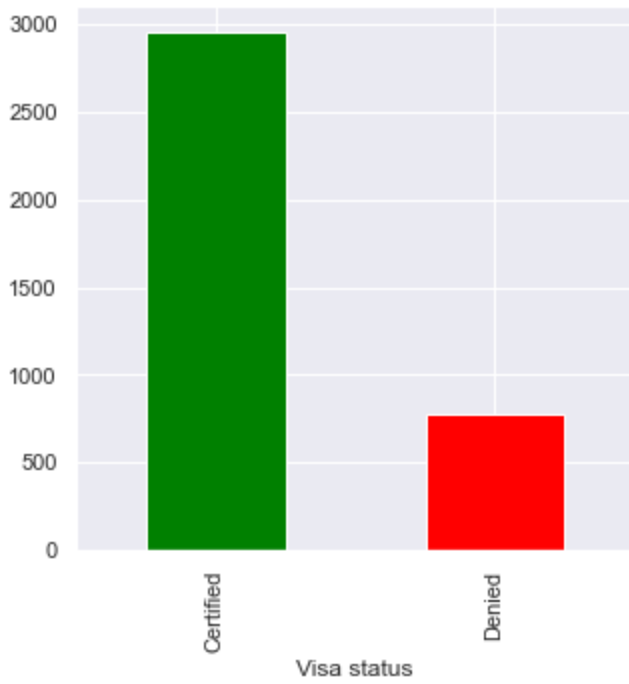
```
In [131... #continent wise visa acceptance status
visa_copy=visa.copy()
for continents in visa_copy['continent'].unique():
    visa_copy[visa_copy['continent']==continents].value_counts('case_status').plot.bar(c
plt.xlabel('Visa status')
plt.title('continent wise visa acceptance status in {}'.format(continents))
plt.show()
```

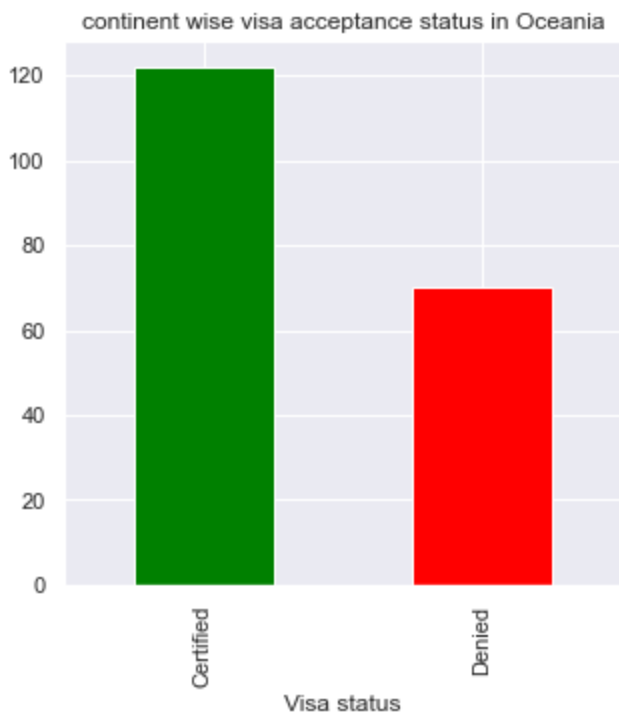
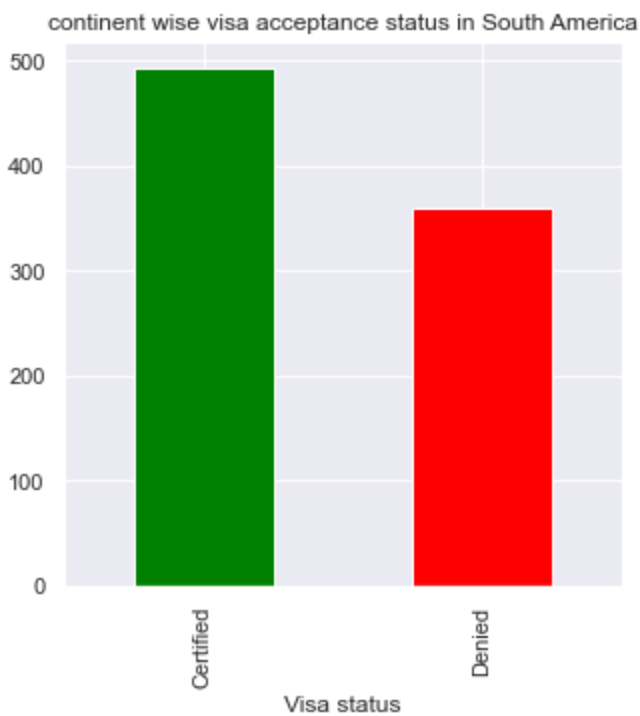


continent wise visa acceptance status in North America



continent wise visa acceptance status in Europe





Observation

- Europe has highest acceptance rate
- South America has lowest acceptance rate

```
In [173... #encoding the 'case_status' and 'has_job_experience' features for better analysis
visa_copy['case_status_new']=visa_copy['case_status'].apply(lambda x: 0 if x=='Denied' e
visa_copy['has_job_experience_new']=visa_copy['has_job_experience'].apply(lambda x: 0 if
```

```
In [195... visa_copy.head()
```

Out[195]:

	case_id	continent	education_of_employee	has_job_experience	requires_job_training	no_of_employees	yr
0	EZYV01	Asia	High School	N	N	14513	
1	EZYV02	Asia	Master's	Y	N	2412	
2	EZYV03	Asia	Bachelor's	N	Y	44444	
3	EZYV04	Asia	Bachelor's	N	N	98	
4	EZYV05	Africa	Master's	Y	N	1082	

In [207...

```
#grouping the data by continents, education and job experience to analyse visa acceptance
visa_acceptance=visa_copy.groupby(by=['continent','education_of_employee']).sum()
visa_acceptance.head()
```

Out[207]:

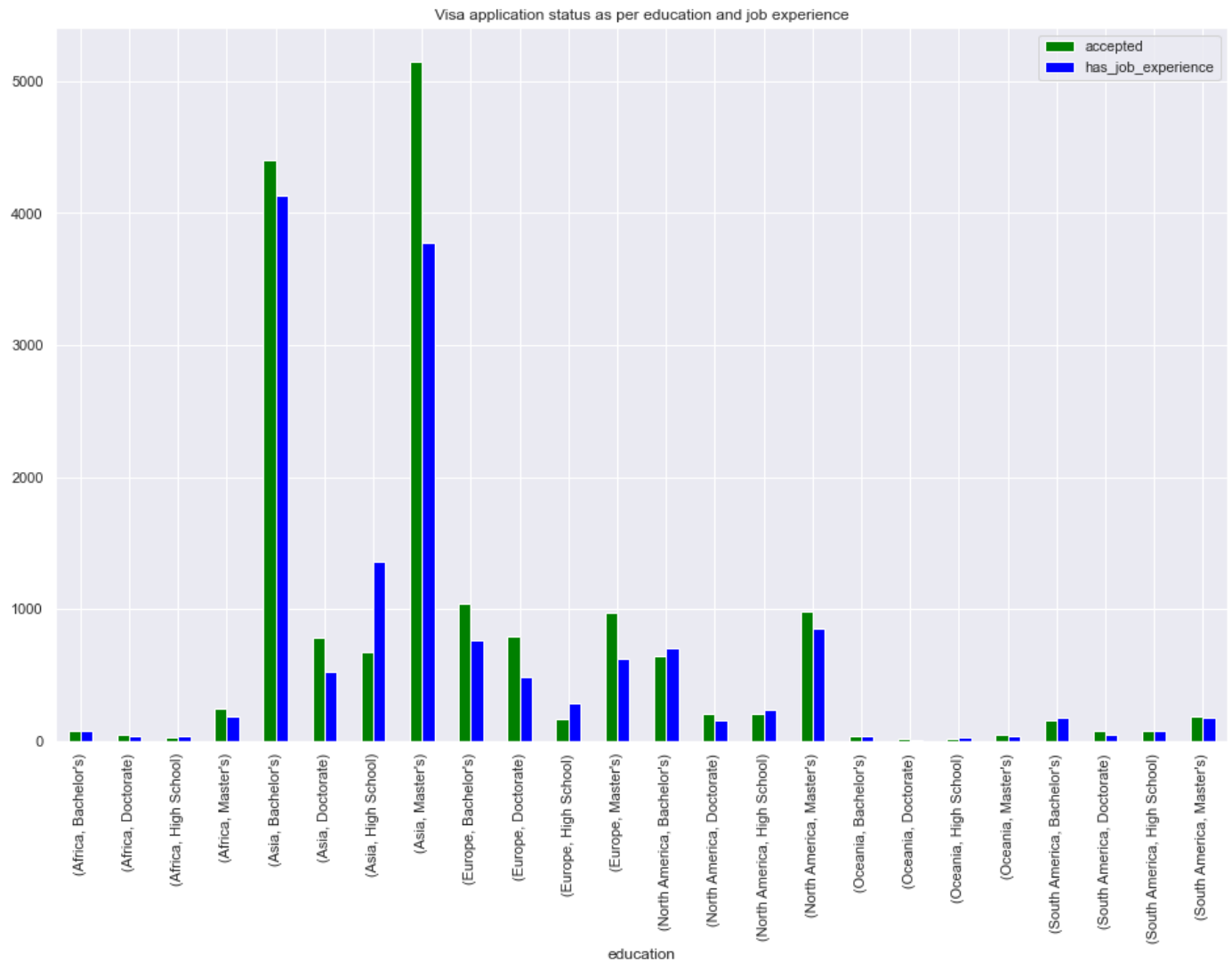
		no_of_employees	yr_of_estab	prevailing_wage	case_status_new	has_job_experience
continent		education_of_employee				
Africa	Bachelor's	1219325	282763	1.015771e+07	81	
	Doctorate	436448	106362	3.668420e+06	43	
	High School	151351	130356	4.664011e+06	23	
	Master's	2004767	570045	2.417154e+07	250	
Asia	Bachelor's	34272894	14198534	5.556157e+08	4407	

In [211...

```
visa_acceptance.rename(columns={'case_status_new':'accepted','has_job_experience_new':'has_job_experience'})
```

In [214...

```
#plotting the visa application status as per education and job experience across continents
visa_acceptance.iloc[:,3:].plot.bar(color=['green', 'blue'],figsize=(16,10))
plt.xlabel('education')
plt.title('Visa application status as per education and job experience')
plt.show()
```

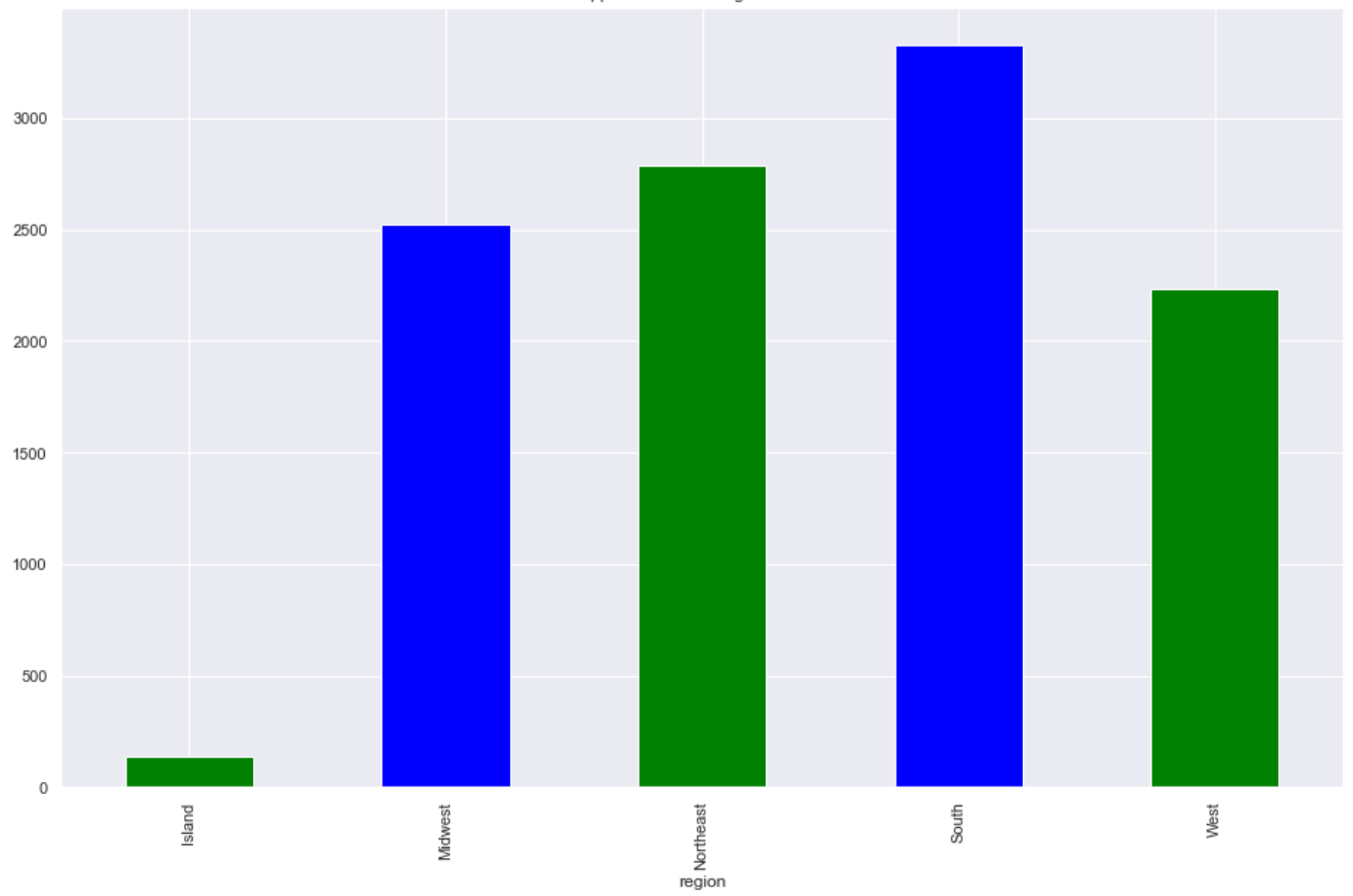


Observation

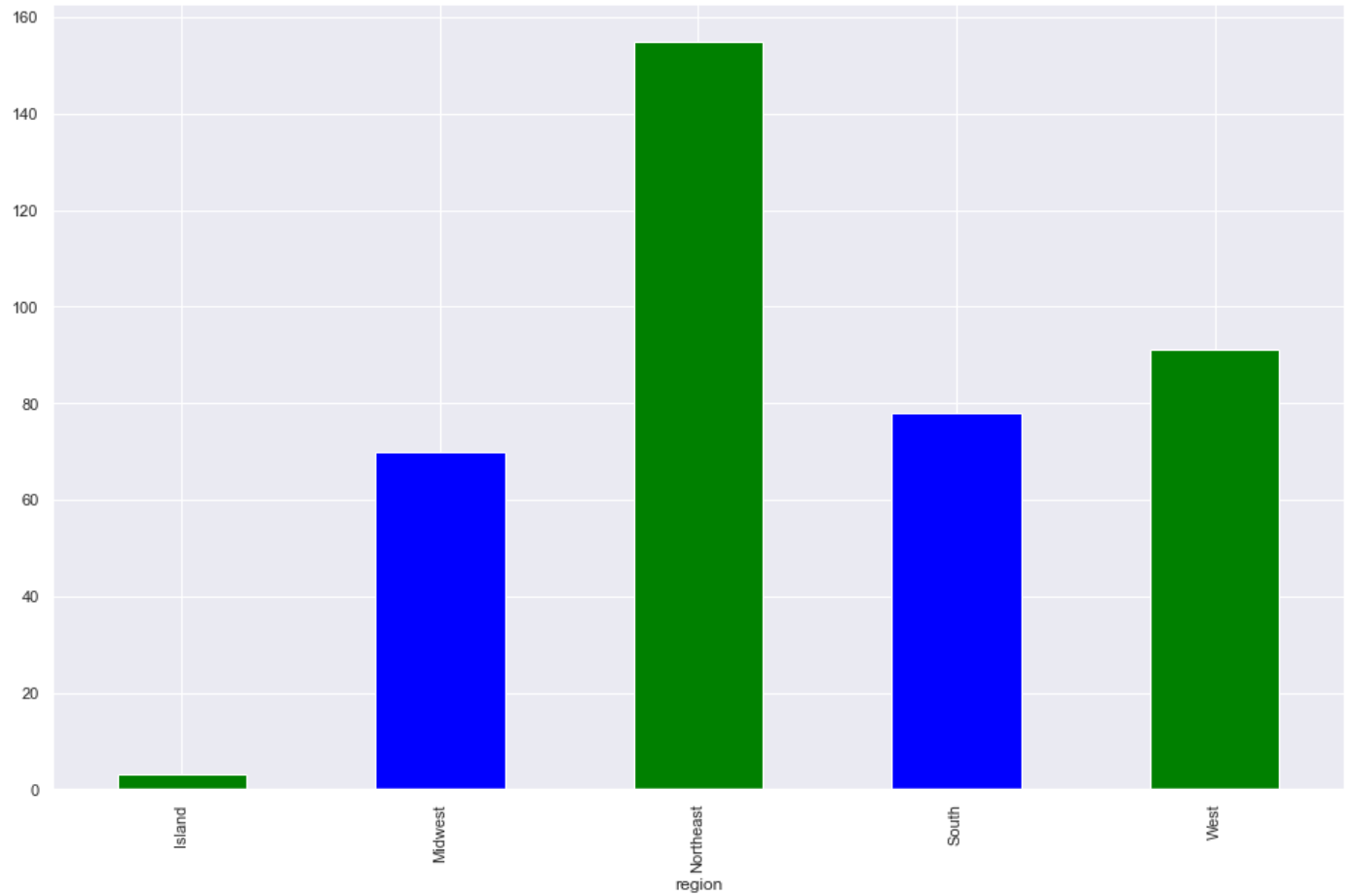
- It is quite evident from the above graphical analysis that people having job experience have upperhand in visa acceptance across all continents

```
In [233... #region wise visa application status
visa_copy=visa.copy()
for continents in visa_copy['continent'].unique():
    visa_copy[visa_copy['continent']==continents].groupby(by='region_of_employment').sum
    plt.xlabel('region')
    plt.title('Visa application status region wise in {}'.format(continents))
    plt.show()
```

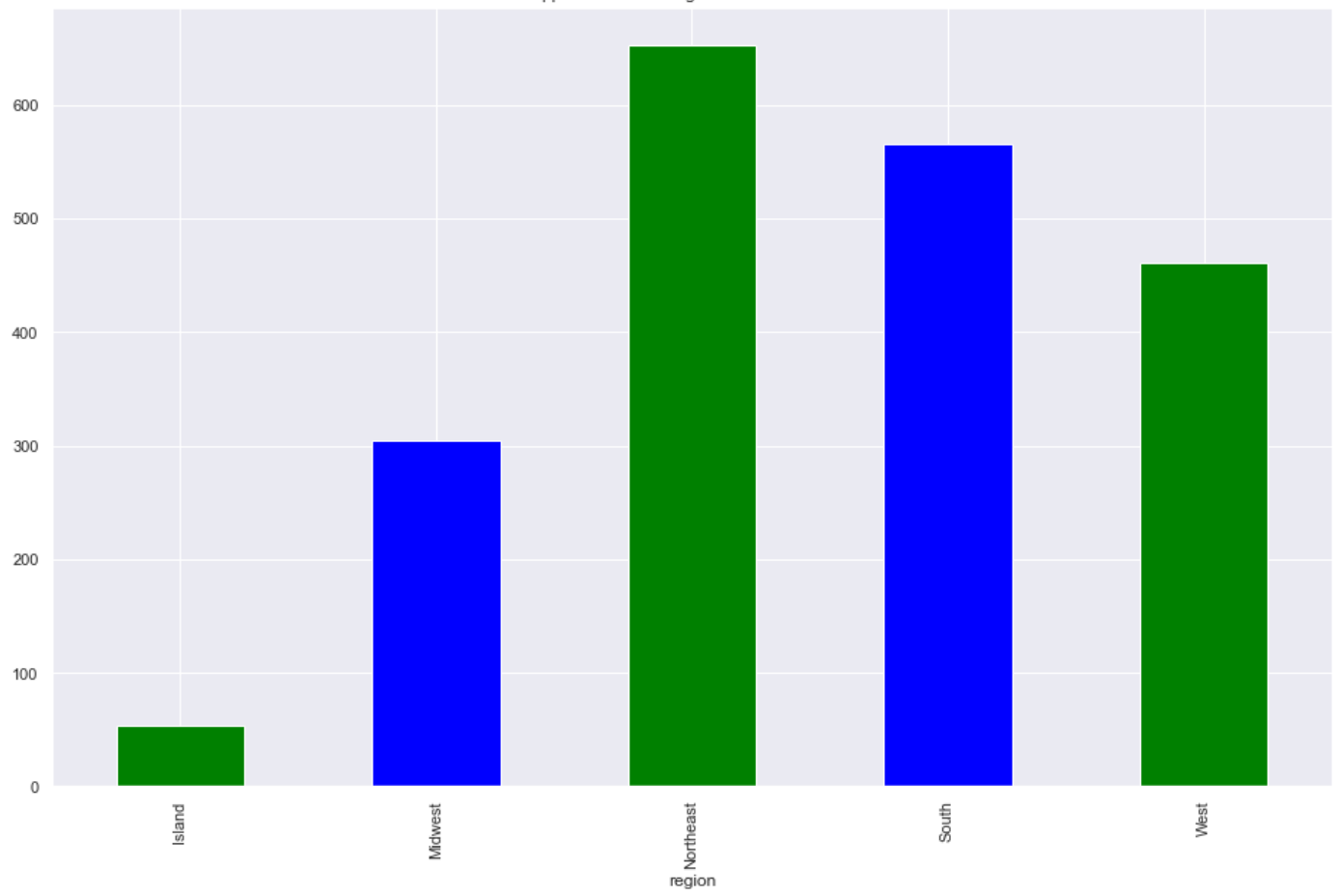
Visa application status region wise in Asia



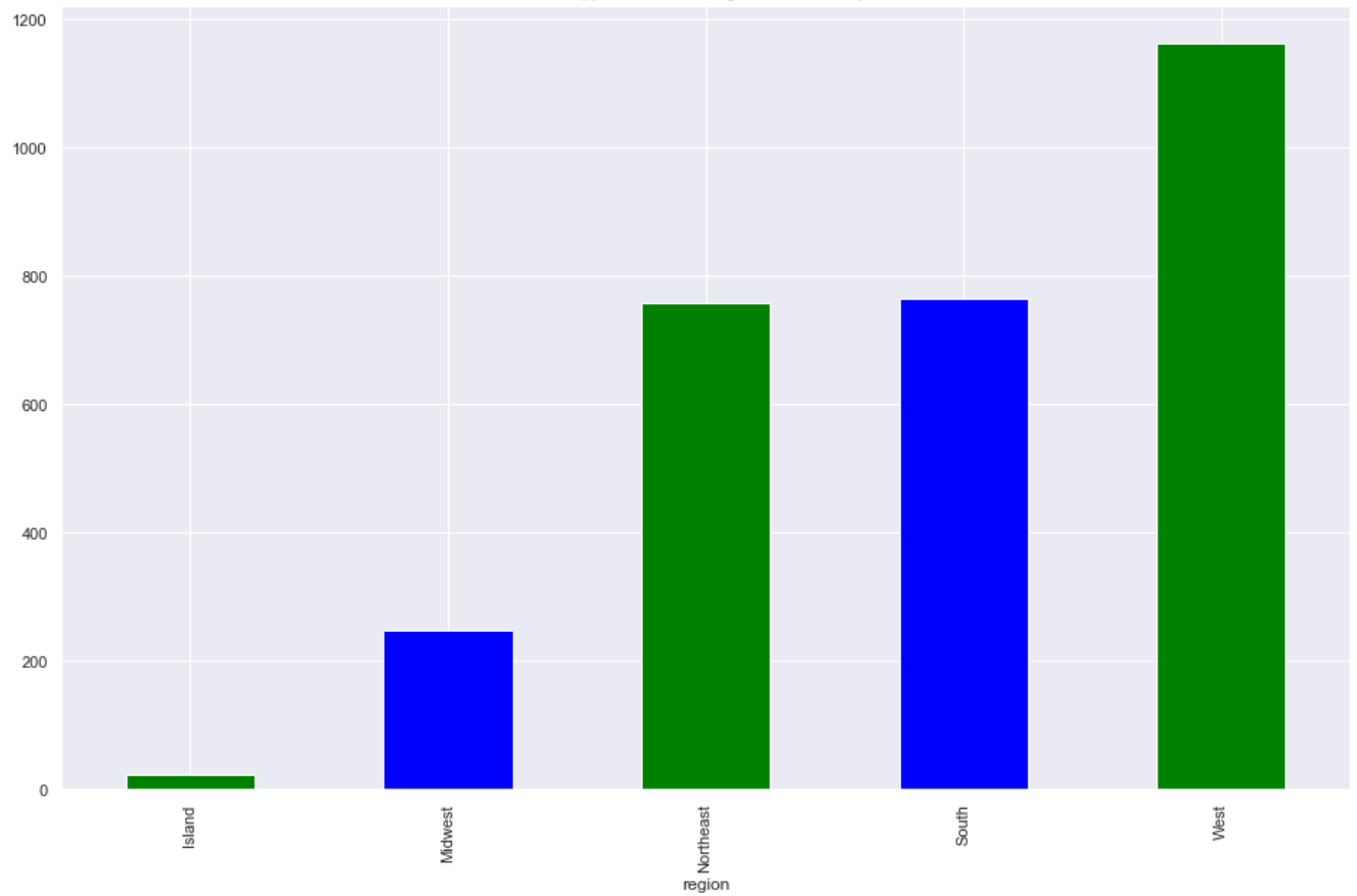
Visa application status region wise in Africa



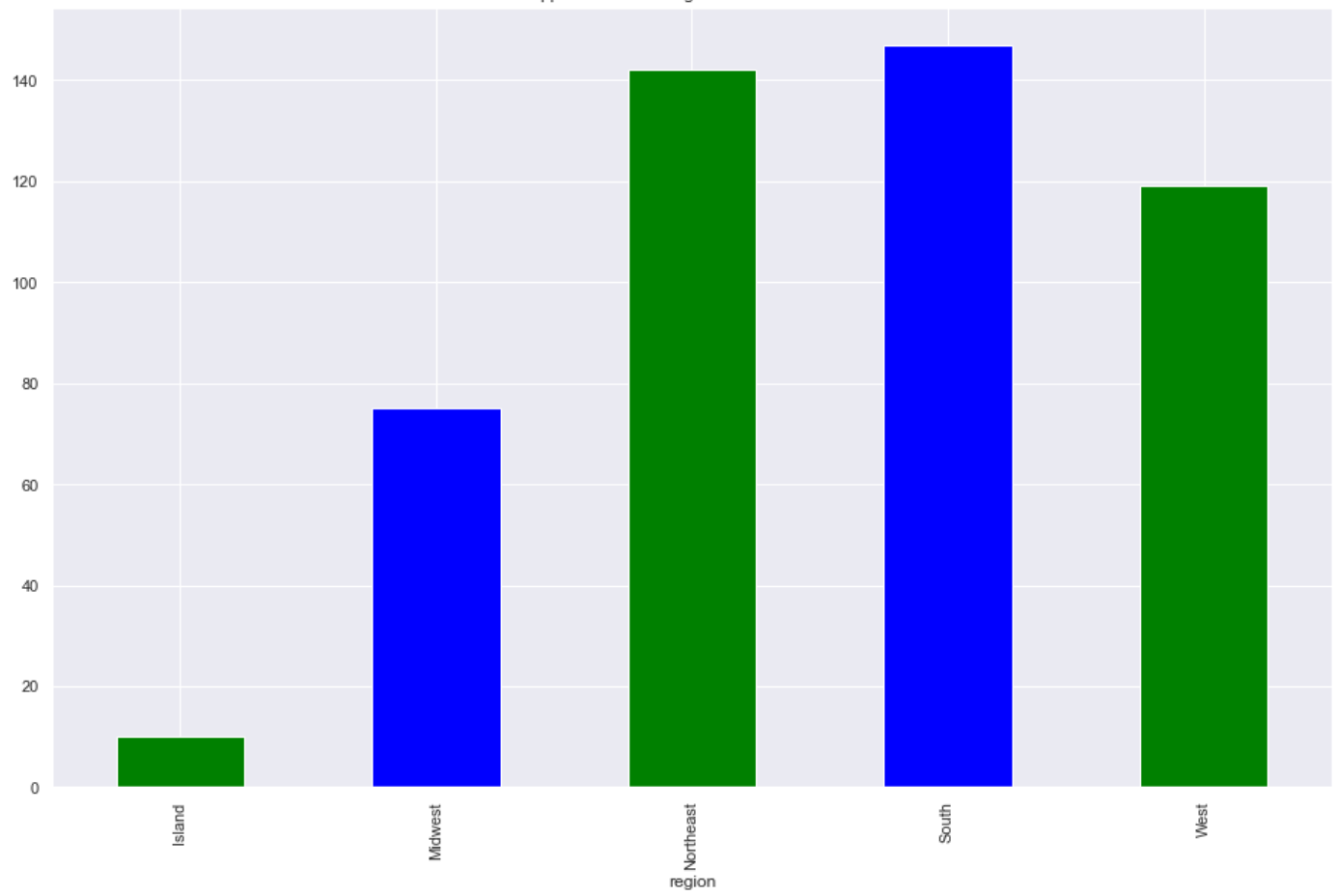
Visa application status region wise in North America



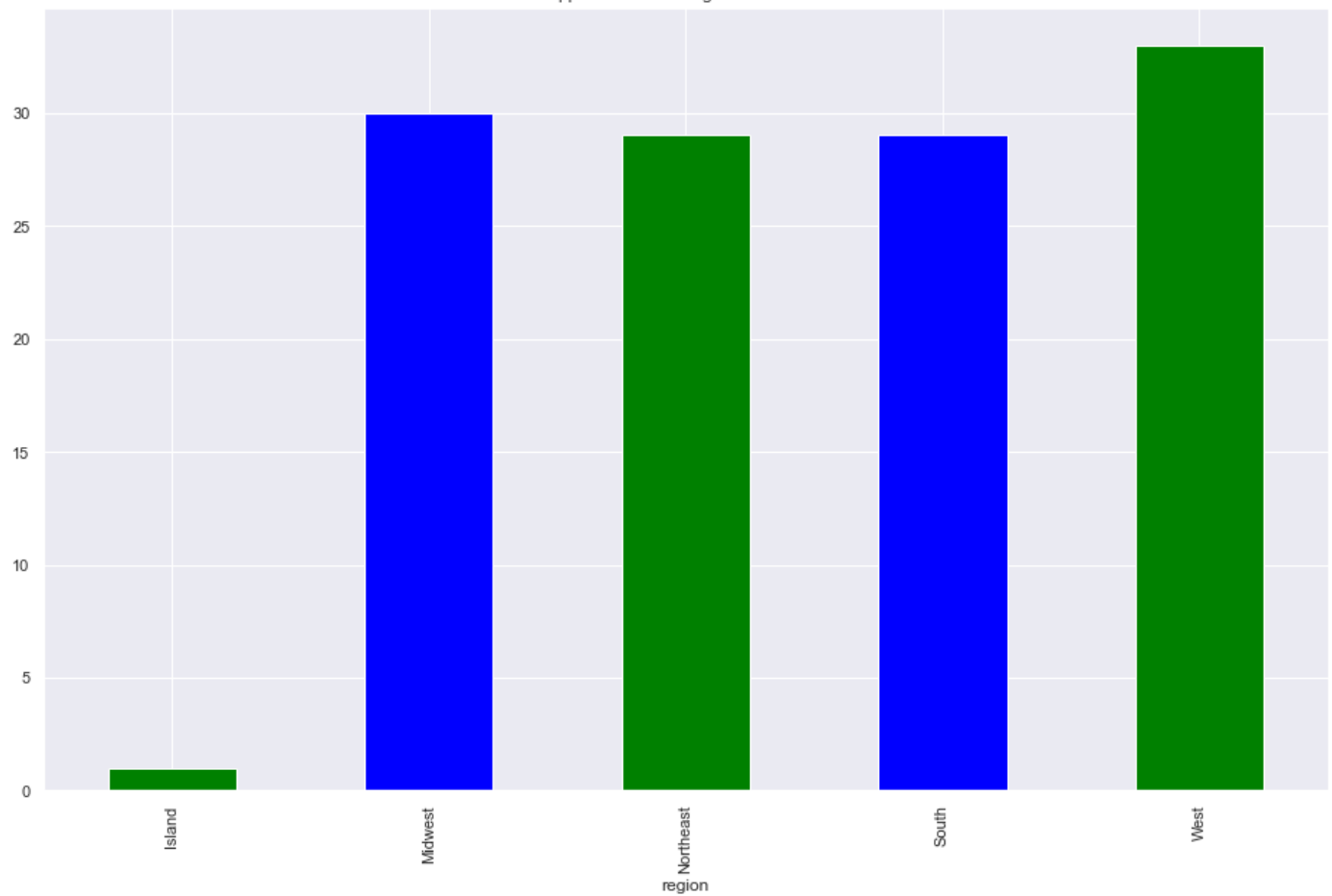
Visa application status region wise in Europe



Visa application status region wise in South America



Visa application status region wise in Oceania



In []: