Project: Bank Marketing (Campaign) -- Group Project

Group Name: Kesimoji
Names: Kemal Cagin Sertkaya, Jinwen Li, Mohamed Elmorsy, Sirui Zhang
Emails: cagin24@gmail.com (mailto:cagin24@gmail.com), jinwen@uw.edu (mailto:jinwen@uw.edu), mmsobhy7@gmail.com (mailto:mmsobhy7@gmail.com), zhangsirui261918@126.com (mailto:zhangsirui261918@126.com)
Colleges: Bogazici University, University of Washington, Mcmaster University, UCL
Specialization: Data Science
Countries: Turkey, US, Canada, UK

Problem description:

One bank wants to sell its term deposit product to customers before launching the product. To save their resource and time, they want to know what kind of customers they should focus on, and then they can put more advertisements to these customers, who have more chances of buying the product. Thus, our problem is to pick up this kind of customer, based on customers' past interaction with this bank or other financial institutions. We are going to use the customers' data to build some machine learning models and then, select customers who most likely buy the product.

In [111]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
data = pd.read_csv("bank-additional-full.csv",sep=';')
data.head()
```

Out[111]:

	age	job	marital	education	default	housing	loan	contact	month	day_of_week	..
0	56	housemaid	married	basic.4y	no	no	no	telephone	may	mon	..
1	57	services	married	high.school	unknown	no	no	telephone	may	mon	..
2	37	services	married	high.school	no	yes	no	telephone	may	mon	..
3	40	admin.	married	basic.6y	no	no	no	telephone	may	mon	..
4	56	services	married	high.school	no	no	yes	telephone	may	mon	..

5 rows × 21 columns

Explore Data

In [112]:
```
data.dtypes
```

Out[112]:
```
age                int64
job               object
marital           object
education         object
default           object
housing           object
loan              object
contact           object
month             object
day_of_week       object
duration           int64
campaign           int64
pdays              int64
previous           int64
poutcome          object
emp.var.rate     float64
cons.price.idx   float64
cons.conf.idx    float64
euribor3m        float64
nr.employed      float64
y                 object
dtype: object
```

In [113]:
```
col = data.columns.tolist()
col_num = data.select_dtypes(include=np.number).columns.tolist()
```

In [114]:
```
print("Number of unique values stat:")
data.nunique()
```

```
Number of unique values stat:
```

Out[114]:
```
age                78
job                12
marital             4
education           8
default             3
housing             3
loan                3
contact             2
month              10
day_of_week         5
duration         1544
campaign           42
pdays              27
previous            8
poutcome            3
emp.var.rate       10
cons.price.idx     26
cons.conf.idx      26
euribor3m         316
nr.employed        11
y                   2
dtype: int64
```

In [115]:
```
data.describe().applymap('{:,.0f}'.format)
```

Out[115]:

	age	duration	campaign	pdays	previous	emp.var.rate	cons.price.idx	cons.conf.idx	eur
count	41,188	41,188	41,188	41,188	41,188	41,188	41,188	41,188	
mean	40	258	3	962	0	0	94	-41	
std	10	259	3	187	0	2	1	5	
min	17	0	1	0	0	-3	92	-51	
25%	32	102	1	999	0	-2	93	-43	
50%	38	180	2	999	0	1	94	-42	
75%	47	319	3	999	0	1	94	-36	
max	98	4,918	56	999	7	1	95	-27	

Outliers Removal

In [116]:
```
# Outliers removal using Interquartile range(IQR) statistical method
def outliers_iqr(df, feature):
    Q1= df[feature].quantile(0.25)
    Q3 = df[feature].quantile(0.75)
    IQR = Q3 - Q1
    upper_limit = Q3 + 1.5 * IQR
    lower_limit = Q1 - 1.5 * IQR
    return upper_limit, lower_limit

for col in col_num:
    upper, lower = outliers_iqr(data, col)
    print(str(col)+":")
    print("Upper limit: ", upper)
    print("Lower limit: ", lower)
    if upper > lower:
        data_iqr = data[(data[col] > lower) & (data[col] < upper)]

data_iqr.describe().applymap('{:,.0f}'.format)
```

```
age:
Upper limit:  69.5
Lower limit:  9.5
duration:
Upper limit:  644.5
Lower limit:  -223.5
campaign:
Upper limit:  6.0
Lower limit:  -2.0
pdays:
Upper limit:  999.0
Lower limit:  999.0
previous:
Upper limit:  0.0
Lower limit:  0.0
emp.var.rate:
Upper limit:  6.200000000000001
Lower limit:  -6.6000000000000005
cons.price.idx:
Upper limit:  95.3725
Lower limit:  91.69650000000001
cons.conf.idx:
Upper limit:  -26.949999999999992
Lower limit:  -52.150000000000006
euribor3m:
Upper limit:  10.3865
Lower limit:  -4.081499999999999
nr.employed:
Upper limit:  5421.6
Lower limit:  4905.6
```

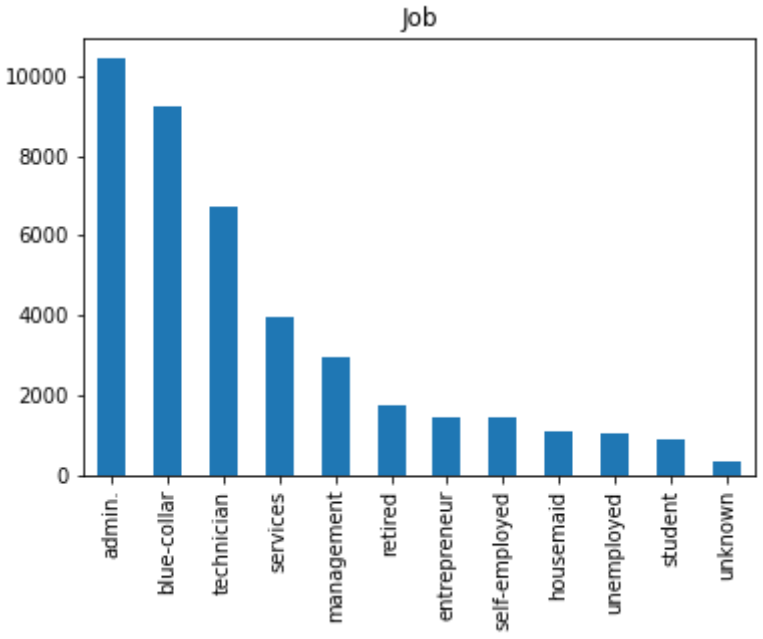
Out[116]:

	age	duration	campaign	pdays	previous	emp.var.rate	cons.price.idx	cons.conf.idx	eur
count	41,188	41,188	41,188	41,188	41,188	41,188	41,188	41,188	
mean	40	258	3	962	0	0	94	-41	
std	10	259	3	187	0	2	1	5	

	age	duration	campaign	pdays	previous	emp.var.rate	cons.price.idx	cons.conf.idx	eur
min	17	0	1	0	0	-3	92	-51	
25%	32	102	1	999	0	-2	93	-43	
50%	38	180	2	999	0	1	94	-42	
75%	47	319	3	999	0	1	94	-36	
max	98	4,918	56	999	7	1	95	-27	

Handling with NA values

In [117]:
```
plt.title('Job')
data.job.value_counts().plot(kind='bar')
plt.show()
plt.title('Marital')
data.marital.value_counts().plot(kind='bar')
plt.show()
plt.title('Education')
data.education.value_counts().plot(kind='bar')
plt.show()
plt.title('Default')
data.default.value_counts().plot(kind='bar')
plt.show()
plt.title('Housing')
data.housing.value_counts().plot(kind='bar')
plt.show()
plt.title('Loan')
data.loan.value_counts().plot(kind='bar')
plt.show()
plt.title('Contact')
data.contact.value_counts().plot(kind='bar')
plt.show()
plt.title('Poutcome')
data.poutcome.value_counts().plot(kind='bar')
plt.show()
plt.title('Y')
data.y.value_counts().plot(kind='bar')
plt.show()
```



In [118]:
```
data.isnull().sum()
```

Out[118]:
```
age               0
job               0
marital           0
education         0
default           0
housing           0
loan              0
contact           0
month             0
day_of_week       0
duration          0
campaign          0
pdays             0
previous          0
poutcome          0
emp.var.rate      0
cons.price.idx    0
cons.conf.idx     0
euribor3m         0
nr.employed       0
y                 0
dtype: int64
```

In [119]:
```
strings = [x for x in data.columns if type(data[x].loc[data[x].first_valid_

for columns in strings:
  print(columns, ':', len(data[data[columns].str.contains('unknown')]))
```

```
job : 330
marital : 80
education : 1731
default : 8597
housing : 990
loan : 990
contact : 0
month : 0
day_of_week : 0
poutcome : 0
y : 0
```

In [120]:
```
#There are 288 unknown in Job column, 1857 in education, 13020 in contact a
data['job'] = data['job'].replace(['unknown'],np.nan)
data['education'] = data['education'].replace(['unknown'],np.nan)
data['contact'] = data['contact'].replace(['unknown'],np.nan)
data['poutcome'] = data['poutcome'].replace(['unknown'],np.nan)
```

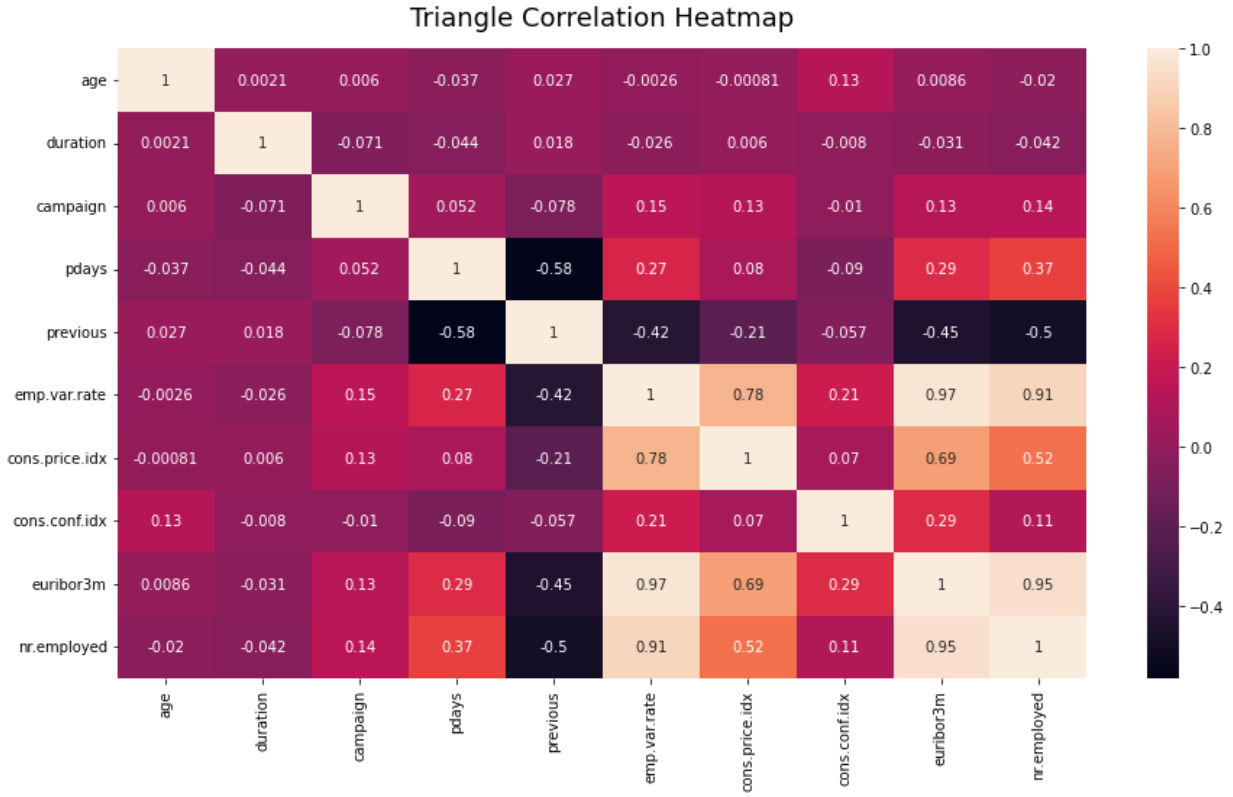
In [121]:
```
data=data.dropna()
```

In [122]:
```
data.isnull().mean().sum()
```

Out[122]:
```
0.0
```

Data Visualization

In [123]:
```
plt.figure(figsize=(15, 8))
heatmap = sns.heatmap(data.corr(), annot=True)
heatmap.set_title('Triangle Correlation Heatmap', fontdict={'fontsize':18},
```



In the above correlation map, it's seen that emp.var.rate, cons.price.idx, euribor3m, nr.employed have a high correlation ratio.

In [124]:
```
data.columns
```

Out[124]:
```
Index(['age', 'job', 'marital', 'education', 'default', 'housing', 'loa
n',
       'contact', 'month', 'day_of_week', 'duration', 'campaign', 'pday
s',
       'previous', 'poutcome', 'emp.var.rate', 'cons.price.idx',
       'cons.conf.idx', 'euribor3m', 'nr.employed', 'y'],
      dtype='object')
```

Column Analysis

In [125]:
```
# Housing Column Analysis
# It's seen that the housing credit ratio is divided nearly half by half.

data_housing_column=data.groupby("housing")["age"].count()
data_housing_column=pd.DataFrame(data_housing_column)
data_housing_column = data_housing_column.rename_axis('housing').reset_inde
data_housing_column.rename(columns = {'age':'user'}, inplace = True)
data_housing_column.head()
```

Out[125]:

	housing	user
0	no	17706
1	unknown	947
2	yes	20605

In [126]:
```
# Loan Column Analysis
# Most of the users don't have a loan.

data_loan_column=data.groupby("loan")["age"].count()
data_loan_column=pd.DataFrame(data_loan_column)
data_loan_column = data_loan_column.rename_axis('loan').reset_index()
data_loan_column.rename(columns = {'age':'user'}, inplace = True)
data_loan_column.head()
```

Out[126]:

	loan	user
0	no	32344
1	unknown	947
2	yes	5967

In [127]:
```
# Default Column Analysis
# It's seen that most of the users don't have credit.

data_default_column=data.groupby("default")["age"].count()
data_default_column=pd.DataFrame(data_default_column)
data_default_column = data_default_column.rename_axis('default').reset_inde
data_default_column.rename(columns = {'age':'user'}, inplace = True)
data_default_column.head()
```

Out[127]:

	default	user
0	no	31284
1	unknown	7971
2	yes	3

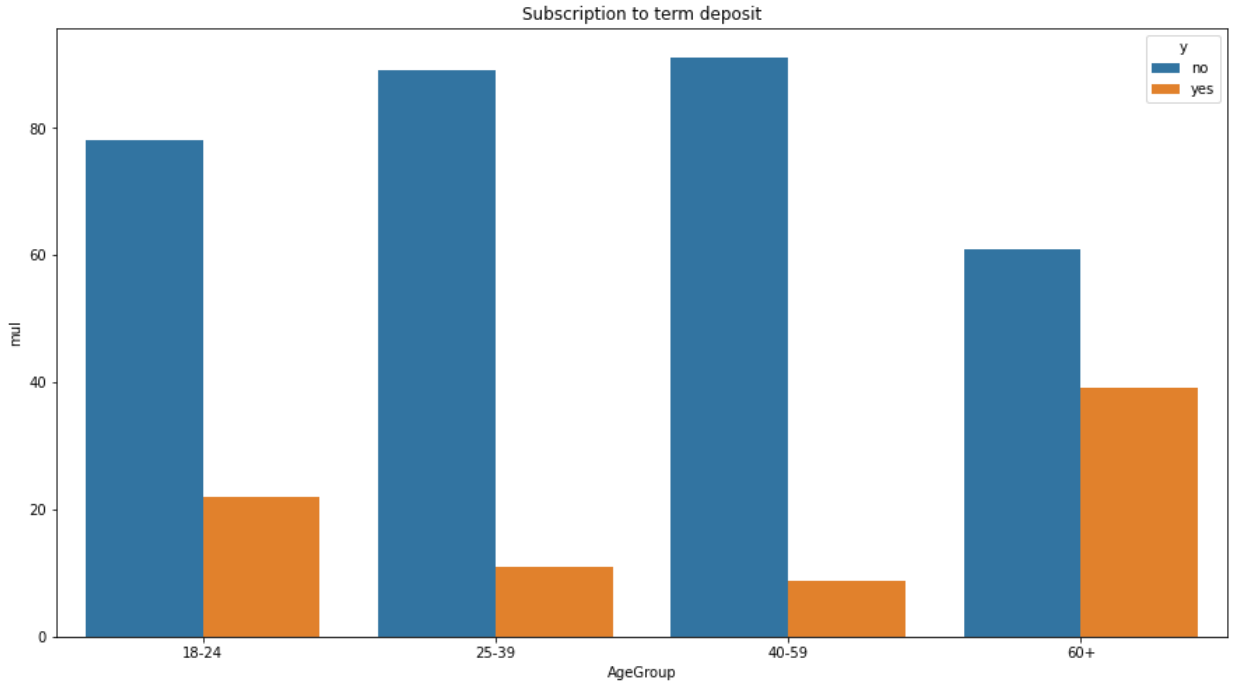
In [128]:
```
# y Column Analysis

data_y_column=data.groupby("y")["age"].count()
data_y_column=pd.DataFrame(data_y_column)
data_y_column = data_y_column.rename_axis('y').reset_index()
data_y_column.rename(columns = {'age':'user'}, inplace = True)
data_y_column.head()
```

Out[128]:

	y	user
0	no	34889
1	yes	4369

In [129]:
```
# Age Column Analysis

bins= [18,25,40,60,100]
labels = ['18-24','25-39','40-59','60+']
data['AgeGroup'] = pd.cut(data['age'], bins=bins, labels=labels, right=Fals
```

In [130]:
```
# Normalize to understand better
data_age_column=data.groupby("AgeGroup")["y"].value_counts(normalize=True).
data_age_column=pd.DataFrame(data_age_column)

data_age_column.rename(columns = {'y':'mul'}, inplace = True)
data_age_column=data_age_column.reset_index()

plt.figure(figsize=(15,8))
plt.title("Subscription to term deposit by age")
sns.barplot(data=data_age_column,hue="y",x="AgeGroup",y="mul");

# It's seen that nearly half of the 60+ users had subscribed to term deposi
```



In [136]:
```
# Job Column Analsis

data_job_column=data.groupby("job")["age"].count()
data_job_column=pd.DataFrame(data_job_column)
data_job_column = data_job_column.rename_axis('job').reset_index()
data_job_column.rename(columns = {'age':'user'}, inplace = True)
data_job_column.head()
```

Out[136]:

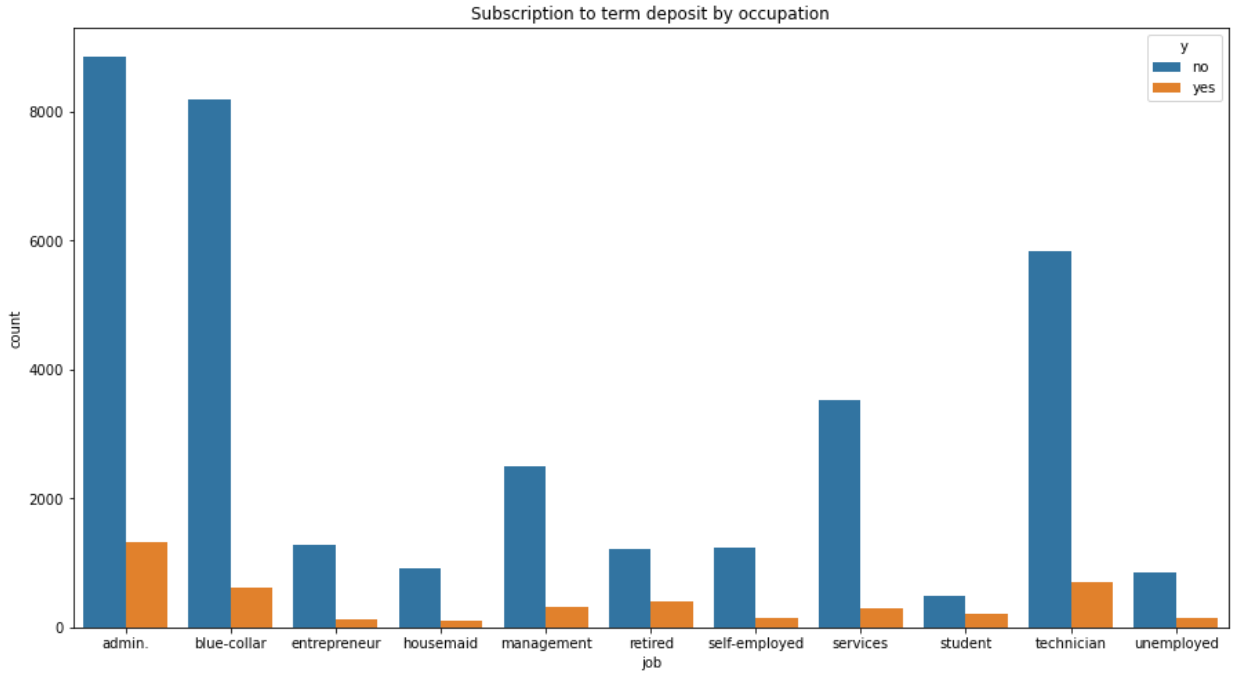
	job	user
0	admin.	10173
1	blue-collar	8800
2	entrepreneur	1399
3	housemaid	1018
4	management	2801

In [162]:
```
job_count=data.groupby(["y","job"])["job"].agg(["count"])
job_count=job_count.reset_index()
job_count
```

Out[162]:

	y	job	count
0	no	admin.	8859
1	no	blue-collar	8186
2	no	entrepreneur	1279
3	no	housemaid	917
4	no	management	2493
5	no	retired	1221
6	no	self-employed	1245
7	no	services	3515
8	no	student	492
9	no	technician	5826
10	no	unemployed	856
11	yes	admin.	1314
12	yes	blue-collar	614
13	yes	entrepreneur	120
14	yes	housemaid	101
15	yes	management	308
16	yes	retired	401
17	yes	self-employed	147
18	yes	services	304
19	yes	student	216
20	yes	technician	705
21	yes	unemployed	139

In [164]:
```
plt.figure(figsize=(15,8))
plt.title("Subscription to term deposit by occupation")
sns.barplot(data=job_count,hue="y",x="job",y="count");
```



In [141]:
```
# Martial Column Analysis

data_marital_column=data.groupby("marital")["age"].count()
data_marital_column=pd.DataFrame(data_marital_column)
data_marital_column = data_marital_column.rename_axis('marital').reset_inde
data_marital_column.rename(columns = {'age':'user'}, inplace = True)
data_marital_column.head()
```

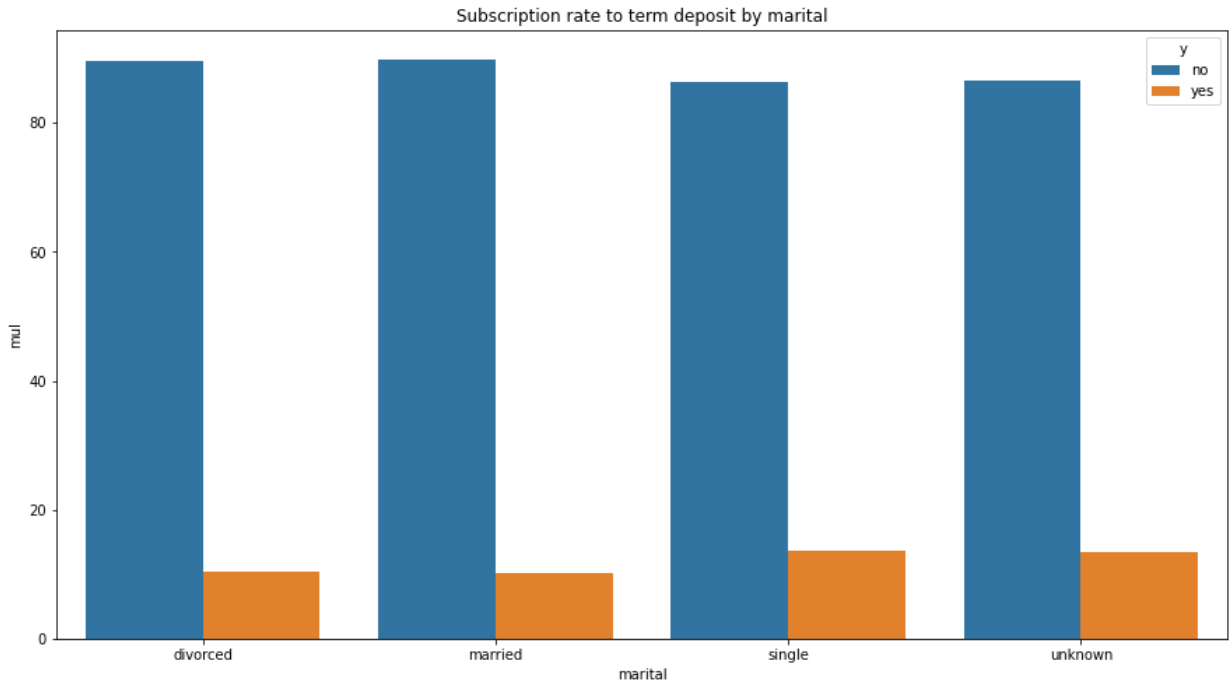
Out[141]:

	marital	user
0	divorced	4417
1	married	23748
2	single	11026
3	unknown	67

In [145]:
```
data_ratio_marital=data.groupby("AgeGroup")["marital"].value_counts()
data_ratio_marital
# It can be said that younger people mostly single while older ones aree ma
```

Out[145]:
```
AgeGroup  marital
18-24     single        829
          married       127
          divorced        4
25-39     married     10908
          single       8420
          divorced     1524
          unknown        43
40-59     married     11907
          divorced     2677
          single       1739
          unknown        22
60+       married       806
          divorced      212
          single         35
          unknown         2
Name: marital, dtype: int64
```

In [146]:
```
data_marital_column=data.groupby("marital")["y"].value_counts(normalize=Tru
data_marital_column=pd.DataFrame(data_marital_column)
data_marital_column.rename(columns = {'y':'mul'}, inplace = True)
data_marital_column=data_marital_column.reset_index()
plt.figure(figsize=(15,8))
plt.title("Subscription rate to term deposit by marital")
sns.barplot(data=data_marital_column,hue="y",x="marital",y="mul");
```

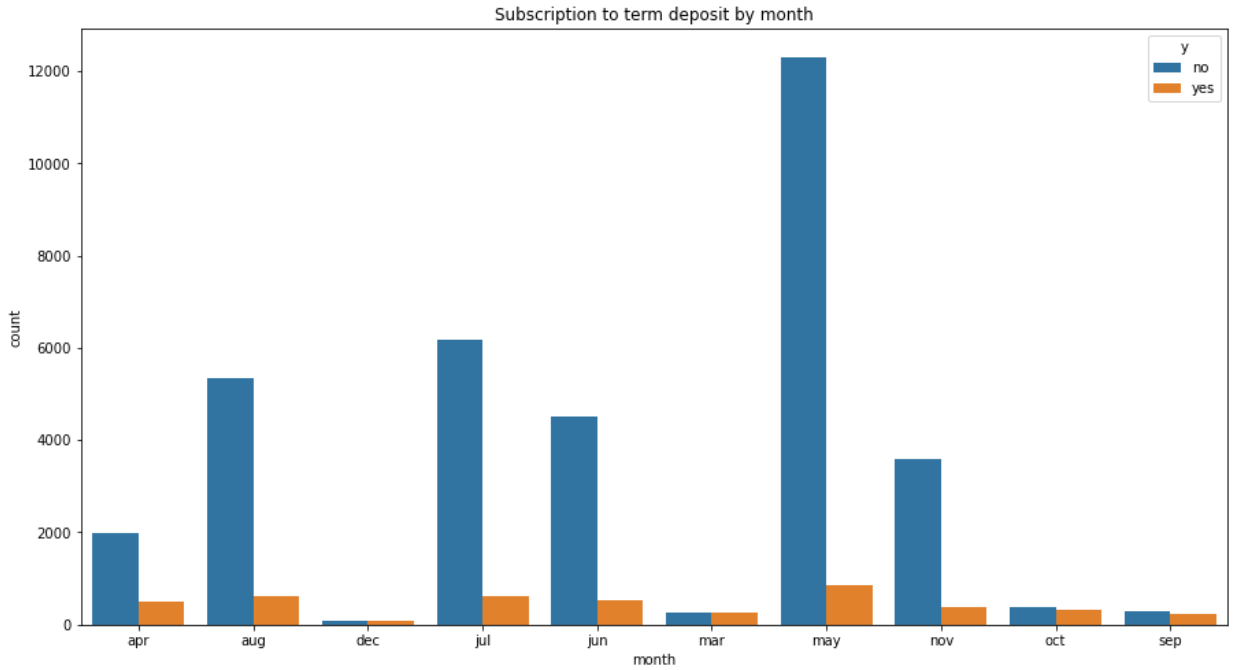


In [151]:
```
# Month Column Analysis

data_month_column=data.groupby("month")["age"].count()
data_month_column=pd.DataFrame(data_month_column)
data_month_column = data_month_column.rename_axis('month').reset_index()
data_month_column.rename(columns = {'age':'user'}, inplace = True)
data_month_column
```

Out[151]:

	month	user
0	apr	2496
1	aug	5957
2	dec	167
3	jul	6771
4	jun	5023
5	mar	511
6	may	13156
7	nov	3980
8	oct	681
9	sep	516

In [156]:
```
month_count=data.groupby(["y","month"])['month'].agg(["count"])
month_count=month_count.reset_index()
plt.figure(figsize=(15,8))
plt.title("Subscription to term deposit by month")
sns.barplot(data=month_count,hue="y",x="month",y="count");
```

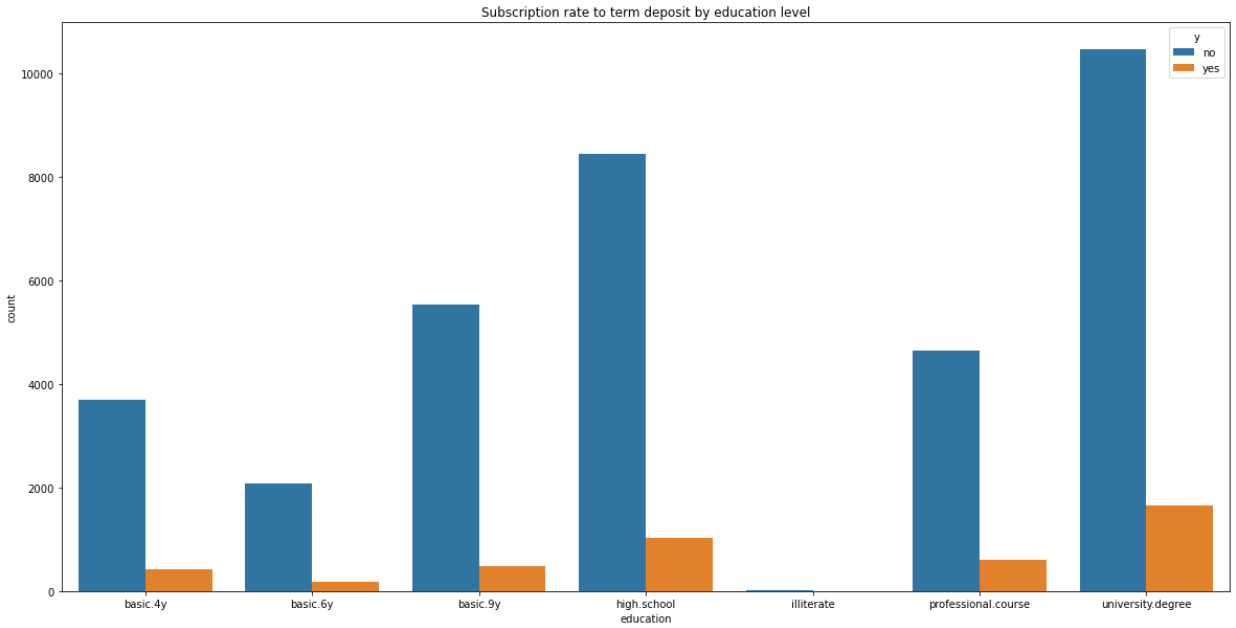


In [157]:
```
# Education Column Analysis

data_education_column=data.groupby("education")["age"].count()
data_education_column=pd.DataFrame(data_education_column)
data_education_column = data_education_column.rename_axis('education').rese
data_education_column.rename(columns = {'age':'user'}, inplace = True)
data_education_column.head()
```

Out[157]:

	education	user
0	basic.4y	4124
1	basic.6y	2270
2	basic.9y	6014
3	high.school	9478
4	illiterate	18

In [159]:
```
education_count=data.groupby(["y","education"])["education"].agg(["count"])
education_count=education_count.reset_index()
plt.figure(figsize=(20,10))
plt.title("Subscription rate to term deposit by education level")
sns.barplot(data=education_count,hue="y",x="education",y="count");
```



In [ ]: