Importing Libraries

In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import OneHotEncoder
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier

%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
```

Read csv file

In [2]:

```
bnk = pd.read_csv(r"C:\Users\SST190000\Downloads\Applied ML\archive\bank_marketing.csv",
sep = ';')
```

In [3]:

```
bnk
```

Out[3]:

	age	job	marital	education	default	housing	loan	contact	month	day_of_week	...	campaign
0	56	housemaid	married	basic.4y	no	no	no	telephone	may	mon	...	1
1	57	services	married	high.school	unknown	no	no	telephone	may	mon	...	1
2	37	services	married	high.school	no	yes	no	telephone	may	mon	...	1
3	40	admin.	married	basic.6y	no	no	no	telephone	may	mon	...	1
4	56	services	married	high.school	no	no	yes	telephone	may	mon	...	1
...	...	...	...	...	...	...	...	...	...	...	...	...
41183	73	retired	married	professional.course	no	yes	no	cellular	nov	fri	...	1
41184	46	blue-collar	married	professional.course	no	no	no	cellular	nov	fri	...	1
41185	56	retired	married	university.degree	no	yes	no	cellular	nov	fri	...	2
41186	44	technician	married	professional.course	no	no	no	cellular	nov	fri	...	1
41187	74	retired	married	professional.course	no	yes	no	cellular	nov	fri	...	3

41188 rows × 21 columns

Getting information about the dataset

In [4]:

```
bnk.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 41188 entries, 0 to 41187
Data columns (total 21 columns):
 #   Column          Non-Null Count  Dtype
```

```
                                      --
 ---  ------          --------------  -----
 0    age             41188 non-null  int64
 1    job             41188 non-null  object
 2    marital         41188 non-null  object
 3    education       41188 non-null  object
 4    default         41188 non-null  object
 5    housing         41188 non-null  object
 6    loan            41188 non-null  object
 7    contact         41188 non-null  object
 8    month           41188 non-null  object
 9    day_of_week     41188 non-null  object
 10   duration        41188 non-null  int64
 11   campaign        41188 non-null  int64
 12   pdays           41188 non-null  int64
 13   previous        41188 non-null  int64
 14   poutcome        41188 non-null  object
 15   emp.var.rate    41188 non-null  float64
 16   cons.price.idx  41188 non-null  float64
 17   cons.conf.idx   41188 non-null  float64
 18   euribor3m       41188 non-null  float64
 19   nr.employed     41188 non-null  float64
 20   y               41188 non-null  object
dtypes: float64(5), int64(5), object(11)
memory usage: 6.6+ MB
```

In [5]:

```
bnk.describe()
```

Out[5]:

	age	duration	campaign	pdays	previous	emp.var.rate	cons.price.idx	cons.conf.idx	e
count	41188.00000	41188.000000	41188.000000	41188.000000	41188.000000	41188.000000	41188.000000	41188.000000	411
mean	40.02406	258.285010	2.567593	962.475454	0.172963	0.081886	93.575664	-40.502600	
std	10.42125	259.279249	2.770014	186.910907	0.494901	1.570960	0.578840	4.628198	
min	17.00000	0.000000	1.000000	0.000000	0.000000	-3.400000	92.201000	-50.800000	
25%	32.00000	102.000000	1.000000	999.000000	0.000000	-1.800000	93.075000	-42.700000	
50%	38.00000	180.000000	2.000000	999.000000	0.000000	1.100000	93.749000	-41.800000	
75%	47.00000	319.000000	3.000000	999.000000	0.000000	1.400000	93.994000	-36.400000	
max	98.00000	4918.000000	56.000000	999.000000	7.000000	1.400000	94.767000	-26.900000	

In [6]:

```
bnk.columns
```

Out[6]:

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

In [7]:

```
bnk.shape
```

Out[7]:

```
(41188, 21)
```

Getting information about the dataset

In [8]:

In [8]:

```
bnk.isnull().sum()
```

Out[8]:

```
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
```

Check for Duplicates and Null values

In [9]:

```
bnk.duplicated().sum()
```

Out[9]:

```
12
```

In [10]:

```
duplicates = bnk[bnk.duplicated()]
print("Duplicate rows : ")
duplicates
```

```
Duplicate rows :
```

Out[10]:

	age	job	marital	education	default	housing	loan	contact	month	day_of_week	...	campaigr
1266	39	blue-collar	married	basic.6y	no	no	no	telephone	may	thu	...	1
12261	36	retired	married	unknown	no	no	no	telephone	jul	thu	...	1
14234	27	technician	single	professional.course	no	no	no	cellular	jul	mon	...	2
16956	47	technician	divorced	high.school	no	yes	no	cellular	jul	thu	...	3
18465	32	technician	single	professional.course	no	yes	no	cellular	jul	thu	...	1
20216	55	services	married	high.school	unknown	no	no	cellular	aug	mon	...	1
20534	41	technician	married	professional.course	no	yes	no	cellular	aug	tue	...	1
25217	39	admin.	married	university.degree	no	no	no	cellular	nov	tue	...	2
28477	24	services	single	high.school	no	yes	no	cellular	apr	tue	...	1
32516	35	admin.	married	university.degree	no	yes	no	cellular	may	fri	...	4
36951	45	admin.	married	university.degree	no	no	no	cellular	jul	thu	...	1
38281	71	retired	single	university.degree	no	no	no	telephone	oct	tue	...	1

12 rows × 21 columns

Drop duplicates

In [11]:

```
bnk.drop_duplicates(keep=False, inplace=True)
bnk.duplicated().sum()
```

Out[11]:

```
0
```

In [12]:

```
bnk.isna().sum()
```

Out[12]:

```
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
```

Imputing 5%-10% null values

In [13]:

```
bnk['emp.var.rate'] = bnk['emp.var.rate'].mask(np.random.random(bnk['emp.var.rate'].shape
) < .1)
bnk['duration'] = bnk['duration'].mask(np.random.random(bnk['duration'].shape) < .05)
bnk['campaign'] = bnk['campaign'].mask(np.random.random(bnk['campaign'].shape) < .1)
bnk['pdays'] = bnk['pdays'].mask(np.random.random(bnk['pdays'].shape) < .1)
bnk['previous'] = bnk['previous'].mask(np.random.random(bnk['previous'].shape) < .05)
```

In [14]:

```
bnk.isna().sum()
```

Out[14]:

```
age                  0
job                  0
marital              0
education            0
default              0
housing              0
loan                 0
contact              0
month                0
```

```
day_of_week          0
duration          2138
campaign          4085
pdays             4088
previous          1980
poutcome             0
emp.var.rate      4192
cons.price.idx       0
cons.conf.idx        0
euribor3m            0
nr.employed          0
y                    0
dtype: int64
```

In [15]:

```
bnk.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 41164 entries, 0 to 41187
Data columns (total 21 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   age             41164 non-null  int64  
 1   job             41164 non-null  object 
 2   marital         41164 non-null  object 
 3   education       41164 non-null  object 
 4   default         41164 non-null  object 
 5   housing         41164 non-null  object 
 6   loan            41164 non-null  object 
 7   contact         41164 non-null  object 
 8   month           41164 non-null  object 
 9   day_of_week     41164 non-null  object 
 10  duration        39026 non-null  float64
 11  campaign        37079 non-null  float64
 12  pdays           37076 non-null  float64
 13  previous        39184 non-null  float64
 14  poutcome        41164 non-null  object 
 15  emp.var.rate    36972 non-null  float64
 16  cons.price.idx  41164 non-null  float64
 17  cons.conf.idx   41164 non-null  float64
 18  euribor3m       41164 non-null  float64
 19  nr.employed     41164 non-null  float64
 20  y               41164 non-null  object 
dtypes: float64(9), int64(1), object(11)
memory usage: 6.9+ MB
```

Replace null values with mean

In [16]:

```
bnk['emp.var.rate'].fillna(bnk['emp.var.rate'].mean(),inplace=True)
bnk['duration'].fillna(bnk['duration'].mean(),inplace=True)
bnk['campaign'].fillna(bnk['campaign'].mean(),inplace=True)
bnk['pdays'].fillna(bnk['pdays'].mean(),inplace=True)
bnk['previous'].fillna(bnk['previous'].mean(),inplace=True)
```

In [17]:

```
bnk.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 41164 entries, 0 to 41187
Data columns (total 21 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   age             41164 non-null  int64  
 1   job             41164 non-null  object 
 2   marital         41164 non-null  object 
 3   education       41164 non-null  object 
 4   default         41164 non-null  object 
```

```
 4   default         41164 non-null  object
 5   housing         41164 non-null  object
 6   loan            41164 non-null  object
 7   contact         41164 non-null  object
 8   month           41164 non-null  object
 9   day_of_week     41164 non-null  object
 10  duration        41164 non-null  float64
 11  campaign        41164 non-null  float64
 12  pdays           41164 non-null  float64
 13  previous        41164 non-null  float64
 14  poutcome        41164 non-null  object
 15  emp.var.rate    41164 non-null  float64
 16  cons.price.idx  41164 non-null  float64
 17  cons.conf.idx   41164 non-null  float64
 18  euribor3m       41164 non-null  float64
 19  nr.employed     41164 non-null  float64
 20  y               41164 non-null  object
dtypes: float64(9), int64(1), object(11)
memory usage: 6.9+ MB
```

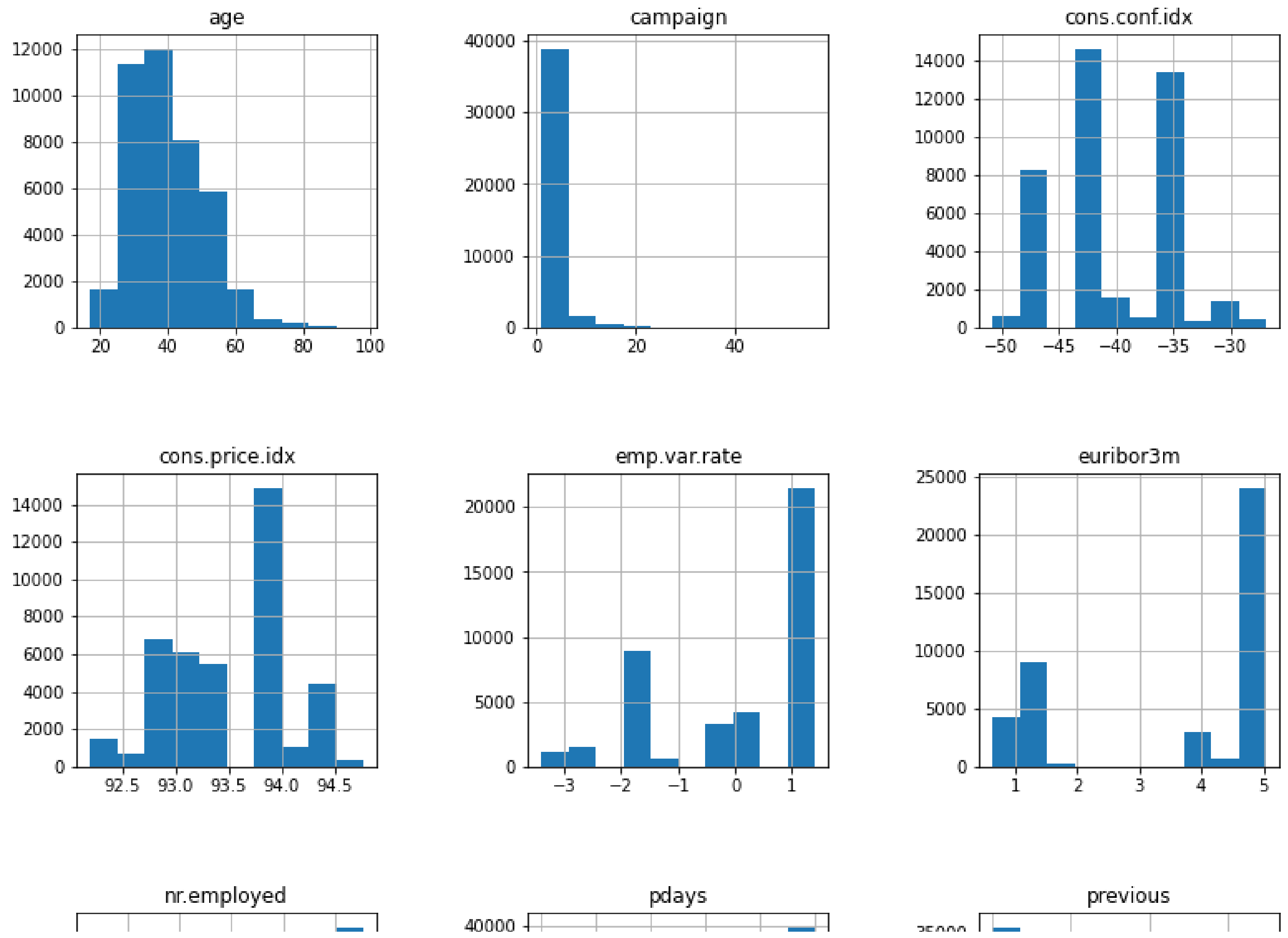
Exploratory Data Analysis

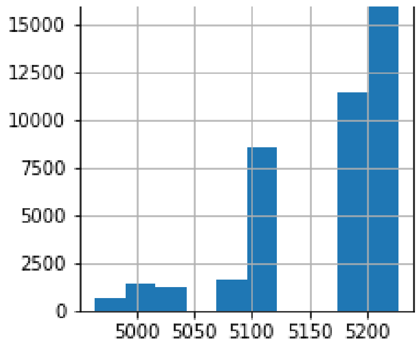
Exploring numerical variables in 'bnk'

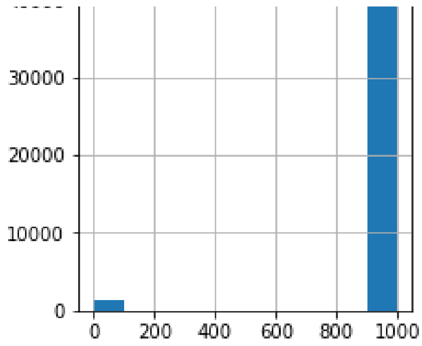
Histogram Subplots

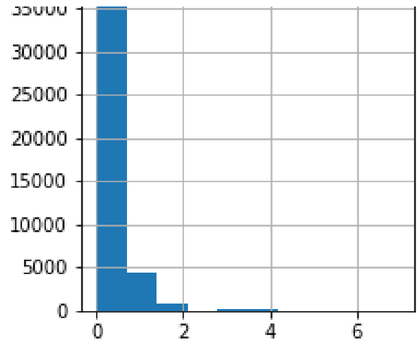
In [18]:

```
col = ['age','campaign','pdays','previous','emp.var.rate','cons.price.idx','cons.conf.idx
','euribor3m','nr.employed']
bnk.hist(column=col,figsize=(13,13))
plt.subplots_adjust(wspace = 0.5, hspace = 0.5)
plt.show()
```









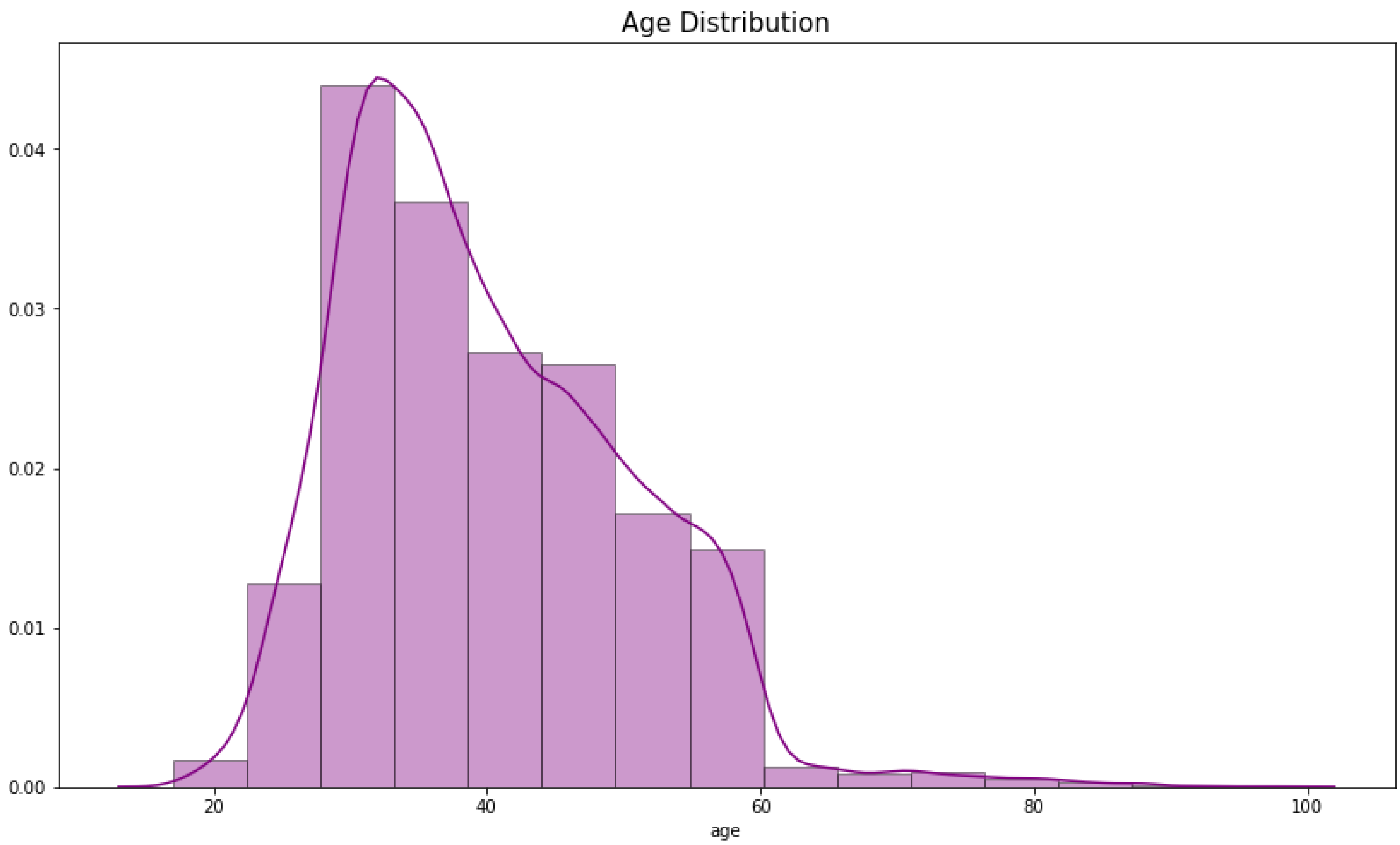
Distribution of age variable

In [19]:

```
fig, bca = plt.subplots()
fig.set_size_inches(14, 8)
sns.distplot(bnk['age'], hist=True, kde=True,
             bins=int(150/10), color = 'purple',
             hist_kws={'edgecolor':'black'})
bca.set_title('Age Distribution', fontsize=15)
```

Out[19]:

```
Text(0.5, 1.0, 'Age Distribution')
```



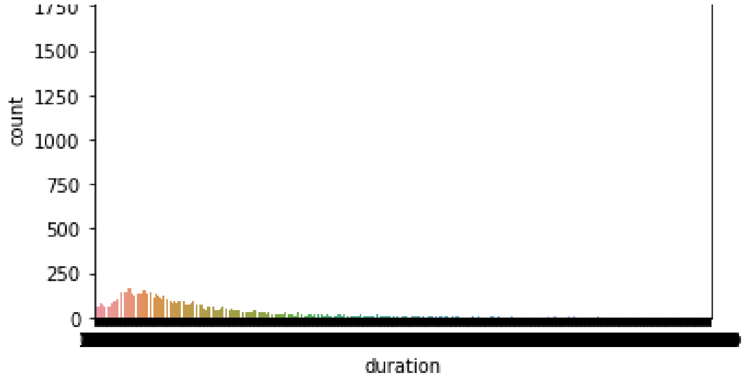
Count of Duration

In [20]:

```
sns.countplot(x='duration',data=bnk)
bca.set_title('Count of Duration', fontsize=15)
```

Out[20]:

```
Text(0.5, 1.0, 'Count of Duration')
```



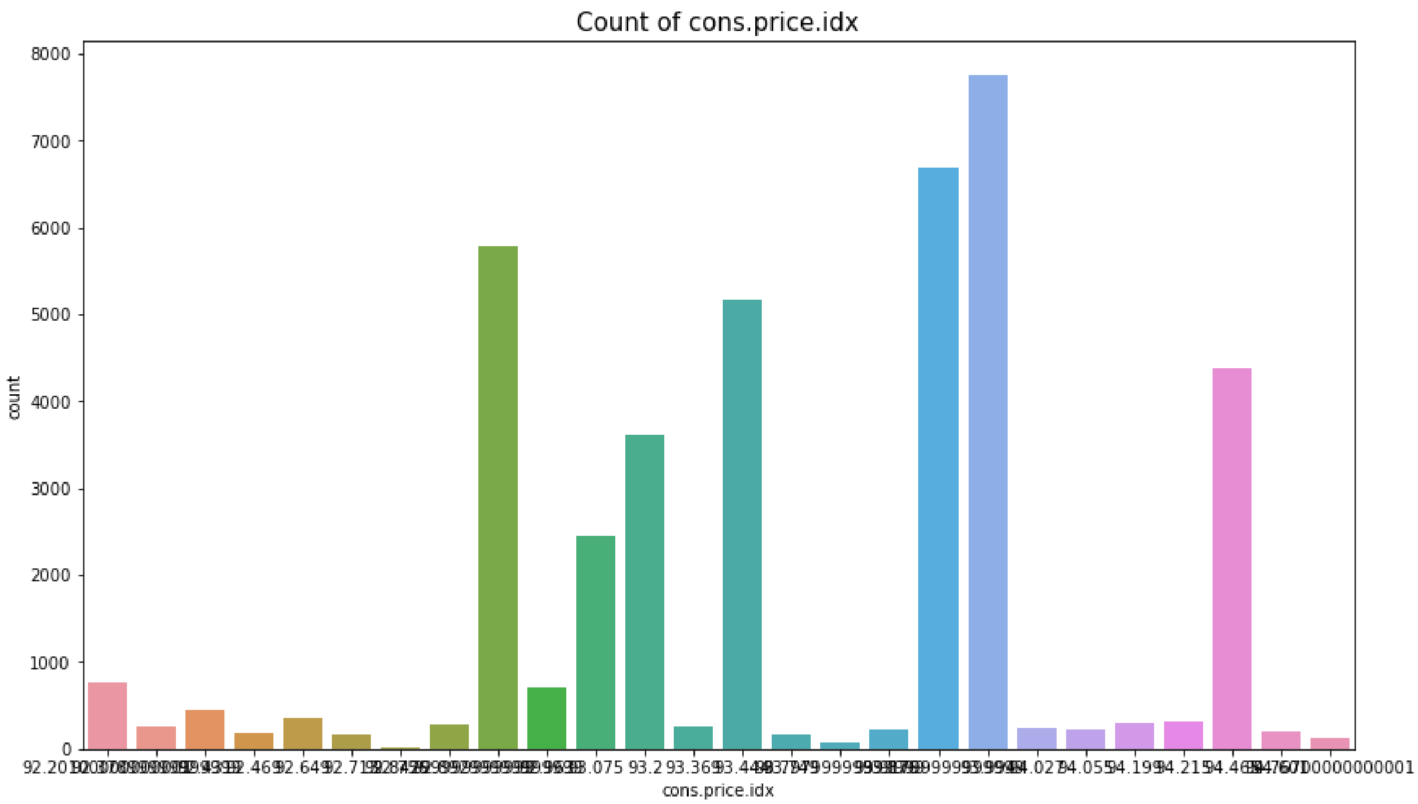
Count of cons.price.idx

In [21]:

```
fig, bca = plt.subplots()
fig.set_size_inches(14, 8)
sns.countplot(x='cons.price.idx',data=bnk)
bca.set_title('Count of cons.price.idx', fontsize=15)
```

Out[21]:

```
Text(0.5, 1.0, 'Count of cons.price.idx')
```



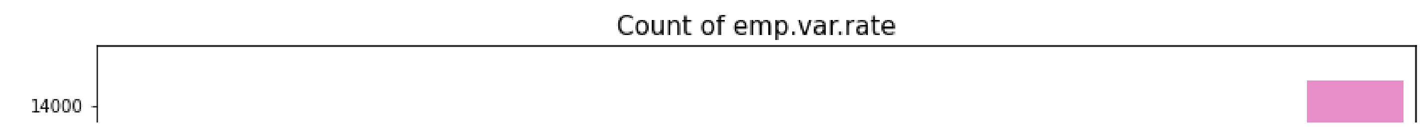
Count of emp.var.rate

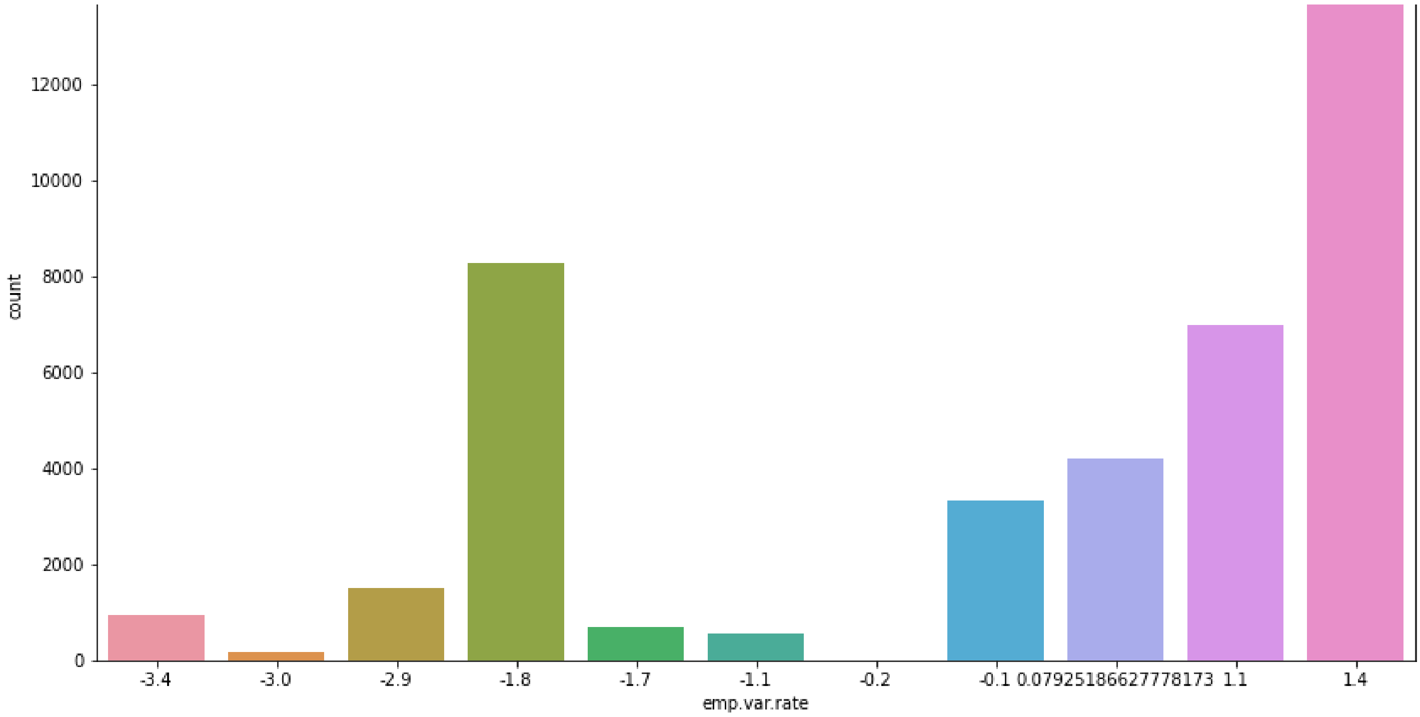
In [22]:

```
fig, bca = plt.subplots()
fig.set_size_inches(14, 8)
sns.countplot(x='emp.var.rate',data=bnk)
bca.set_title('Count of emp.var.rate', fontsize=15)
```

Out[22]:

```
Text(0.5, 1.0, 'Count of emp.var.rate')
```





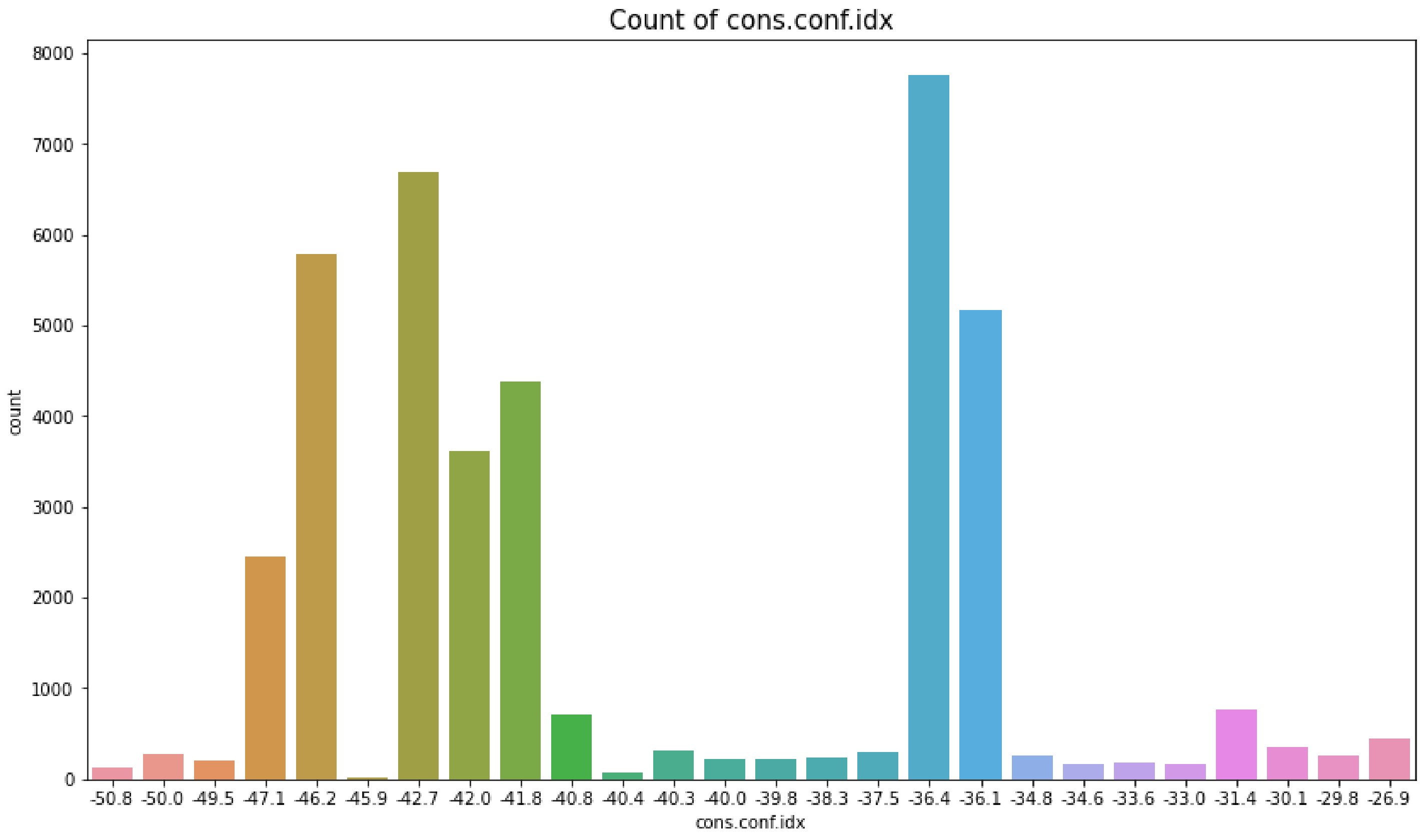
Count of cons.conf.idx

In [23]:

```
fig, bca = plt.subplots()
fig.set_size_inches(14, 8)
sns.countplot(x='cons.conf.idx',data=bnk)
bca.set_title('Count of cons.conf.idx', fontsize=15)
```

Out[23]:

```
Text(0.5, 1.0, 'Count of cons.conf.idx')
```



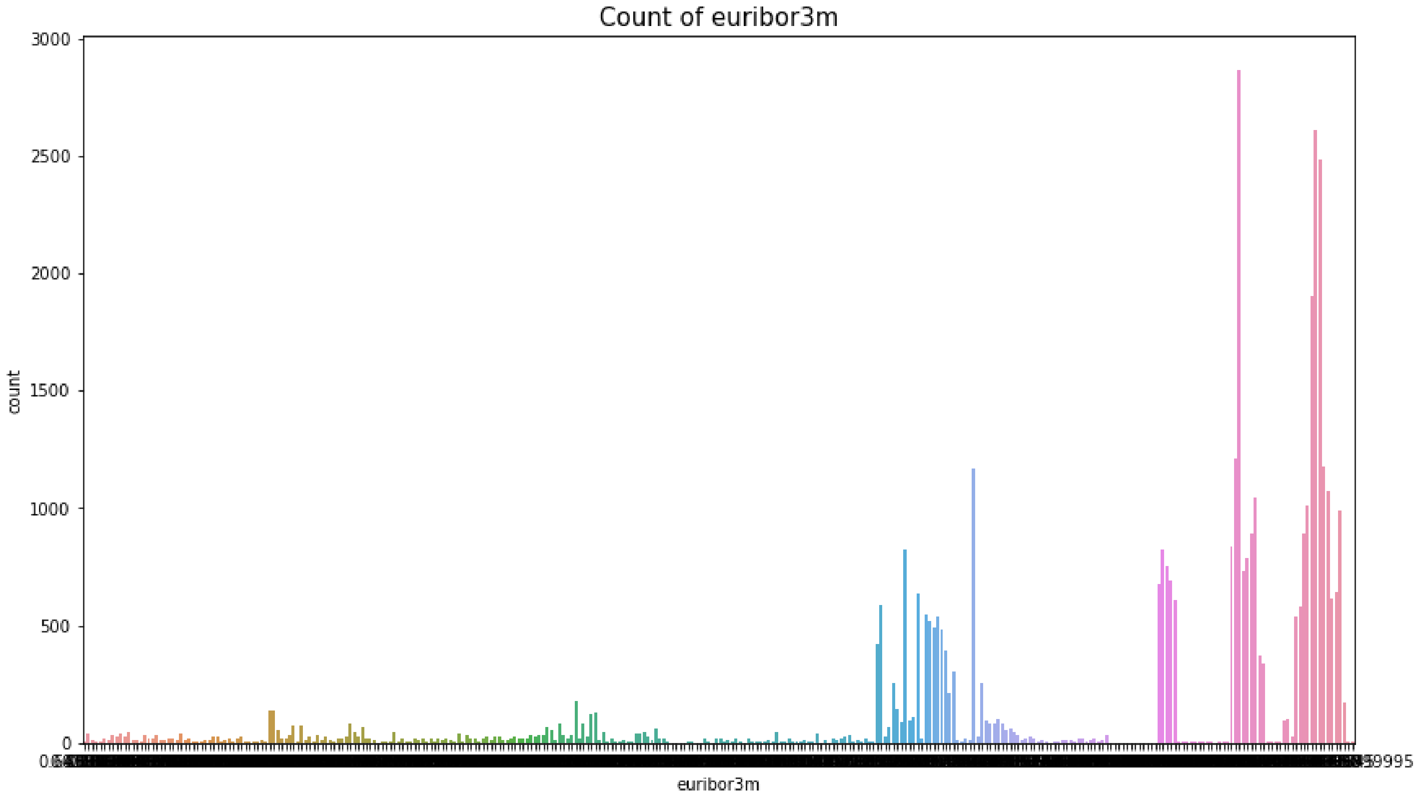
Count of euribor3m

In [24]:

```
fig, bca = plt.subplots()
fig.set_size_inches(14, 8)
sns.countplot(x='euribor3m',data=bnk)
bca.set_title('Count of euribor3m', fontsize=15)
```

Out[24]:

```
Text(0.5, 1.0, 'Count of euribor3m')
```

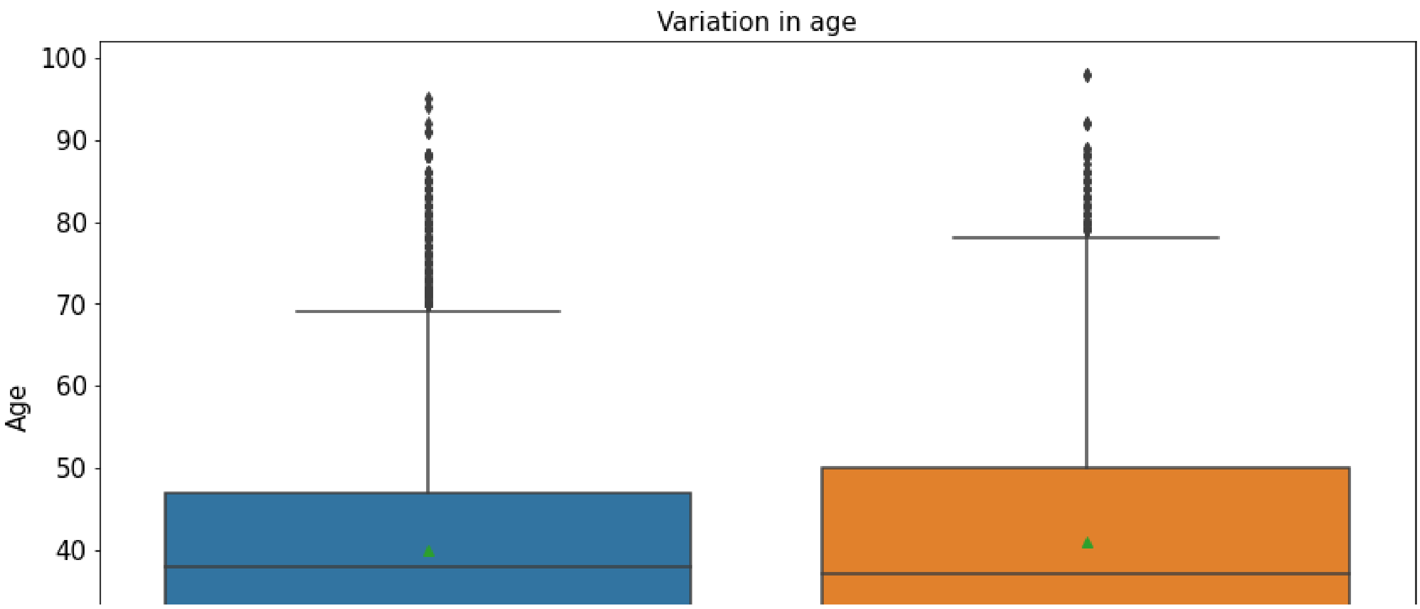


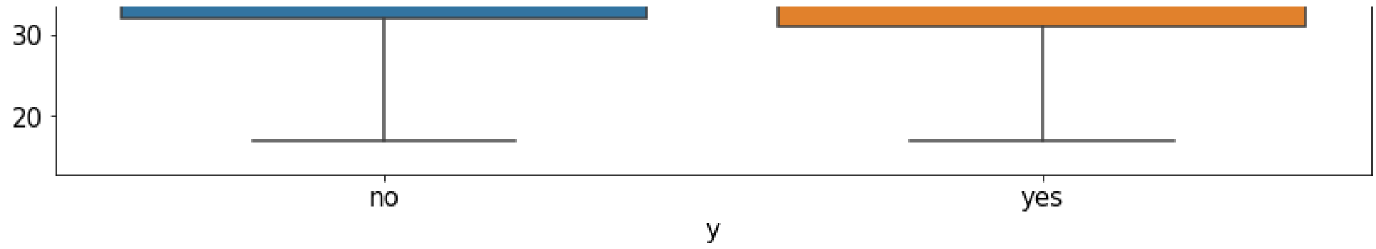
Exploring variation of numerical variables w.r.t target variable y

Variation in age

In [25]:

```
fig, bca = plt.subplots()
fig.set_size_inches(14, 8)
bca1 =sns.boxplot( x='y', y= 'age', data =bnk, showmeans=True)
bca1.set_xlabel('y', fontsize=15)
bca1.set_ylabel('Age', fontsize=15)
bca1.set_title('Variation in age', fontsize=15)
bca1.tick_params(labelsize=15)
```

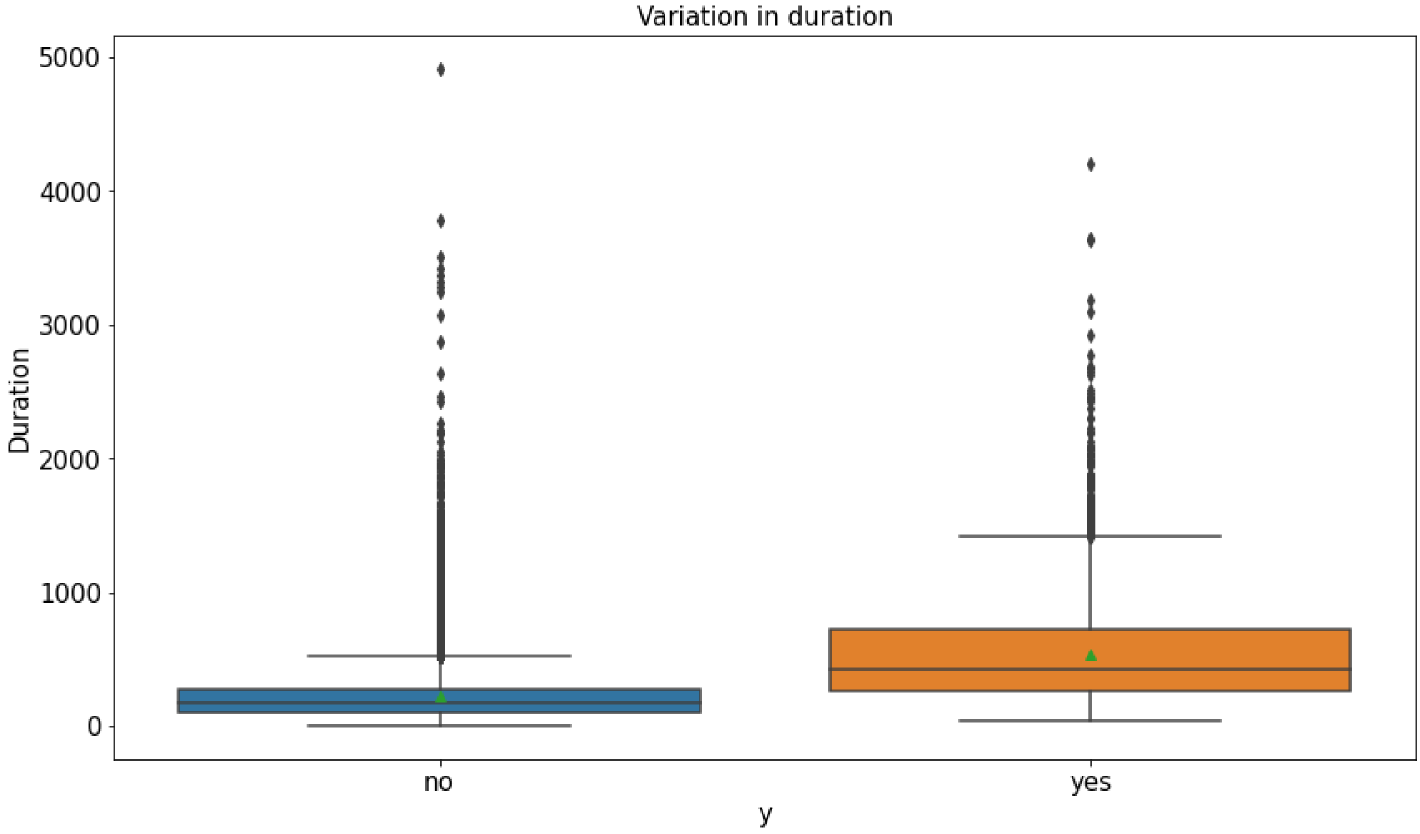




Variation in duration

In [26]:

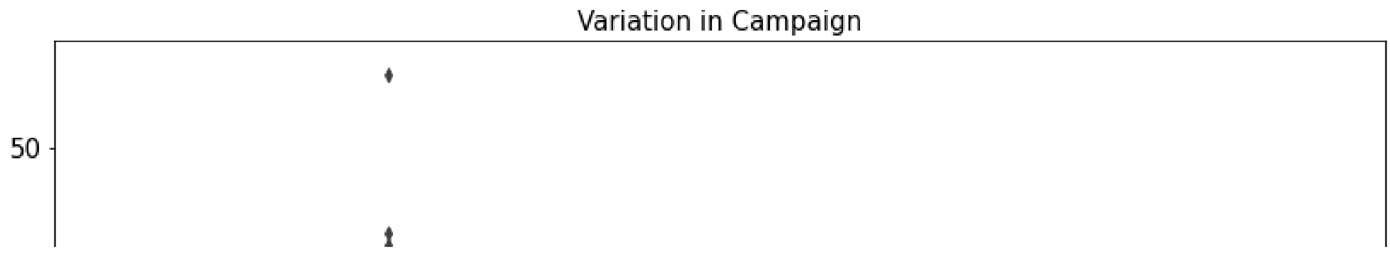
```
fig, bca = plt.subplots()
fig.set_size_inches(14, 8)
bca1 =sns.boxplot( x='y', y= 'duration', data =bnk, showmeans=True)
bca1.set_xlabel('y', fontsize=15)
bca1.set_ylabel('Duration', fontsize=15)
bca1.set_title('Variation in duration', fontsize=15)
bca1.tick_params(labelsize=15)
```

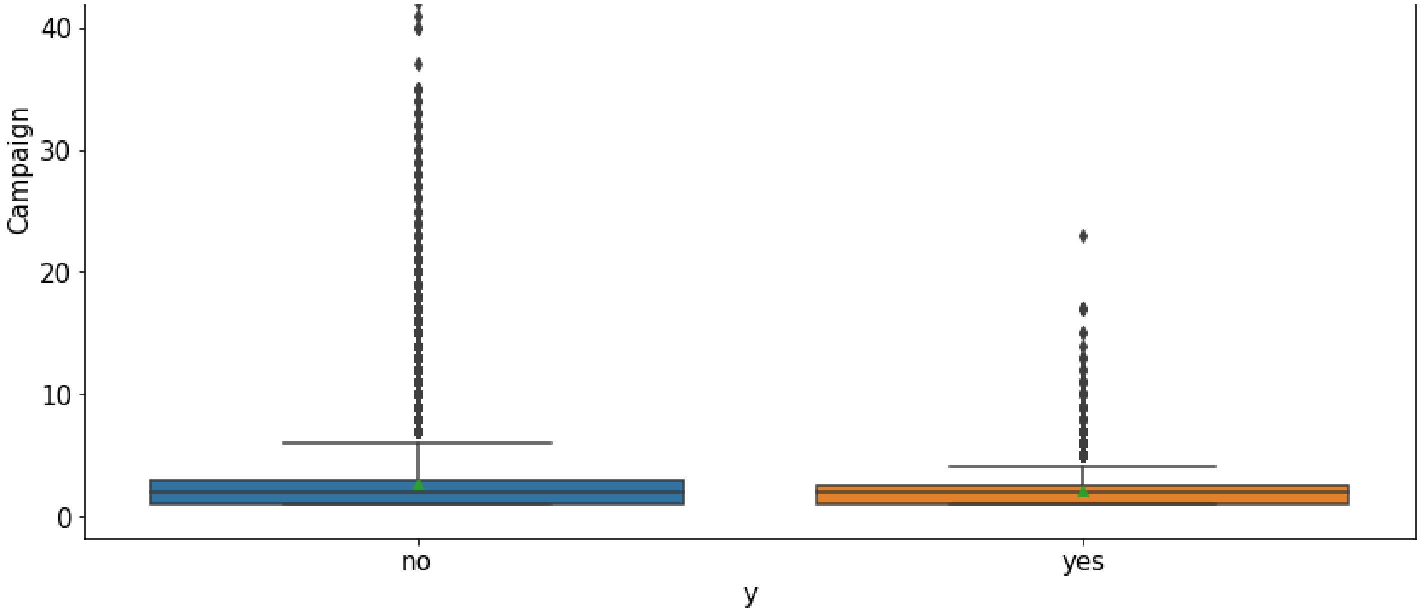


Variation in Campaign

In [27]:

```
fig, bca = plt.subplots()
fig.set_size_inches(14, 8)
bca1 =sns.boxplot( x='y', y= 'campaign', data =bnk, showmeans=True)
bca1.set_xlabel('y', fontsize=15)
bca1.set_ylabel('Campaign', fontsize=15)
bca1.set_title('Variation in Campaign', fontsize=15)
bca1.tick_params(labelsize=15)
```

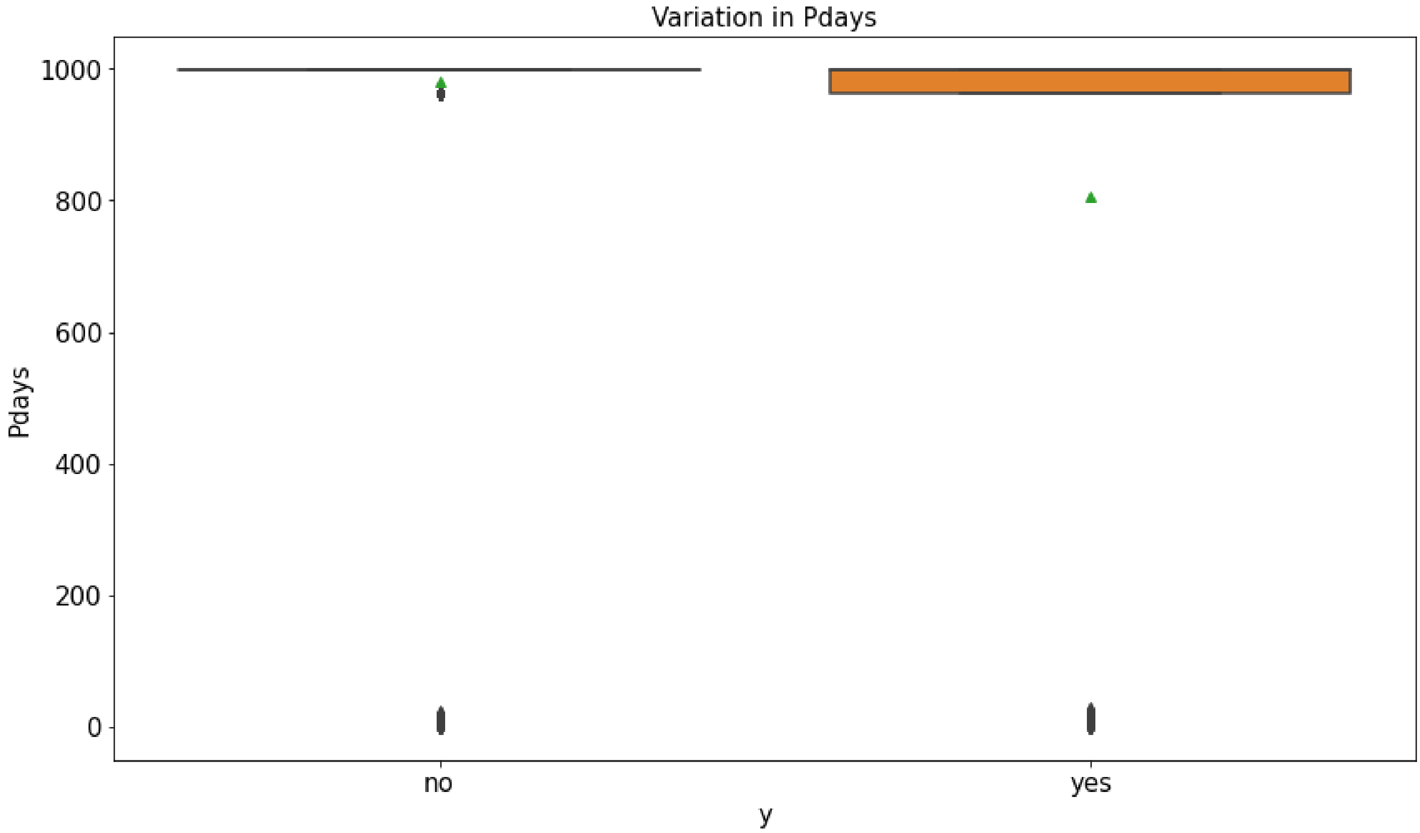




Variation in Pdays

In [28]:

```
fig, bca = plt.subplots()
fig.set_size_inches(14, 8)
bca1 =sns.boxplot( x='y', y= 'pdays', data =bnk, showmeans=True)
bca1.set_xlabel('y', fontsize=15)
bca1.set_ylabel('Pdays', fontsize=15)
bca1.set_title('Variation in Pdays', fontsize=15)
bca1.tick_params(labelsize=15)
```

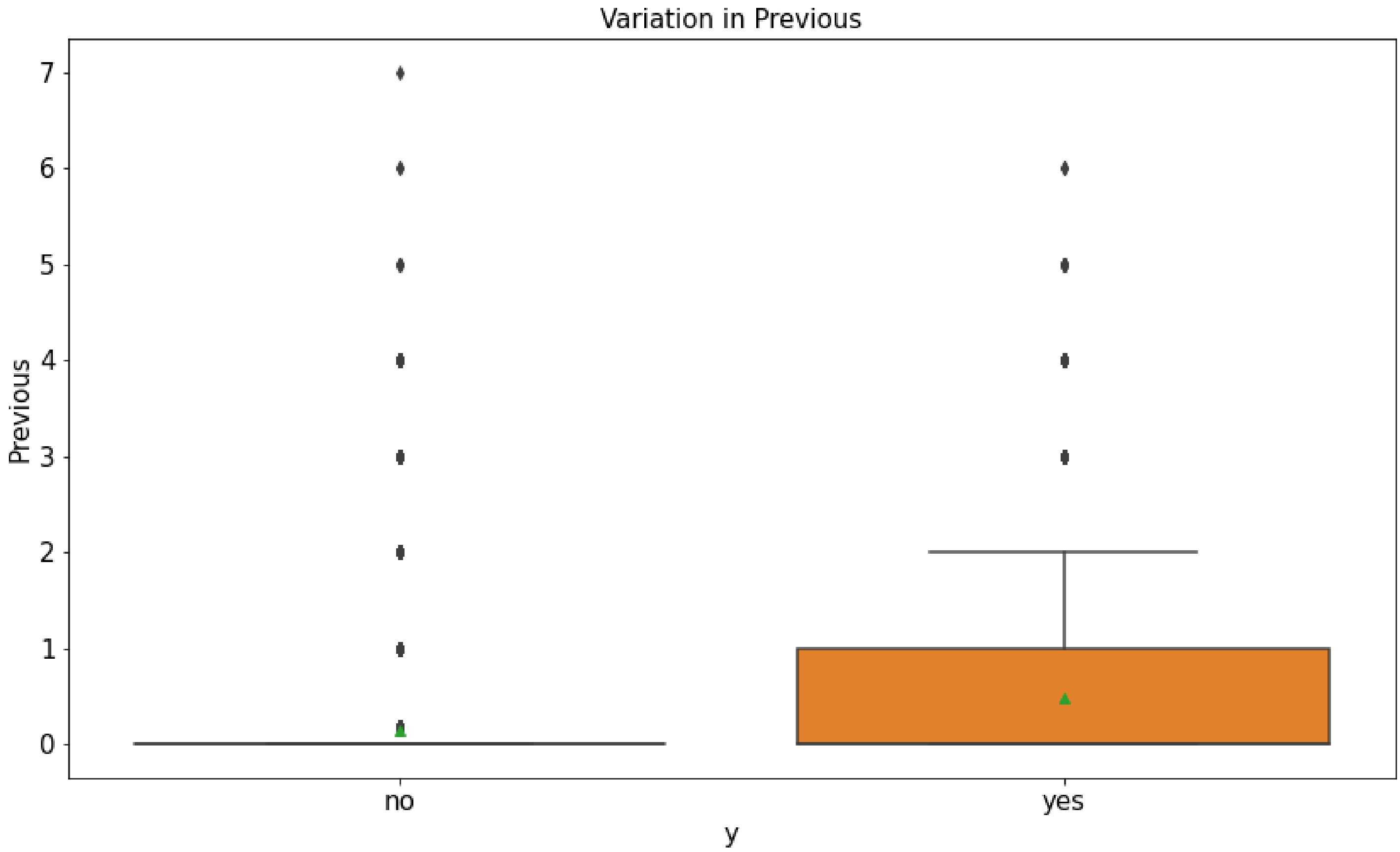


Variation in Previous

In [29]:

```
fig, bca = plt.subplots()
fig.set_size_inches(14, 8)
bca1 =sns.boxplot( x='y', y= 'previous', data =bnk, showmeans=True)
```

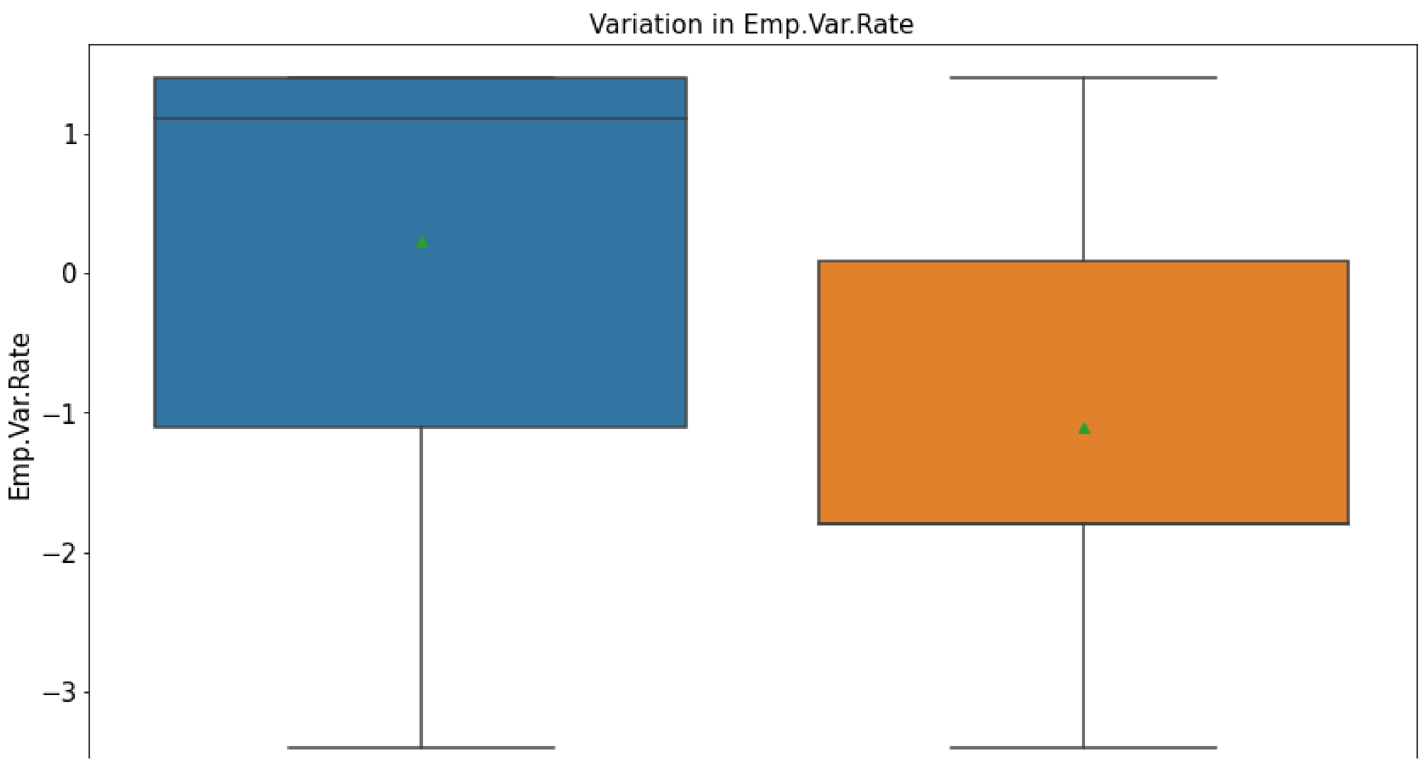
```
bca1.set_xlabel('y', fontsize=15)
bca1.set_ylabel('Previous', fontsize=15)
bca1.set_title('Variation in Previous', fontsize=15)
bca1.tick_params(labelsize=15)
```

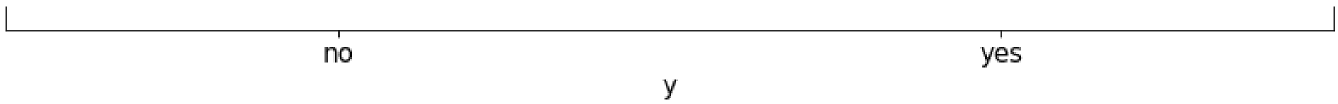


Variation in Emp.Var.Rate

In [30]:

```
fig, bca = plt.subplots()
fig.set_size_inches(14, 8)
bca1 =sns.boxplot( x='y', y= 'emp.var.rate', data =bnk, showmeans=True)
bca1.set_xlabel('y', fontsize=15)
bca1.set_ylabel('Emp.Var.Rate', fontsize=15)
bca1.set_title('Variation in Emp.Var.Rate', fontsize=15)
bca1.tick_params(labelsize=15)
```

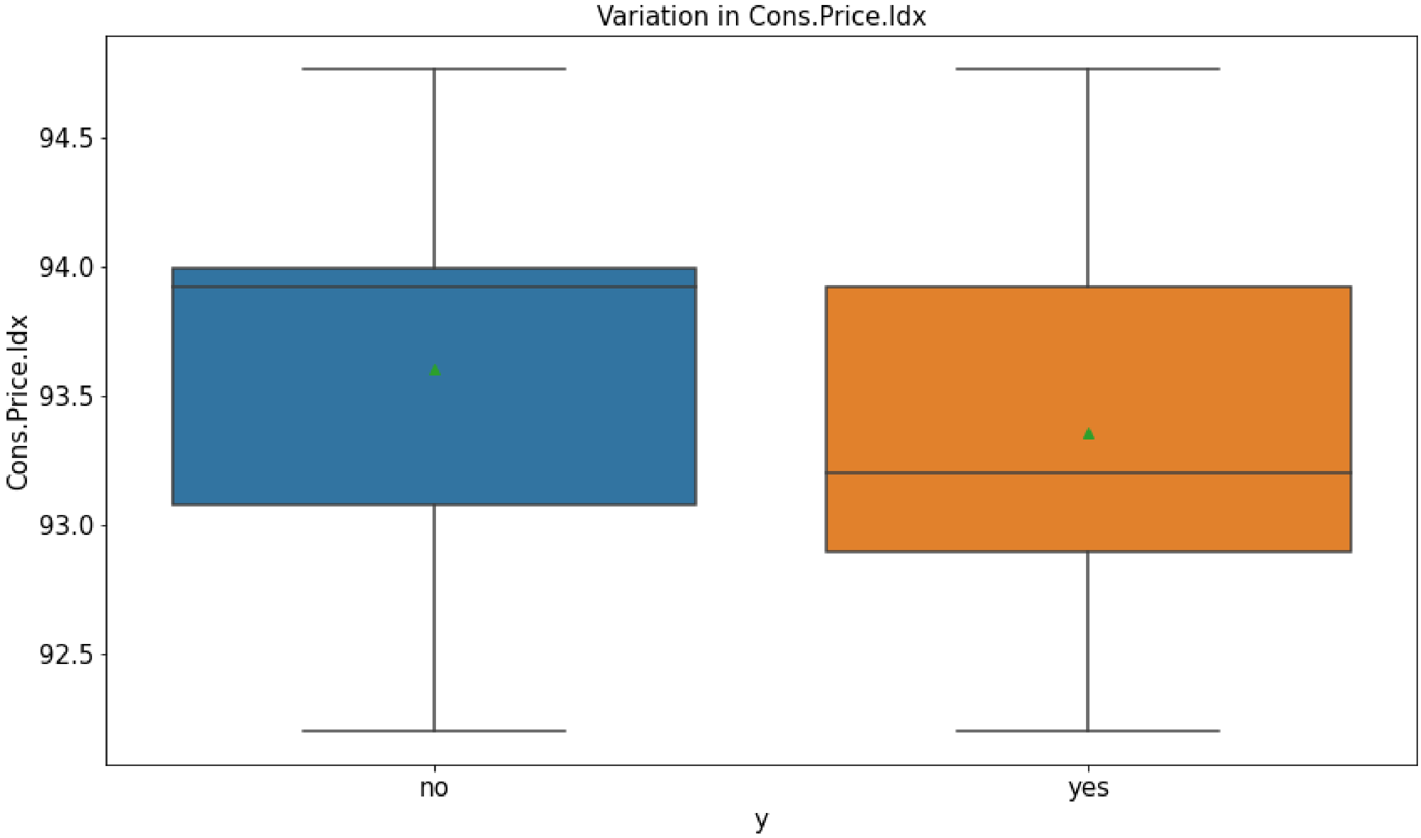




Variation in Cons.Price.Idx

In [31]:

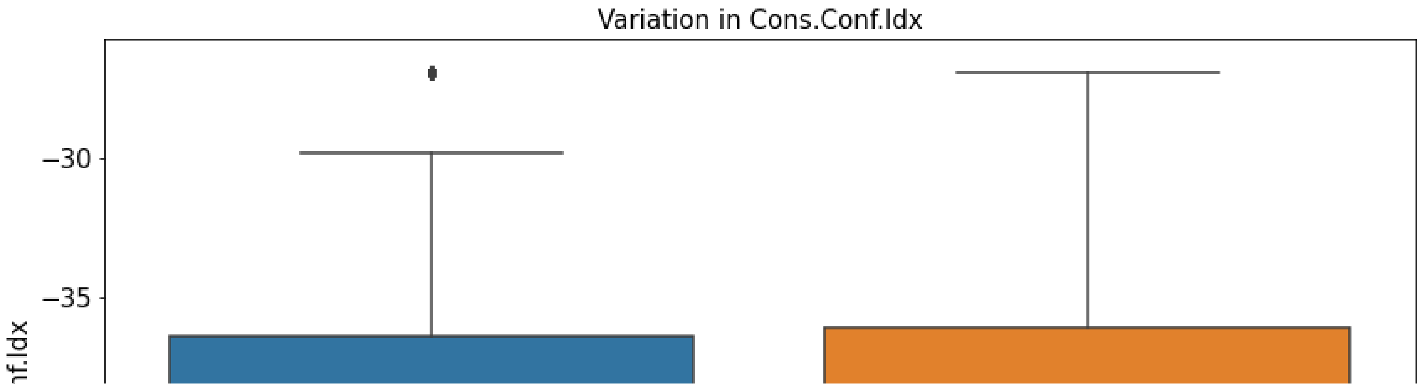
```
fig, bca = plt.subplots()
fig.set_size_inches(14, 8)
bca1 =sns.boxplot( x='y', y= 'cons.price.idx', data =bnk, showmeans=True)
bca1.set_xlabel('y', fontsize=15)
bca1.set_ylabel('Cons.Price.Idx', fontsize=15)
bca1.set_title('Variation in Cons.Price.Idx', fontsize=15)
bca1.tick_params(labelsize=15)
```

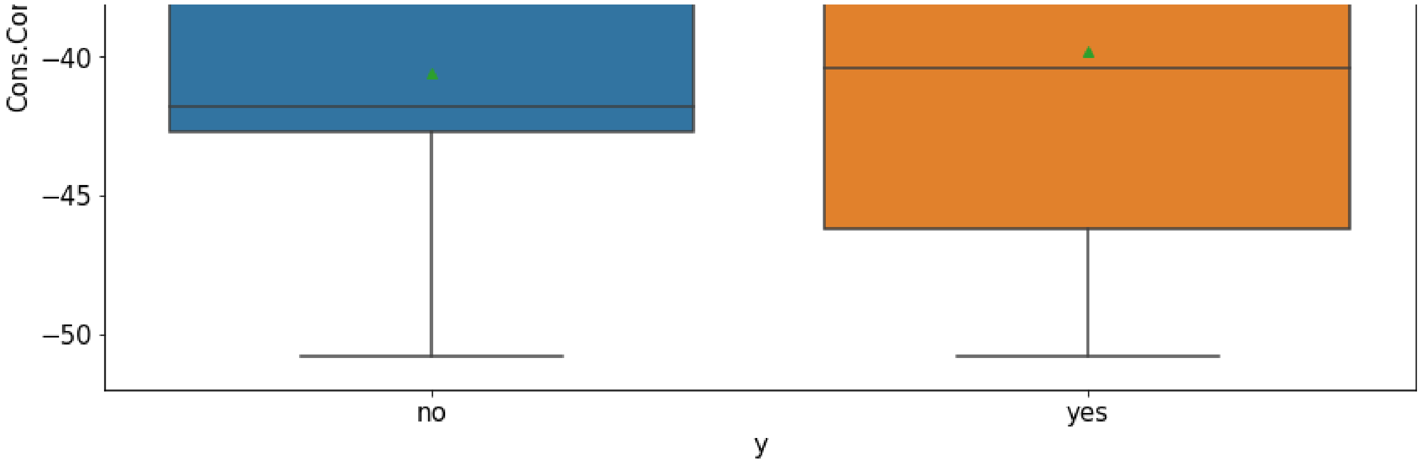


Variation in Cons.Conf.Idx

In [32]:

```
fig, bca = plt.subplots()
fig.set_size_inches(14, 8)
bca1 =sns.boxplot( x='y', y= 'cons.conf.idx', data =bnk, showmeans=True)
bca1.set_xlabel('y', fontsize=15)
bca1.set_ylabel('Cons.Conf.Idx', fontsize=15)
bca1.set_title('Variation in Cons.Conf.Idx', fontsize=15)
bca1.tick_params(labelsize=15)
```

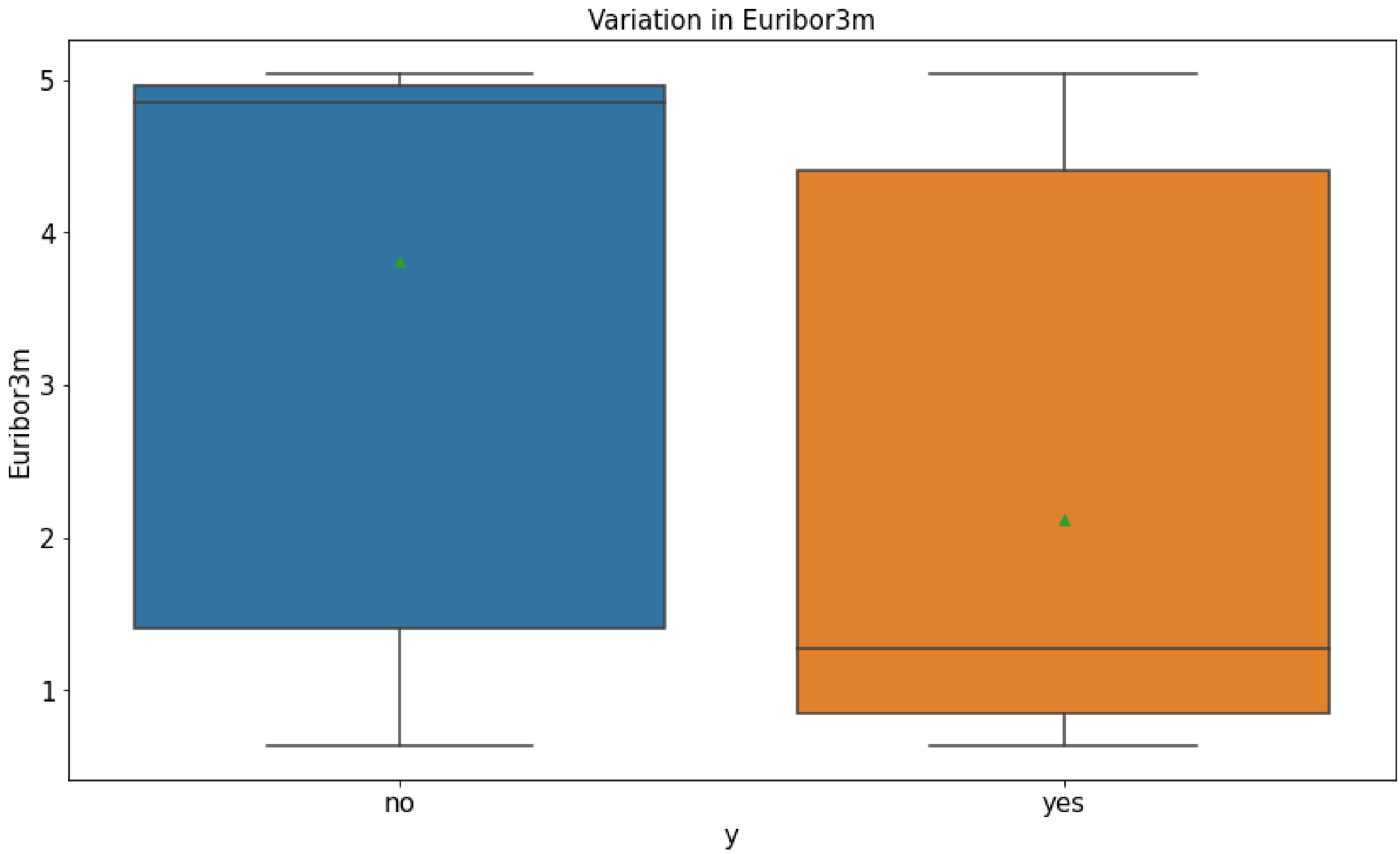




Variation in Euribor3m

In [33]:

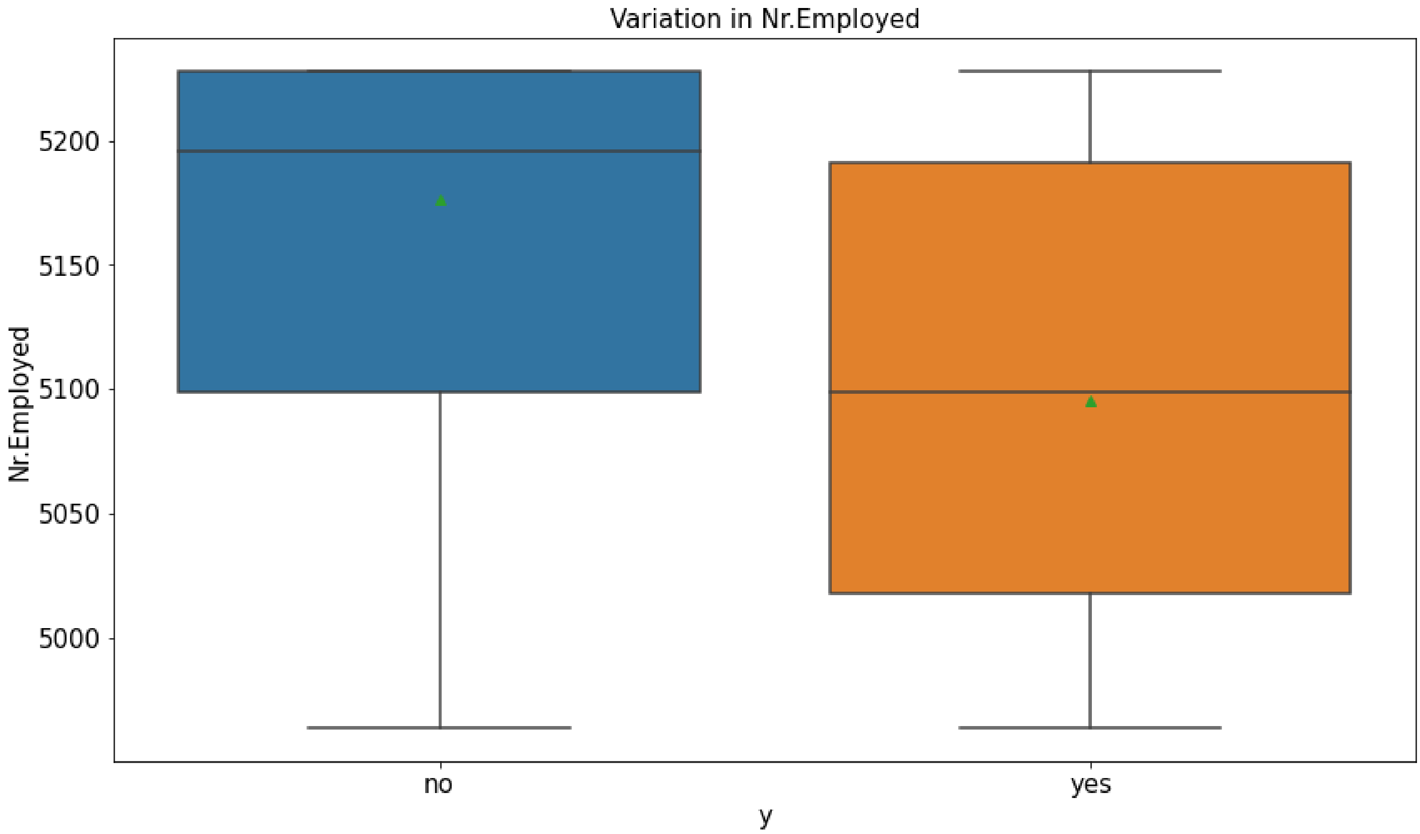
```
fig, bca = plt.subplots()
fig.set_size_inches(14, 8)
bca1 =sns.boxplot( x='y', y= 'euribor3m', data =bnk, showmeans=True)
bca1.set_xlabel('y', fontsize=15)
bca1.set_ylabel('Euribor3m', fontsize=15)
bca1.set_title('Variation in Euribor3m', fontsize=15)
bca1.tick_params(labelsize=15)
```



Variation in Nr.Employed

In [34]:

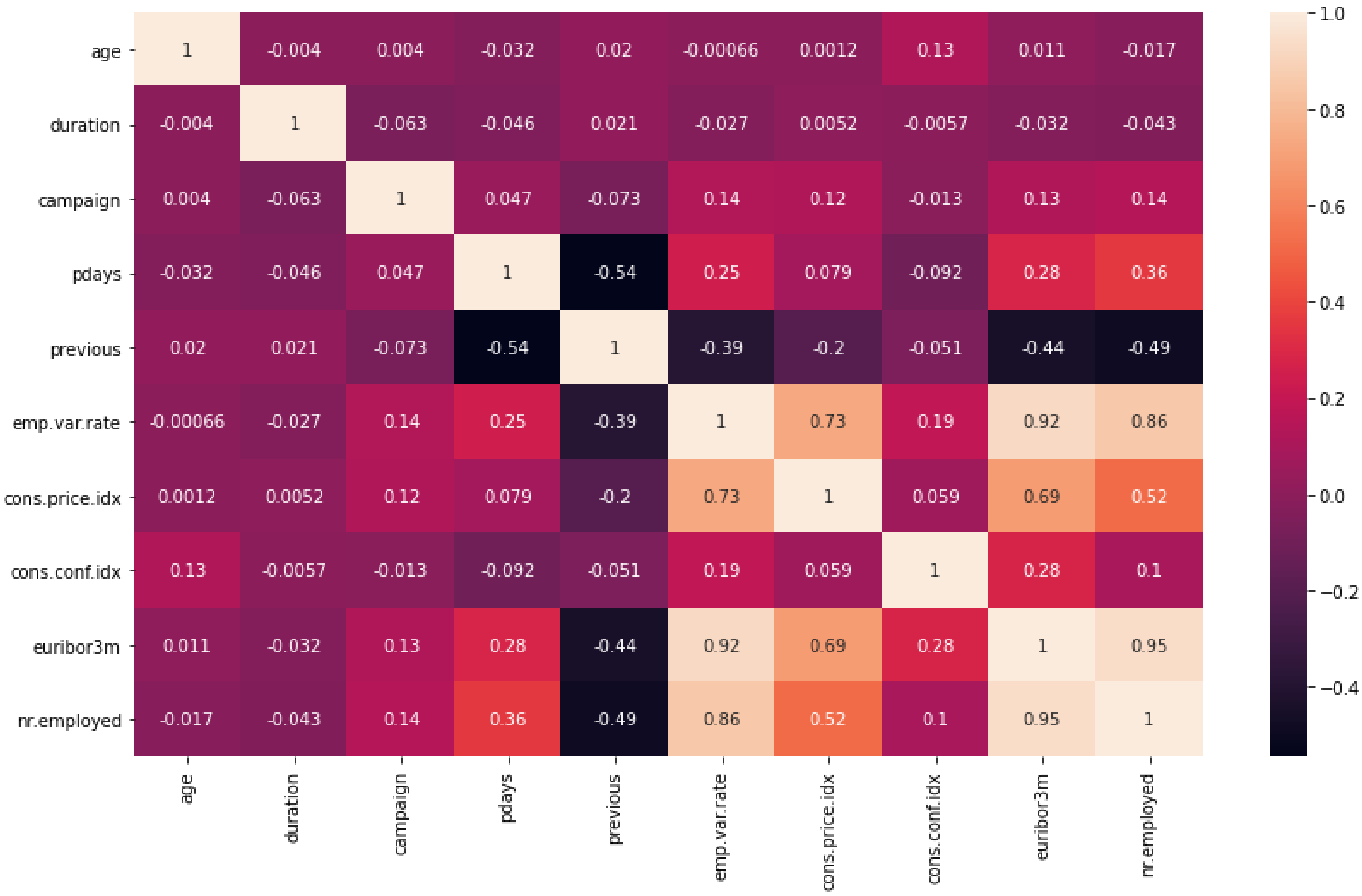
```
fig, bca = plt.subplots()
fig.set_size_inches(14, 8)
bca1 =sns.boxplot( x='y', y= 'nr.employed', data =bnk, showmeans=True)
bca1.set_xlabel('y', fontsize=15)
bca1.set_ylabel('Nr.Employed', fontsize=15)
bca1.set_title('Variation in Nr.Employed', fontsize=15)
bca1.tick_params(labelsize=15)
```



Heatmap depicting correlation between all numerical variables

In [35]:

```
plt.subplots(figsize=(14,8))
sns.heatmap(bnk.corr(), annot=True)
plt.show()
```



Encoding and storing target variable 'y'

We perform one-hot-encoding on target variable 'y' in bnk dataframe as it is categorical data. We store the result in a new variable 'y'.

In [36]:

```
y = pd.get_dummies(bnk['y'], columns = ['y'], prefix = ['y'], drop_first = True)
bnk.head()
```

Out[36]:

	age	job	marital	education	default	housing	loan	contact	month	day_of_week	...	campaign	pdays	pre
0	56	housemaid	married	basic.4y	no	no	no	telephone	may	mon	...	2.570404	999.0	0.1
1	57	services	married	high.school	unknown	no	no	telephone	may	mon	...	1.000000	999.0	0.0
2	37	services	married	high.school	no	yes	no	telephone	may	mon	...	1.000000	999.0	0.0
3	40	admin.	married	basic.6y	no	no	no	telephone	may	mon	...	1.000000	999.0	0.0
4	56	services	married	high.school	no	no	yes	telephone	may	mon	...	1.000000	999.0	0.0

5 rows × 21 columns

Creating a new dataframe 'bank_client'

We are creating the bank_client dataset to store information of bank clients. The attributes included are namely - age, job, marital, education, default, housing, loan

In [37]:

```
bank_client = bnk.iloc[: , 0:7]
bank_client.head()
```

Out[37]:

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

Exploring variables in bank_client

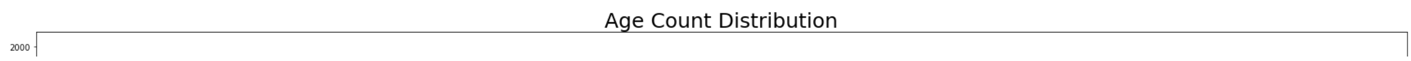
Age Count distribution

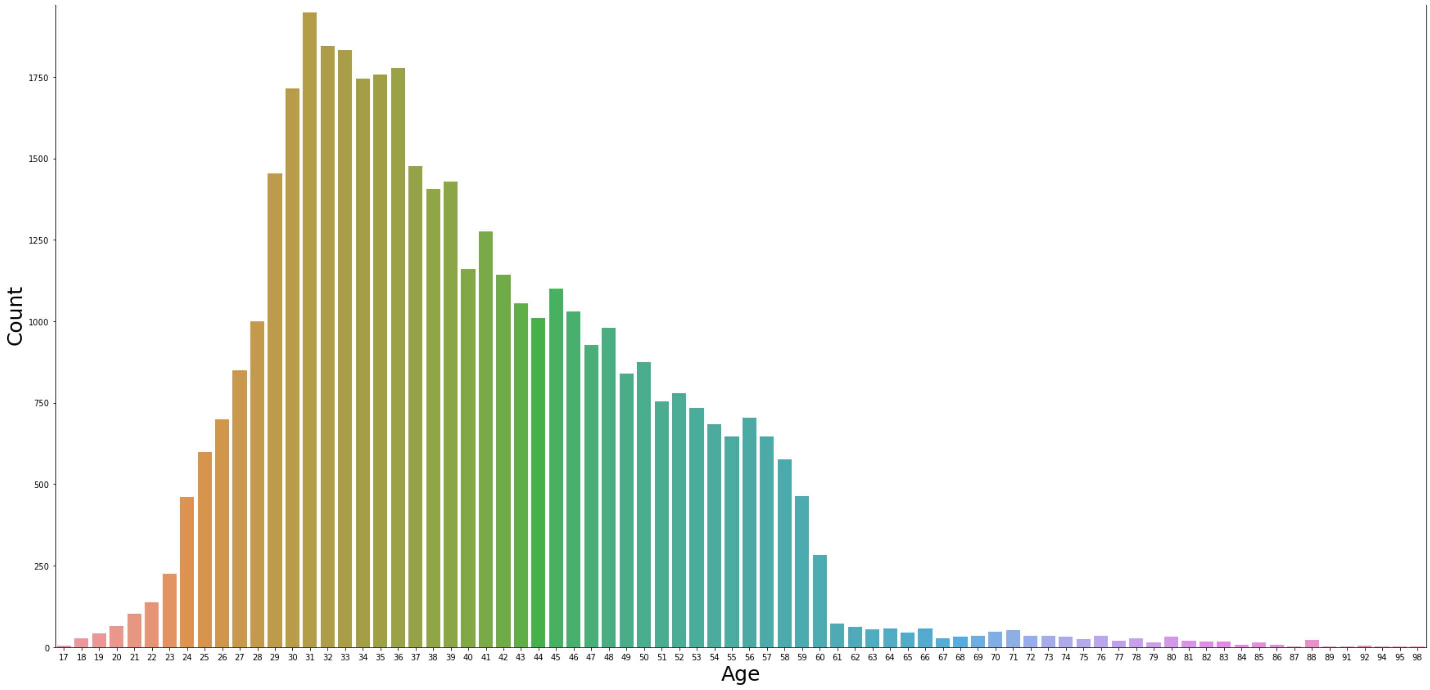
In [38]:

```
fig, bca = plt.subplots()
fig.set_size_inches(30, 15)
sns.countplot(x = 'age', data = bank_client)
bca.set_xlabel('Age', fontsize=25)
bca.set_ylabel('Count', fontsize=25)
bca.set_title('Age Count Distribution', fontsize=25)
```

Out[38]:

```
Text(0.5, 1.0, 'Age Count Distribution')
```

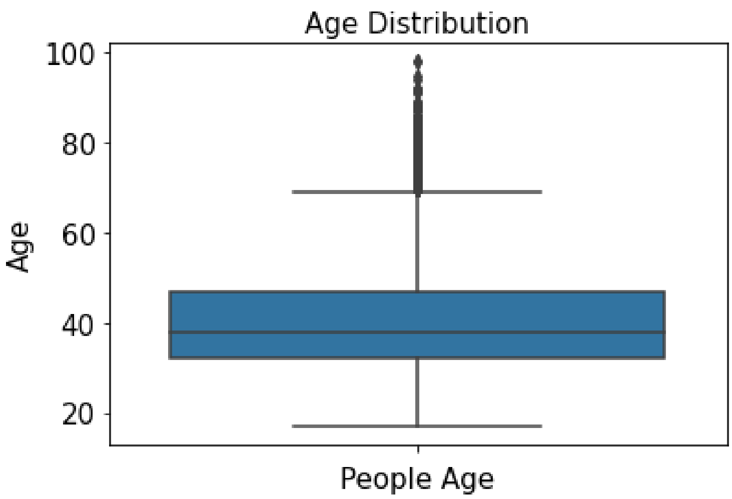




Age Distribution

In [39]:

```
bca1 =sns.boxplot( y=bank_client["age"] )
bca1.set_xlabel('People Age', fontsize=15)
bca1.set_ylabel('Age', fontsize=15)
bca1.set_title('Age Distribution', fontsize=15)
bca1.tick_params(labelsize=15)
```



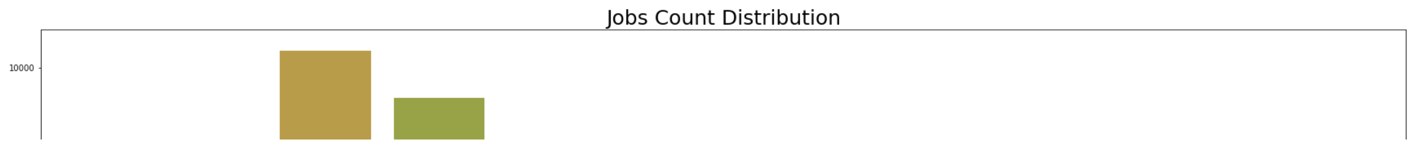
Jobs Count Distribution

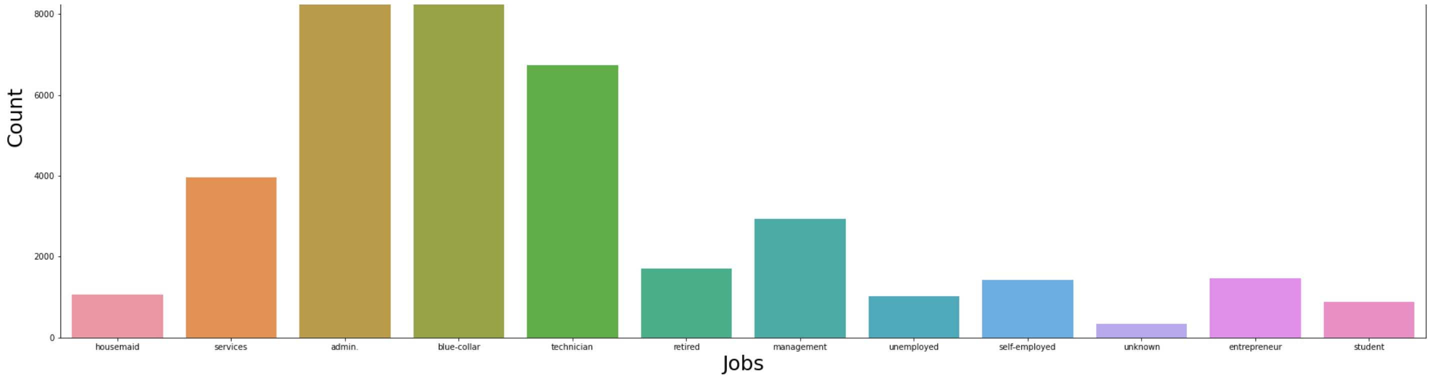
In [40]:

```
fig, bca = plt.subplots()
fig.set_size_inches(30, 10)
sns.countplot(x = 'job', data = bank_client)
bca.set_xlabel('Jobs', fontsize=25)
bca.set_ylabel('Count', fontsize=25)
bca.set_title('Jobs Count Distribution', fontsize=25)
```

Out[40]:

```
Text(0.5, 1.0, 'Jobs Count Distribution')
```





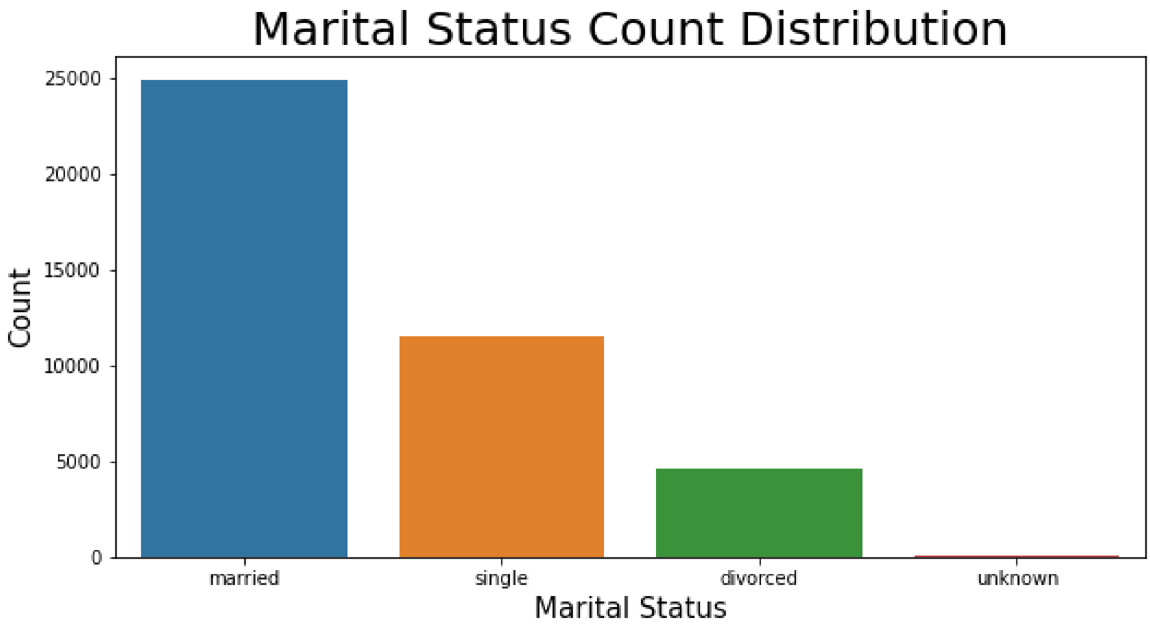
Marital Status Count Distribution

In [41]:

```
fig, bca = plt.subplots()
fig.set_size_inches(10, 5)
sns.countplot(x = 'marital', data = bank_client)
bca.set_xlabel('Marital Status', fontsize=15)
bca.set_ylabel('Count', fontsize=15)
bca.set_title('Marital Status Count Distribution', fontsize=25)
```

Out[41]:

```
Text(0.5, 1.0, 'Marital Status Count Distribution')
```



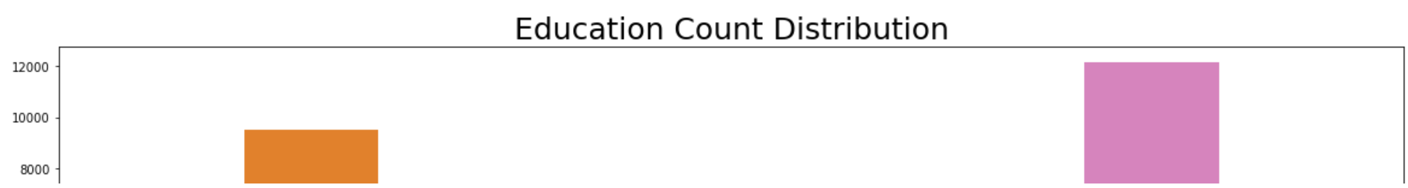
Education Count Distribution

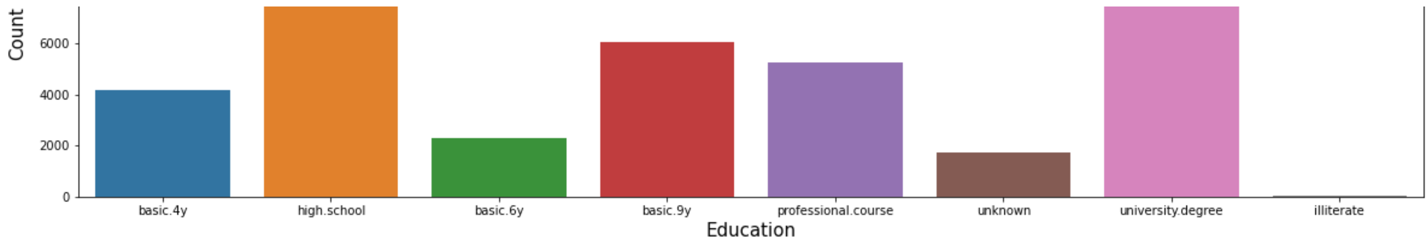
In [42]:

```
fig, bca = plt.subplots()
fig.set_size_inches(20, 5)
sns.countplot(x = 'education', data = bank_client)
bca.set_xlabel('Education', fontsize=15)
bca.set_ylabel('Count', fontsize=15)
bca.set_title('Education Count Distribution', fontsize=25)
```

Out[42]:

```
Text(0.5, 1.0, 'Education Count Distribution')
```





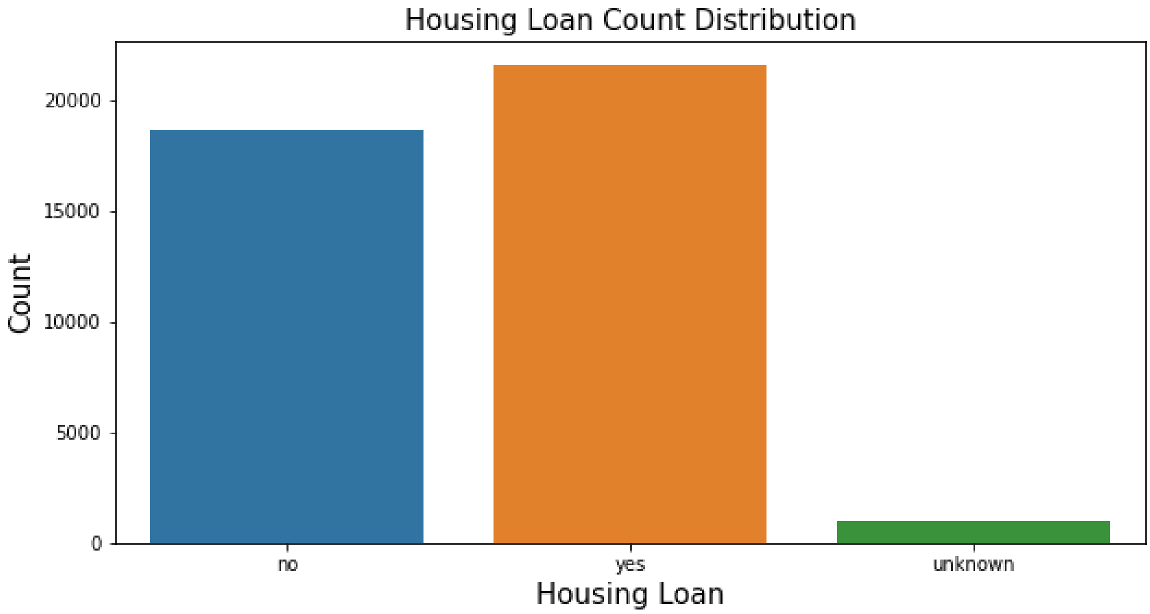
Housing Loan Count Distribution

In [43]:

```
fig, bca = plt.subplots()
fig.set_size_inches(10, 5)
sns.countplot(x = 'housing', data = bank_client)
bca.set_xlabel('Housing Loan', fontsize=15)
bca.set_ylabel('Count', fontsize=15)
bca.set_title('Housing Loan Count Distribution', fontsize=15)
```

Out[43]:

```
Text(0.5, 1.0, 'Housing Loan Count Distribution')
```



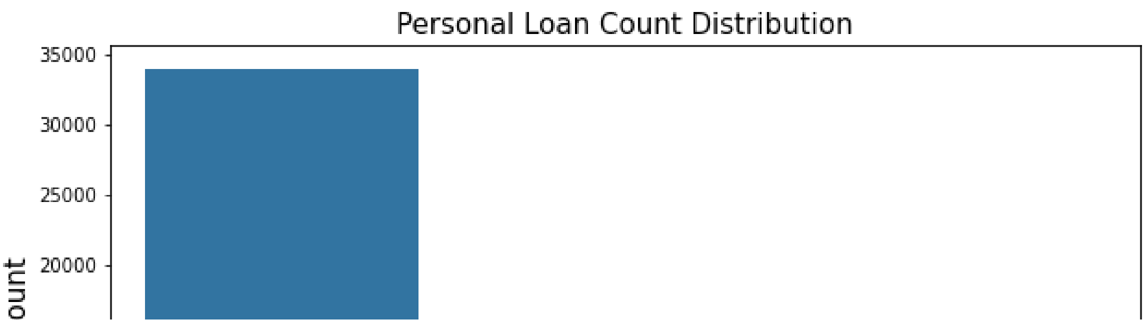
Personal Loan Count Distribution

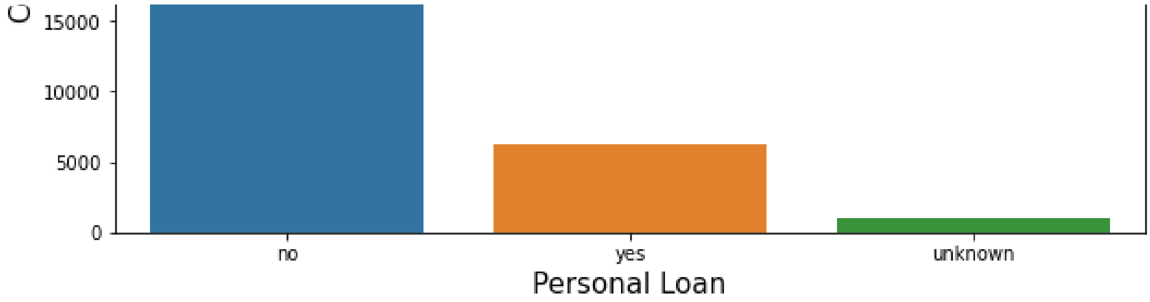
In [44]:

```
fig, bca = plt.subplots()
fig.set_size_inches(10, 5)
sns.countplot(x = 'loan', data = bank_client)
bca.set_xlabel('Personal Loan', fontsize=15)
bca.set_ylabel('Count', fontsize=15)
bca.set_title('Personal Loan Count Distribution', fontsize=15)
```

Out[44]:

```
Text(0.5, 1.0, 'Personal Loan Count Distribution')
```





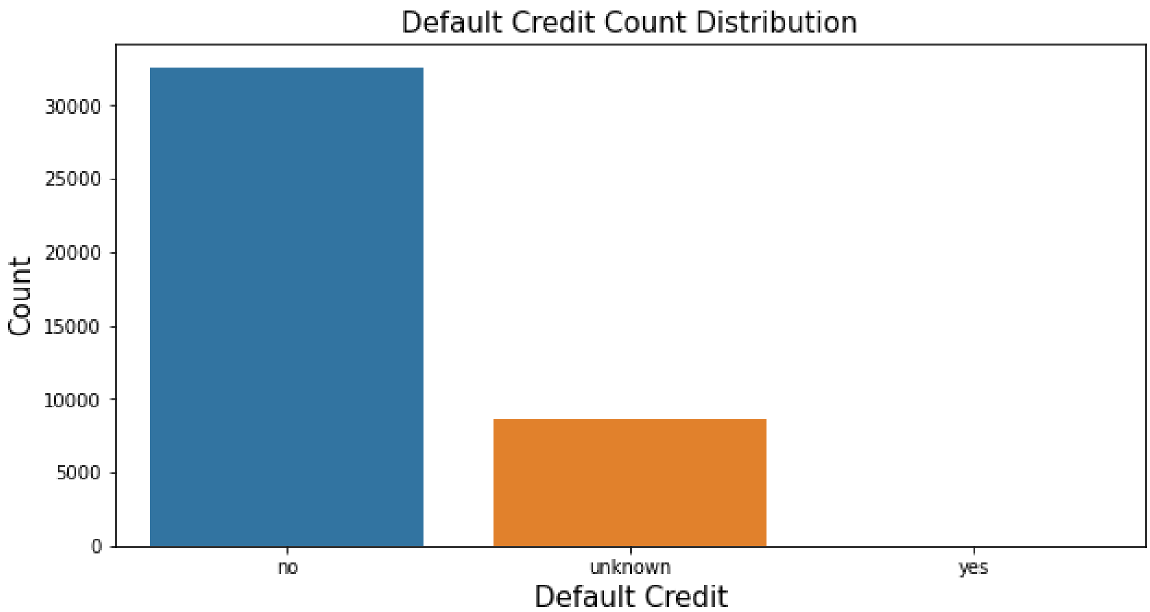
Default Credit Count Distribution

In [45]:

```
fig, bca = plt.subplots()
fig.set_size_inches(10, 5)
sns.countplot(x = 'default', data = bank_client)
bca.set_xlabel('Default Credit', fontsize=15)
bca.set_ylabel('Count', fontsize=15)
bca.set_title('Default Credit Count Distribution', fontsize=15)
```

Out[45]:

```
Text(0.5, 1.0, 'Default Credit Count Distribution')
```



Treating categorical variables

In [46]:

```
bank_client['job'].unique()
```

Out[46]:

```
array(['housemaid', 'services', 'admin.', 'blue-collar', 'technician',
       'retired', 'management', 'unemployed', 'self-employed', 'unknown',
       'entrepreneur', 'student'], dtype=object)
```

In [47]:

```
dummy = pd.get_dummies(bank_client['job'],prefix = 'Job_N')
print(dummy)
```

```
       Job_N_admin.  Job_N_blue-collar  Job_N_entrepreneur  Job_N_housemaid  \
0                 0                  0                   0                1
1                 0                  0                   0                0
2                 0                  0                   0                0
3                 1                  0                   0                0
4                 0                  0                   0                0
```

```
...            ...               ...                  ...          ...
41183            0                 0                    0            0
41184            0                 1                    0            0
41185            0                 0                    0            0
41186            0                 0                    0            0
41187            0                 0                    0            0

       Job_N_management  Job_N_retired  Job_N_self-employed  Job_N_services  \
0                     0              0                    0               0
1                     0              0                    0               1
2                     0              0                    0               1
3                     0              0                    0               0
4                     0              0                    0               1
...                 ...            ...                  ...             ...
41183                 0              1                    0               0
41184                 0              0                    0               0
41185                 0              1                    0               0
41186                 0              0                    0               0
41187                 0              1                    0               0

       Job_N_student  Job_N_technician  Job_N_unemployed  Job_N_unknown
0                  0                 0                 0              0
1                  0                 0                 0              0
2                  0                 0                 0              0
3                  0                 0                 0              0
4                  0                 0                 0              0
...              ...               ...               ...            ...
41183              0                 0                 0              0
41184              0                 0                 0              0
41185              0                 0                 0              0
41186              0                 1                 0              0
41187              0                 0                 0              0

[41164 rows x 12 columns]
```

In [48]:

```
bank_client = bank_client.join(dummy)
bank_client
```

Out[48]:

	age	job	marital	education	default	housing	loan	Job_N_admin.	Job_N_blue-collar	Job_N_entreprene
0	56	housemaid	married	basic.4y	no	no	no	0	0	
1	57	services	married	high.school	unknown	no	no	0	0	
2	37	services	married	high.school	no	yes	no	0	0	
3	40	admin.	married	basic.6y	no	no	no	1	0	
4	56	services	married	high.school	no	no	yes	0	0	
...	...	...	...	...	...	...	...	...	...	
41183	73	retired	married	professional.course	no	yes	no	0	0	
41184	46	blue-collar	married	professional.course	no	no	no	0	1	
41185	56	retired	married	university.degree	no	yes	no	0	0	
41186	44	technician	married	professional.course	no	no	no	0	0	
41187	74	retired	married	professional.course	no	yes	no	0	0	

41164 rows × 19 columns

In [49]:

```
bank_client['marital'].unique()
```

Out[49]:

```
array(['married', 'single', 'divorced', 'unknown'], dtype=object)
```

In [50]:

```
lc=LabelEncoder()
bank_client['Marital_N']=lc.fit_transform(bank_client['marital'])
bank_client
```

Out[50]:

	age	job	marital	education	default	housing	loan	Job_N_admin.	Job_N_blue-collar	Job_N_entreprene
0	56	housemaid	married	basic.4y	no	no	no	0	0	
1	57	services	married	high.school	unknown	no	no	0	0	
2	37	services	married	high.school	no	yes	no	0	0	
3	40	admin.	married	basic.6y	no	no	no	1	0	
4	56	services	married	high.school	no	no	yes	0	0	
...	...	...	...	...	...	...	...	...	...	
41183	73	retired	married	professional.course	no	yes	no	0	0	
41184	46	blue-collar	married	professional.course	no	no	no	0	1	
41185	56	retired	married	university.degree	no	yes	no	0	0	
41186	44	technician	married	professional.course	no	no	no	0	0	
41187	74	retired	married	professional.course	no	yes	no	0	0	

41164 rows × 20 columns

In [51]:

```
bank_client['education'].unique()
```

Out[51]:

```
array(['basic.4y', 'high.school', 'basic.6y', 'basic.9y',
       'professional.course', 'unknown', 'university.degree',
       'illiterate'], dtype=object)
```

In [52]:

```
bank_client=pd.concat((bank_client,pd.get_dummies(bank_client['education'])),axis=1)
```

In [53]:

```
bank_client['default'].unique()
```

Out[53]:

```
array(['no', 'unknown', 'yes'], dtype=object)
```

In [54]:

```
bank_client['housing'].unique()
```

Out[54]:

```
array(['no', 'yes', 'unknown'], dtype=object)
```

In [55]:

```
bank_client['loan'].unique()
```

Out[55]:

```
array(['no', 'yes', 'unknown'], dtype=object)
```

In [56]:

```
lc=LabelEncoder()
bank_client['Default_N']=lc.fit_transform(bank_client['default'])
```

In [57]:

```
lc=LabelEncoder()
bank_client['Housing_N']=lc.fit_transform(bank_client['housing'])
```

In [58]:

```
lc=LabelEncoder()
bank_client['Loan_N']=lc.fit_transform(bank_client['loan'])
```

In [59]:

```
bank_client.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 41164 entries, 0 to 41187
Data columns (total 31 columns):
 #   Column                Non-Null Count  Dtype 
---  ------                --------------  ----- 
 0   age                   41164 non-null  int64 
 1   job                   41164 non-null  object
 2   marital               41164 non-null  object
 3   education             41164 non-null  object
 4   default               41164 non-null  object
 5   housing               41164 non-null  object
 6   loan                  41164 non-null  object
 7   Job_N_admin.          41164 non-null  uint8 
 8   Job_N_blue-collar     41164 non-null  uint8 
 9   Job_N_entrepreneur    41164 non-null  uint8 
 10  Job_N_housemaid       41164 non-null  uint8 
 11  Job_N_management      41164 non-null  uint8 
 12  Job_N_retired         41164 non-null  uint8 
 13  Job_N_self-employed   41164 non-null  uint8 
 14  Job_N_services        41164 non-null  uint8 
 15  Job_N_student         41164 non-null  uint8 
 16  Job_N_technician      41164 non-null  uint8 
 17  Job_N_unemployed      41164 non-null  uint8 
 18  Job_N_unknown         41164 non-null  uint8 
 19  Marital_N             41164 non-null  int32 
 20  basic.4y              41164 non-null  uint8 
 21  basic.6y              41164 non-null  uint8 
 22  basic.9y              41164 non-null  uint8 
 23  high.school           41164 non-null  uint8 
 24  illiterate            41164 non-null  uint8 
 25  professional.course   41164 non-null  uint8 
 26  university.degree     41164 non-null  uint8 
 27  unknown               41164 non-null  uint8 
 28  Default_N             41164 non-null  int32 
 29  Housing_N             41164 non-null  int32 
 30  Loan_N                41164 non-null  int32 
dtypes: int32(4), int64(1), object(6), uint8(20)
memory usage: 5.2+ MB
```

In [60]:

```
bank_client = bank_client.drop(['job', 'marital', 'education', 'housing', 'default', 'lo
an'], axis = 1)
```

In [61]:

```
bank_client.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 41164 entries, 0 to 41187
Data columns (total 25 columns):
 #   Column                Non-Null Count  Dtype 
---  ------                --------------  ----- 
```

```
---  ------              --------------  -----
 0   age                 41164 non-null  int64
 1   Job_N_admin.        41164 non-null  uint8
 2   Job_N_blue-collar   41164 non-null  uint8
 3   Job_N_entrepreneur  41164 non-null  uint8
 4   Job_N_housemaid     41164 non-null  uint8
 5   Job_N_management    41164 non-null  uint8
 6   Job_N_retired       41164 non-null  uint8
 7   Job_N_self-employed 41164 non-null  uint8
 8   Job_N_services      41164 non-null  uint8
 9   Job_N_student       41164 non-null  uint8
 10  Job_N_technician    41164 non-null  uint8
 11  Job_N_unemployed    41164 non-null  uint8
 12  Job_N_unknown       41164 non-null  uint8
 13  Marital_N           41164 non-null  int32
 14  basic.4y            41164 non-null  uint8
 15  basic.6y            41164 non-null  uint8
 16  basic.9y            41164 non-null  uint8
 17  high.school         41164 non-null  uint8
 18  illiterate          41164 non-null  uint8
 19  professional.course 41164 non-null  uint8
 20  university.degree   41164 non-null  uint8
 21  unknown             41164 non-null  uint8
 22  Default_N           41164 non-null  int32
 23  Housing_N           41164 non-null  int32
 24  Loan_N              41164 non-null  int32
dtypes: int32(4), int64(1), uint8(20)
memory usage: 3.3 MB
```

In [62]:

```
bank_client['age'] = bank_client['age'].astype(int)
```

In [63]:

```
bank_client.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 41164 entries, 0 to 41187
Data columns (total 25 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   age                 41164 non-null  int32
 1   Job_N_admin.        41164 non-null  uint8
 2   Job_N_blue-collar   41164 non-null  uint8
 3   Job_N_entrepreneur  41164 non-null  uint8
 4   Job_N_housemaid     41164 non-null  uint8
 5   Job_N_management    41164 non-null  uint8
 6   Job_N_retired       41164 non-null  uint8
 7   Job_N_self-employed 41164 non-null  uint8
 8   Job_N_services      41164 non-null  uint8
 9   Job_N_student       41164 non-null  uint8
 10  Job_N_technician    41164 non-null  uint8
 11  Job_N_unemployed    41164 non-null  uint8
 12  Job_N_unknown       41164 non-null  uint8
 13  Marital_N           41164 non-null  int32
 14  basic.4y            41164 non-null  uint8
 15  basic.6y            41164 non-null  uint8
 16  basic.9y            41164 non-null  uint8
 17  high.school         41164 non-null  uint8
 18  illiterate          41164 non-null  uint8
 19  professional.course 41164 non-null  uint8
 20  university.degree   41164 non-null  uint8
 21  unknown             41164 non-null  uint8
 22  Default_N           41164 non-null  int32
 23  Housing_N           41164 non-null  int32
 24  Loan_N              41164 non-null  int32
dtypes: int32(5), uint8(20)
memory usage: 3.1 MB
```

In [64]:

```python
def age(dataframe):
    dataframe.loc[dataframe['age'] <= 32, 'age'] = 1
    dataframe.loc[(dataframe['age'] > 32) & (dataframe['age'] <= 47), 'age'] = 2
    dataframe.loc[(dataframe['age'] > 47) & (dataframe['age'] <= 70), 'age'] = 3
    dataframe.loc[(dataframe['age'] > 70) & (dataframe['age'] <= 98), 'age'] = 4

    return dataframe

age(bank_client) ;
```

In [65]:

```python
bank_client.head()
```

Out[65]:

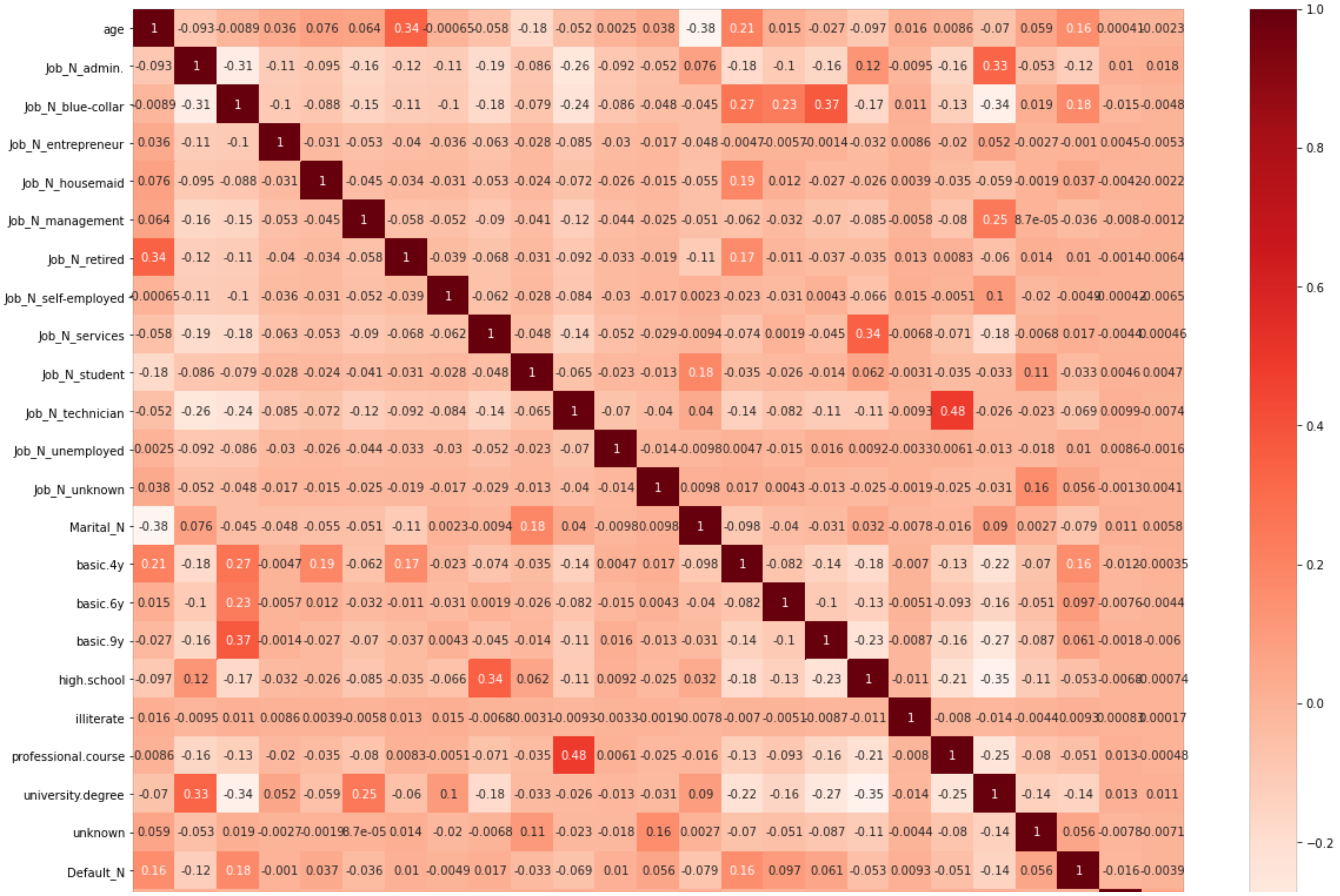
	age	Job_N_admin.	Job_N_blue-collar	Job_N_entrepreneur	Job_N_housemaid	Job_N_management	Job_N_retired	Job_N_self-employed
0	3	0	0	0	1	0	0	0
1	3	0	0	0	0	0	0	0
2	2	0	0	0	0	0	0	0
3	2	1	0	0	0	0	0	0
4	3	0	0	0	0	0	0	0

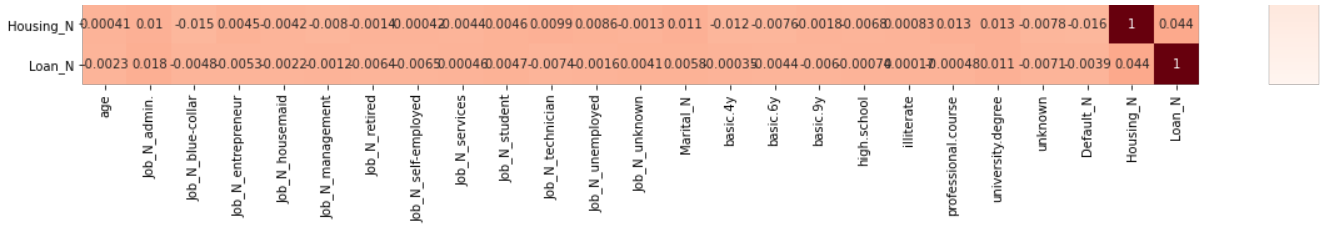
5 rows × 25 columns

Correlation between variables in bank_client dataset

In [66]:

```python
plt.figure(figsize=(20,15))
cor = bank_client.corr()
sns.heatmap(cor, annot=True, cmap=plt.cm.Reds)
plt.show()
```





Creating new dataset 'other_attr'

We are now creating a dataset to store the attributes - contact, month, day_of_week and duration.

In [67]:

```
other_attr = bnk.iloc[: , 7:11]
other_attr.head()
```

Out[67]:

	contact	month	day_of_week	duration
0	telephone	may	mon	261.0
1	telephone	may	mon	149.0
2	telephone	may	mon	226.0
3	telephone	may	mon	151.0
4	telephone	may	mon	307.0

Check for null values

In [68]:

```
other_attr.isnull().sum()
```

Out[68]:

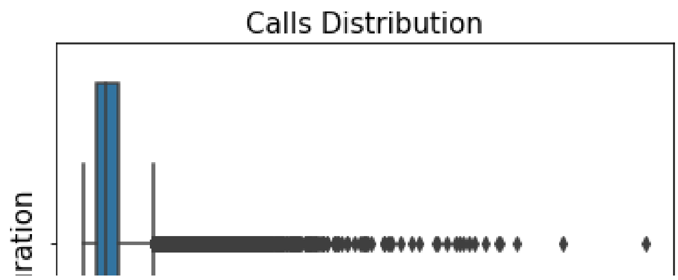
```
contact        0
month          0
day_of_week    0
duration       0
dtype: int64
```

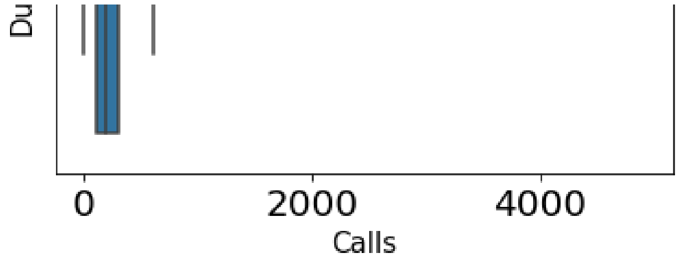
Exploring the attributes in 'other_attr'

Calls duration

In [69]:

```
dur = sns.boxplot(x = 'duration', data = other_attr)
dur.set_xlabel('Calls', fontsize=15)
dur.set_ylabel('Duration', fontsize=15)
dur.set_title('Calls Distribution', fontsize=15)
dur.tick_params(labelsize=20)
```





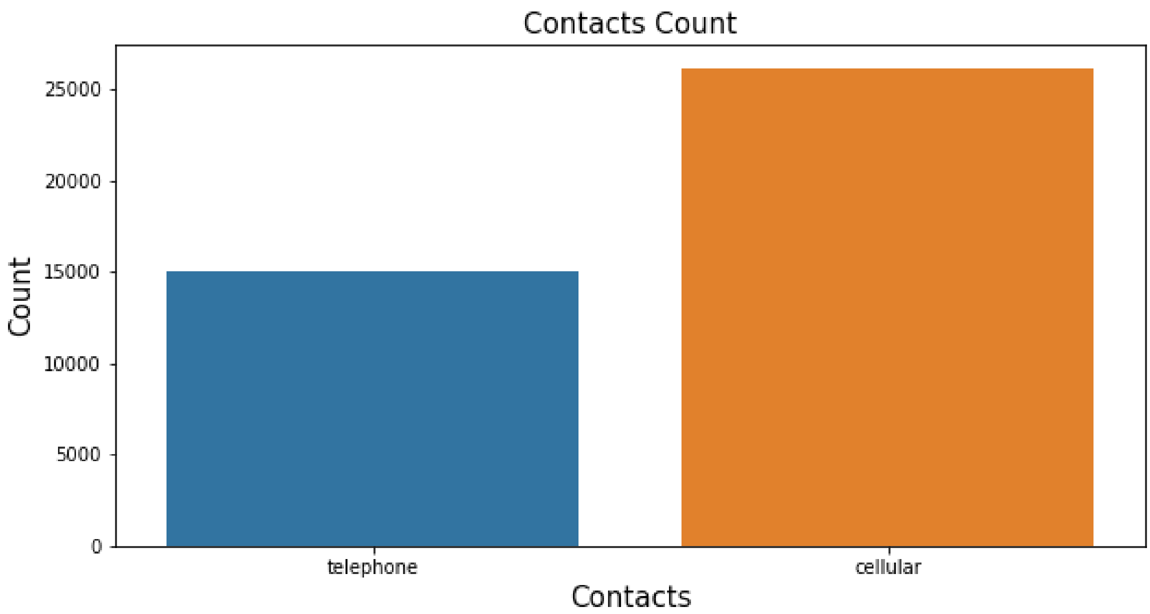
Contacts Count

In [70]:

```
fig, bca = plt.subplots()
fig.set_size_inches(10, 5)
sns.countplot(x = 'contact', data = other_attr)
bca.set_xlabel('Contacts', fontsize=15)
bca.set_ylabel('Count', fontsize=15)
bca.set_title('Contacts Count', fontsize=15)
```

Out[70]:

```
Text(0.5, 1.0, 'Contacts Count')
```



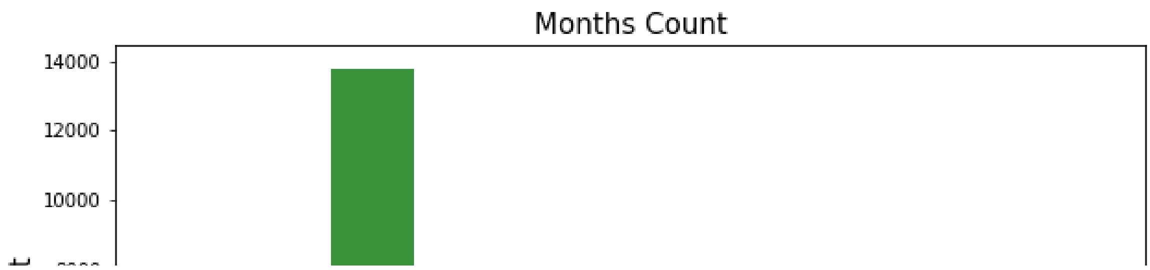
Months Count

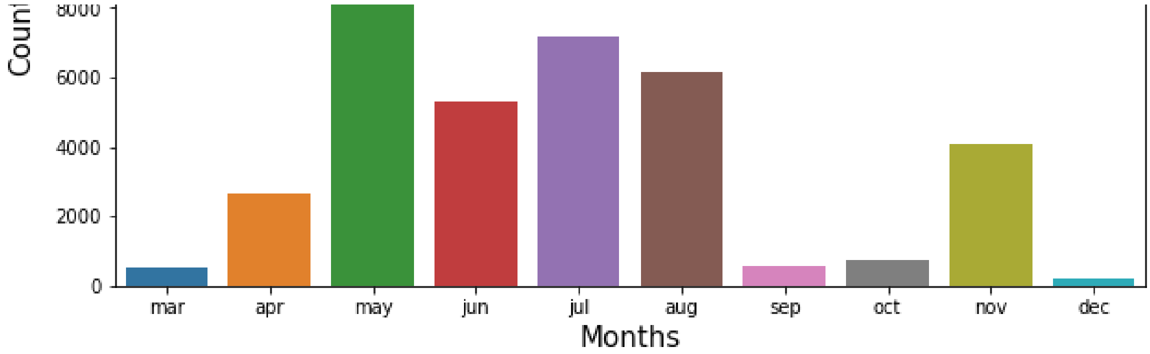
In [71]:

```
fig, bca = plt.subplots()
fig.set_size_inches(10, 5)
sns.countplot(x = 'month', data = other_attr, order = ['mar', 'apr', 'may', 'jun', 'jul'
, 'aug', 'sep', 'oct', 'nov', 'dec'])
bca.set_xlabel('Months', fontsize=15)
bca.set_ylabel('Count', fontsize=15)
bca.set_title('Months Count', fontsize=15)
```

Out[71]:

```
Text(0.5, 1.0, 'Months Count')
```





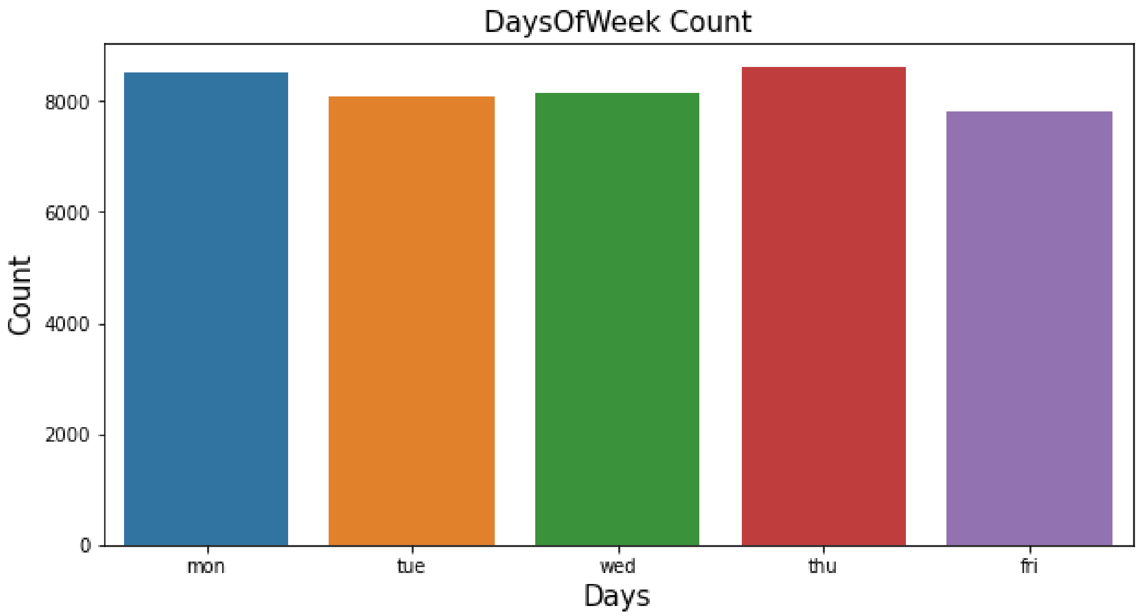
Days Of Week Count

In [72]:

```
fig, bca = plt.subplots()
fig.set_size_inches(10, 5)
sns.countplot(x = 'day_of_week', data = other_attr)
bca.set_xlabel('Days', fontsize=15)
bca.set_ylabel('Count', fontsize=15)
bca.set_title('DaysOfWeek Count', fontsize=15)
```

Out[72]:

```
Text(0.5, 1.0, 'DaysOfWeek Count')
```



Treating categorical variables

In [73]:

```
other_attr.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 41164 entries, 0 to 41187
Data columns (total 4 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   contact      41164 non-null  object 
 1   month        41164 non-null  object 
 2   day_of_week  41164 non-null  object 
 3   duration     41164 non-null  float64
dtypes: float64(1), object(3)
memory usage: 2.8+ MB
```

In [74]:

```
other_attr['contact'].unique()
```

Out[74]:

```
array(['telephone', 'cellular'], dtype=object)
```

In [75]:

```
other_attr['contact'] = other_attr['contact'].map({'telephone':1, 'cellular':2}).astype(
int)
```

In [76]:

```
other_attr['month'].unique()
```

Out[76]:

```
array(['may', 'jun', 'jul', 'aug', 'oct', 'nov', 'dec', 'mar', 'apr',
       'sep'], dtype=object)
```

In [77]:

```
other_attr["month"] = other_attr["month"].str.capitalize()
```

In [78]:

```
other_attr["month"] = pd.to_datetime(other_attr.month, format='%b', errors='coerce').dt.
month
other_attr = other_attr.sort_values(by="month")
```

In [79]:

```
other_attr['month'].unique()
```

Out[79]:

```
array([ 3,  4,  5,  6,  7,  8,  9, 10, 11, 12], dtype=int64)
```

In [80]:

```
other_attr['day_of_week'].unique()
```

Out[80]:

```
array(['tue', 'mon', 'thu', 'wed', 'fri'], dtype=object)
```

In [81]:

```
lc=LabelEncoder()
other_attr['day_of_week']=lc.fit_transform(other_attr['day_of_week'])
```

In [82]:

```
other_attr['day_of_week'].unique()
```

Out[82]:

```
array([3, 1, 2, 4, 0])
```

In [83]:

```
other_attr['duration'] = other_attr['duration'].astype(int)
```

Creating new dataset 'cont_attr'

Here we are creating a new dataset for the social and economic context attributes, which are - emp.var.rate, cons.price.idx, cons.conf.idx, euribor3m, nr.employed.

In [84]:

```
cont_attr= bnk.loc[: , ['emp.var.rate', 'cons.price.idx', 'cons.conf.idx', 'euribor3m',
```

```
'nr.employed']]
cont_attr.head()
```

Out[84]:

	emp.var.rate	cons.price.idx	cons.conf.idx	euribor3m	nr.employed
0	1.100000	93.994	-36.4	4.857	5191.0
1	0.079252	93.994	-36.4	4.857	5191.0
2	1.100000	93.994	-36.4	4.857	5191.0
3	1.100000	93.994	-36.4	4.857	5191.0
4	1.100000	93.994	-36.4	4.857	5191.0

Creating a dataset 'remain_attr'

This dataset contains all the remaining attributes (y excluded). These are - campaign, pdays, previous, poutcome

In [85]:

```
remain_attr = bnk.loc[: , ['campaign', 'pdays','previous', 'poutcome']]
remain_attr.head()
```

Out[85]:

	campaign	pdays	previous	poutcome
0	2.570404	999.0	0.172596	nonexistent
1	1.000000	999.0	0.000000	nonexistent
2	1.000000	999.0	0.000000	nonexistent
3	1.000000	999.0	0.000000	nonexistent
4	1.000000	999.0	0.000000	nonexistent

Treating the categorical attributes

In [86]:

```
remain_attr['poutcome'].unique()
```

Out[86]:

```
array(['nonexistent', 'failure', 'success'], dtype=object)
```

In [87]:

```
remain_attr['poutcome'] = remain_attr['poutcome'].map({'nonexistent':1, 'failure':2, 'su
ccess':3}).astype(int)
```

Creating the 'final_bank' dataset

We will now merge/concat all the above datasets that we created and curated as per need into one final dataset for our analysis.

In [88]:

```
final_bank= pd.concat([bank_client, other_attr, cont_attr, remain_attr], axis = 1)
```

Exploring the dataset

In [89]:

```
final_bank.shape
```

Out[89]:

```
(41164, 38)
```

In [90]:

```
final_bank.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 41164 entries, 0 to 41187
Data columns (total 38 columns):
 #   Column               Non-Null Count  Dtype  
---  ------               --------------  -----  
 0   age                  41164 non-null  int32  
 1   Job_N_admin.         41164 non-null  uint8  
 2   Job_N_blue-collar    41164 non-null  uint8  
 3   Job_N_entrepreneur   41164 non-null  uint8  
 4   Job_N_housemaid      41164 non-null  uint8  
 5   Job_N_management     41164 non-null  uint8  
 6   Job_N_retired        41164 non-null  uint8  
 7   Job_N_self-employed  41164 non-null  uint8  
 8   Job_N_services       41164 non-null  uint8  
 9   Job_N_student        41164 non-null  uint8  
 10  Job_N_technician     41164 non-null  uint8  
 11  Job_N_unemployed     41164 non-null  uint8  
 12  Job_N_unknown        41164 non-null  uint8  
 13  Marital_N            41164 non-null  int32  
 14  basic.4y             41164 non-null  uint8  
 15  basic.6y             41164 non-null  uint8  
 16  basic.9y             41164 non-null  uint8  
 17  high.school          41164 non-null  uint8  
 18  illiterate           41164 non-null  uint8  
 19  professional.course  41164 non-null  uint8  
 20  university.degree    41164 non-null  uint8  
 21  unknown              41164 non-null  uint8  
 22  Default_N            41164 non-null  int32  
 23  Housing_N            41164 non-null  int32  
 24  Loan_N               41164 non-null  int32  
 25  contact              41164 non-null  int32  
 26  month                41164 non-null  int64  
 27  day_of_week          41164 non-null  int32  
 28  duration             41164 non-null  int32  
 29  emp.var.rate         41164 non-null  float64
 30  cons.price.idx       41164 non-null  float64
 31  cons.conf.idx        41164 non-null  float64
 32  euribor3m            41164 non-null  float64
 33  nr.employed          41164 non-null  float64
 34  campaign             41164 non-null  float64
 35  pdays                41164 non-null  float64
 36  previous             41164 non-null  float64
 37  poutcome             41164 non-null  int32  
dtypes: float64(8), int32(9), int64(1), uint8(20)
memory usage: 5.3 MB
```

In [91]:

```
final_bank.isna().sum()
```

Out[91]:

```
age                    0
Job_N_admin.           0
Job_N_blue-collar      0
Job_N_entrepreneur     0
Job_N_housemaid        0
Job_N_management       0
Job_N_retired          0
Job_N_self-employed    0
```

```
Job_N_services          0
Job_N_student           0
Job_N_technician        0
Job_N_unemployed        0
Job_N_unknown           0
Marital_N               0
basic.4y                0
basic.6y                0
basic.9y                0
high.school             0
illiterate              0
professional.course     0
university.degree       0
unknown                 0
Default_N               0
Housing_N               0
Loan_N                  0
contact                 0
month                   0
day_of_week             0
duration                0
emp.var.rate            0
cons.price.idx          0
cons.conf.idx           0
euribor3m               0
nr.employed             0
campaign                0
pdays                   0
previous                0
poutcome                0
dtype: int64
```

In [92]:

```
final_bank['campaign'].unique()
```

Out[92]:

```
array([ 2.57040373,  1.        ,  2.        ,  3.        ,  4.        ,
        5.        ,  6.        ,  7.        ,  8.        ,  9.        ,
       10.        , 11.        , 12.        , 13.        , 19.        ,
       18.        , 23.        , 14.        , 22.        , 25.        ,
       16.        , 17.        , 15.        , 20.        , 56.        ,
       42.        , 28.        , 26.        , 27.        , 32.        ,
       21.        , 24.        , 29.        , 31.        , 30.        ,
       35.        , 41.        , 37.        , 40.        , 33.        ,
       34.        , 43.        ])
```

In [93]:

```
final_bank['campaign'].fillna(final_bank['campaign'].mean(),inplace=True)
```

In [94]:

```
final_bank.isna().sum()
```

Out[94]:

```
age                     0
Job_N_admin.            0
Job_N_blue-collar       0
Job_N_entrepreneur      0
Job_N_housemaid         0
Job_N_management        0
Job_N_retired           0
Job_N_self-employed     0
Job_N_services          0
Job_N_student           0
Job_N_technician        0
Job_N_unemployed        0
Job_N_unknown           0
Marital_N               0
basic.4y                0
```

```
basic.4y                  0
basic.6y                  0
basic.9y                  0
high.school               0
illiterate                0
professional.course       0
university.degree         0
unknown                   0
Default_N                 0
Housing_N                 0
Loan_N                    0
contact                   0
month                     0
day_of_week               0
duration                  0
emp.var.rate              0
cons.price.idx            0
cons.conf.idx             0
euribor3m                 0
nr.employed               0
campaign                  0
pdays                     0
previous                  0
poutcome                  0
dtype: int64
```

In [95]:

```
final_bank.describe()
```

Out[95]:

	age	Job_N_admin.	Job_N_blue-collar	Job_N_entrepreneur	Job_N_housemaid	Job_N_management	Job_N_retired
count	41164.000000	41164.000000	41164.000000	41164.000000	41164.000000	41164.000000	41164.000000
mean	1.978598	0.253037	0.224759	0.035371	0.025751	0.071033	0.041687
std	0.735708	0.434757	0.417429	0.184717	0.158392	0.256883	0.199875
min	1.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	1.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
50%	2.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
75%	2.000000	1.000000	0.000000	0.000000	0.000000	0.000000	0.000000
max	4.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000

8 rows × 38 columns

Splitting the data

We already have our target variable stored in 'y' from the beginning. Also, we have seperately curated our final_bank dataset. So, it does not contain our target variable y from our original dataset.

In [96]:

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(final_bank,y, test_size = 0.2, rando
m_state = 0)
```

In [97]:

```
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
from sklearn.metrics import confusion_matrix, accuracy_score
k_fold = KFold(n_splits=10, shuffle=True, random_state=0)
```

In [98]:

```
X_train.head()
```

Out[98]:

	age	Job_N_admin.	Job_N_blue-collar	Job_N_entrepreneur	Job_N_housemaid	Job_N_management	Job_N_retired	Job_N_self-employ
20018	2	0	0	0	0	0	0	
39695	1	1	0	0	0	0	0	
17238	3	0	0	0	1	0	0	
5924	3	0	1	0	0	0	0	
34656	2	1	0	0	0	0	0	

5 rows × 38 columns

Scaling the data

In our final_bank data, we can see that the minimum and maimum value ranges from quite high to quite low values. For this reason, we are scaling our data with StandardScaler. We do so to scale our features centred around the zero and have unit variance.

In [99]:

```
#train-test split
from sklearn.preprocessing import StandardScaler
sc_X = StandardScaler()
X_train = sc_X.fit_transform(X_train)
X_test = sc_X.transform(X_test)
```

Voting Classifier

In [100]:

```
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC

from sklearn.ensemble import VotingClassifier
```

Hard voting

In [101]:

```
log_reg_clf = LogisticRegression(random_state= 0, C = 100, max_iter = 1000)
log_reg_clf.fit(X_train, y_train)

dtree_clf = DecisionTreeClassifier(max_depth = 1, random_state = 0)
dtree_clf.fit(X_train, y_train)

svc_clf = SVC(C = 0.1, gamma = 0.01, probability = True, random_state= 0)
svc_clf.fit(X_train, y_train)

hard_voting_clf = VotingClassifier(estimators=[('lr', log_reg_clf), ('dt', dtree_clf), (
'svc', svc_clf)], voting='hard')
hard_voting_clf.fit(X_train, y_train)

from sklearn.metrics import accuracy_score
for clf in (log_reg_clf, dtree_clf, svc_clf, hard_voting_clf):
    clf.fit(X_train, y_train)
```

```
    y_pred = clf.predict(X_test)
    print(clf.__class__.__name__, '%.4f'%accuracy_score(y_test, y_pred))
```

```
LogisticRegression 0.9093
DecisionTreeClassifier 0.8876
SVC 0.8987
VotingClassifier 0.9014
```

Soft Voting

In [102]:

```
log_reg_clf = LogisticRegression(random_state= 0, C = 100, max_iter = 1000)
log_reg_clf.fit(X_train, y_train)

dtree_clf = DecisionTreeClassifier(max_depth = 1, random_state = 0)
dtree_clf.fit(X_train, y_train)

svc_clf = SVC(C = 0.1, gamma = 0.01, probability = True, random_state= 0)
svc_clf.fit(X_train, y_train)

soft_voting_clf = VotingClassifier(estimators=[('lr', log_reg_clf), ('dt', dtree_clf), (
'svc', svc_clf)], voting='soft')
soft_voting_clf.fit(X_train, y_train)

from sklearn.metrics import accuracy_score
for clf in (log_reg_clf, dtree_clf, svc_clf, soft_voting_clf):
    clf.fit(X_train, y_train)
    y_pred = clf.predict(X_test)
    print(clf.__class__.__name__, '%.4f'%accuracy_score(y_test, y_pred))
```

```
LogisticRegression 0.9093
DecisionTreeClassifier 0.8876
SVC 0.8987
VotingClassifier 0.9030
```

Bagging

Bagging for Decision Tree Classifier

In [104]:

```
from sklearn.ensemble import BaggingClassifier
from sklearn.tree import DecisionTreeClassifier

dtree_clf = DecisionTreeClassifier(random_state=0)
dtree_bag_clf = BaggingClassifier(dtree_clf, n_estimators=500, max_samples=100, bootstrap
=True, n_jobs=-1, random_state=0)

dtree_bag_clf.fit(X_train, y_train)
y_pred = dtree_bag_clf.predict(X_test)
```

In [105]:

```
dtree_bag_clf.fit(X_train, y_train)

# train and test scores
print('Train score: %.2f'%dtree_bag_clf.score(X_train, y_train))
print('Test score: %.2f'%dtree_bag_clf.score(X_test, y_test))
```

```
Train score: 0.91
Test score: 0.91
```

In [106]:

```
print(confusion_matrix(y_test, dtree_bag_clf.predict(X_test) ))
from sklearn.metrics import classification_report
```

```
print(classification_report(y_train, dtree_bag_clf.predict(X_train)))
```

```
[[7128  180]
 [ 557  368]]
              precision    recall  f1-score   support

           0       0.93      0.98      0.95     29218
           1       0.67      0.39      0.49      3713

    accuracy                           0.91     32931
   macro avg       0.80      0.68      0.72     32931
weighted avg       0.90      0.91      0.90     32931
```

Random Forest Classifier

GridSearch

In [107]:

```
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import RandomForestClassifier

param_grid = {'n_estimators': [200, 300, 400, 500],
              'max_depth': np.arange(1, 10)}

rf_gridsearch = GridSearchCV(RandomForestClassifier(random_state=0), param_grid, cv=10,
return_train_score=True)
rf_gridsearch.fit(X_train, y_train)
print("Best parameters for RandomForest Clf: {}".format(rf_gridsearch.best_params_))
print("Best cross-validation score: {:.2f}".format(rf_gridsearch.best_score_))
```

```
Best parameters for RandomForest Clf: {'max_depth': 9, 'n_estimators': 500}
Best cross-validation score: 0.91
```

Random Forest Classifier

In [108]:

```
rf_clf = RandomForestClassifier(n_estimators=400, max_depth = 9, bootstrap=True, n_jobs=
-1, random_state=0)
rf_clf.fit(X_train, y_train)

pred_rf = rf_clf.predict(X_test)

#train and test scores
print('Train score: {:.2f}'.format(rf_clf.score(X_train, y_train)))
print('Test score: {:.2f}'.format(rf_clf.score(X_test, y_test)))
```

```
Train score: 0.92
Test score: 0.91
```

In [109]:

```
print(confusion_matrix(y_test, rf_clf.predict(X_test)))
from sklearn.metrics import classification_report
print(classification_report(y_train, rf_clf.predict(X_train)))
```

```
[[7189  119]
 [ 641  284]]
              precision    recall  f1-score   support

           0       0.93      0.99      0.96     29218
           1       0.86      0.39      0.54      3713

    accuracy                           0.92     32931
   macro avg       0.89      0.69      0.75     32931
weighted avg       0.92      0.92      0.91     32931
```

Pasting

Decision Tree Classifier

In [110]:

```
from sklearn.ensemble import BaggingClassifier
from sklearn.tree import DecisionTreeClassifier

# pasting: bootstrap = False

dtree_clf = DecisionTreeClassifier(criterion = 'entropy', random_state=0)
dtree_bag_clf = BaggingClassifier(dtree_clf, n_estimators=500, max_samples=100, bootstrap
=False, random_state=0)

dtree_bag_clf.fit(X_train, y_train)
y_pred = dtree_bag_clf.predict(X_test)

from  sklearn.metrics import accuracy_score

# train and test scores
print('Train score: %.2f'%dtree_bag_clf.score(X_train, y_train))
print('Test score: %.2f'%dtree_bag_clf.score(X_test, y_test))
```

```
Train score: 0.91
Test score: 0.91
```

In [111]:

```
print(confusion_matrix(y_test, dtree_bag_clf.predict(X_test)))
from sklearn.metrics import classification_report
print(classification_report(y_train, dtree_bag_clf.predict(X_train)))
```

```
[[7172  136]
 [ 621  304]]
              precision    recall  f1-score   support

           0       0.92      0.98      0.95     29218
           1       0.70      0.32      0.44      3713

    accuracy                           0.91     32931
   macro avg       0.81      0.65      0.69     32931
weighted avg       0.89      0.91      0.89     32931
```

SVC Classifier

In [112]:

```
from sklearn.ensemble import BaggingClassifier
from sklearn.tree import DecisionTreeClassifier

# pasting: bootstrap = False

svc_clf = SVC(C = 0.1, gamma = 0.01, probability = True, random_state= 0)
svc_bag_clf = BaggingClassifier(svc_clf, n_estimators=500, max_samples=100, bootstrap=Fa
lse, random_state=0)

svc_bag_clf.fit(X_train, y_train)
y_pred = svc_bag_clf.predict(X_test)

from  sklearn.metrics import accuracy_score

#train and test scores
print('Train score: %.2f'%svc_bag_clf.score(X_train, y_train))
```

```
print('Test score: %.2f'%svc_bag_clf.score(X_test, y_test))
```

```
Train score: 0.89
Test score: 0.89
```

In [113]:

```
print(confusion_matrix(y_test, svc_bag_clf.predict(X_test)))
from sklearn.metrics import classification_report
print(classification_report(y_train, svc_bag_clf.predict(X_train)))
```

```
[[7289   19]
 [ 875   50]]
              precision    recall  f1-score   support

           0       0.89      1.00      0.94     29218
           1       0.86      0.06      0.11      3713

    accuracy                           0.89     32931
   macro avg       0.87      0.53      0.53     32931
weighted avg       0.89      0.89      0.85     32931
```

ADA Boost Classifier

Decision Tree

In [114]:

```
from sklearn.ensemble import AdaBoostClassifier

dtree_ada_clf = AdaBoostClassifier(DecisionTreeClassifier(max_depth=1), n_estimators=200,

                                   algorithm="SAMME.R", learning_rate=0.5, random_state=0)

dtree_ada_clf.fit(X_train, y_train)
predictions = dtree_ada_clf.predict(X_test)

#train and test scores
print('Train score: %.2f'%dtree_ada_clf.score(X_train, y_train))
print('Test score: %.2f'%dtree_ada_clf.score(X_test, y_test))
```

```
Train score: 0.91
Test score: 0.91
```

In [115]:

```
confusion_matrix(y_test, predictions)
```

Out[115]:

```
array([[7108,  200],
       [ 560,  365]], dtype=int64)
```

In [116]:

```
print(confusion_matrix(y_test, dtree_ada_clf.predict(X_test)))
from sklearn.metrics import classification_report
print(classification_report(y_train, dtree_ada_clf.predict(X_train)))
```

```
[[7108  200]
 [ 560  365]]
              precision    recall  f1-score   support

           0       0.93      0.97      0.95     29218
           1       0.66      0.40      0.50      3713

    accuracy                           0.91     32931
   macro avg       0.79      0.69      0.72     32931
```

```
weighted avg       0.90      0.91      0.90     32931
```

Logistic Regression

In [117]:

```
from sklearn.ensemble import AdaBoostClassifier

log_reg_ada_clf = AdaBoostClassifier(LogisticRegression(solver='liblinear'), n_estimators
=500,
                            algorithm="SAMME.R", learning_rate=0.1, random_state=0)

log_reg_ada_clf.fit(X_train, y_train)
predictions = log_reg_ada_clf.predict(X_test)

#train and test scores
print('Train score: %.2f'%log_reg_ada_clf.score(X_train, y_train))
print('Test score: %.2f'%log_reg_ada_clf.score(X_test, y_test))
```

```
Train score: 0.91
Test score: 0.91
```

In [118]:

```
print(confusion_matrix(y_test, log_reg_ada_clf.predict(X_test)))
from sklearn.metrics import classification_report
print(classification_report(y_train, log_reg_ada_clf.predict(X_train)))
```

```
[[7194  114]
 [ 663  262]]
              precision    recall  f1-score   support

           0       0.92      0.98      0.95     29218
           1       0.70      0.28      0.40      3713

    accuracy                           0.91     32931
   macro avg       0.81      0.63      0.68     32931
weighted avg       0.89      0.91      0.89     32931
```

Gradient Boosting Classifier

In [119]:

```
from  sklearn.ensemble import GradientBoostingClassifier

gbrt = GradientBoostingClassifier(random_state=0, max_depth=5, learning_rate=0.01)
gbrt.fit(X_train, y_train)

#train and test scores
print("Accuracy on training set: {:.3f}".format(gbrt.score(X_train, y_train)))
print("Accuracy on test set: {:.3f}".format(gbrt.score(X_test, y_test)))
```

```
Accuracy on training set: 0.904
Accuracy on test set: 0.901
```

In [120]:

```
print(confusion_matrix(y_test, gbrt.predict(X_test)))
from sklearn.metrics import classification_report
print(classification_report(y_train, gbrt.predict(X_train)))
```

```
[[7276   32]
 [ 779  146]]
              precision    recall  f1-score   support

           0       0.90      1.00      0.95     29218
           1       0.87      0.17      0.28      3713
```

```
    accuracy                           0.90     32931
   macro avg       0.89      0.58      0.62     32931
weighted avg       0.90      0.90      0.87     32931
```

PCA

In [121]:

```
from sklearn.decomposition import PCA

pca = PCA()
pca.fit(X_train)

cumsum = np.cumsum(pca.explained_variance_ratio_)
d = np.argmax(cumsum >= 0.95) + 1
```

In [122]:

```
d
```

Out[122]:

```
29
```

In [123]:

```
pca = PCA(n_components=0.95)
X_reduced = pca.fit_transform(X_train)
```

In [124]:

```
pca.n_components_
```

Out[124]:

```
29
```

In [125]:

```
np.sum(pca.explained_variance_ratio_)
```

Out[125]:

```
0.9538315288981813
```

In [126]:

```
pca = PCA(n_components = 29)
X_reduced = pca.fit_transform(X_train)
X_recovered = pca.inverse_transform(X_reduced)
```

In [127]:

```
X_reduced_pca = X_reduced
```

In [128]:

```
from sklearn.decomposition import IncrementalPCA

n_batches = 100

inc_pca = IncrementalPCA(n_components=29)
for X_batch in np.array_split(X_train, n_batches):
    print(".", end="")
    inc_pca.partial_fit(X_batch)

X_train_reduced = inc_pca.transform(X_train)
```

....

In [129]:

```
from sklearn.decomposition import IncrementalPCA

n_batches = 100

inc_pca = IncrementalPCA(n_components=29)
for X_batch in np.array_split(X_test, n_batches):
    print(".", end="")
    inc_pca.partial_fit(X_batch)

X_test_reduced = inc_pca.transform(X_test)
```

....

In [130]:

```
X_train_reduced.shape
```

Out[130]:

```
(32931, 29)
```

In [131]:

```
X_test_reduced.shape
```

Out[131]:

```
(8233, 29)
```

Models on PCA data

Logistic Regression

In [132]:

```
from sklearn.linear_model import LogisticRegression
log_model = LogisticRegression()
log_model.fit(X_train_reduced,y_train)
log_pred = log_model.predict(X_test_reduced)
```

In [133]:

```
print(confusion_matrix(y_test, log_pred))
from sklearn.metrics import classification_report
print(classification_report(y_train, log_model.predict(X_train_reduced)))
```

```
[[7086  222]
 [ 711  214]]
              precision    recall  f1-score   support

           0       0.92      0.98      0.95     29218
           1       0.65      0.36      0.46      3713

    accuracy                           0.91     32931
   macro avg       0.79      0.67      0.70     32931
weighted avg       0.89      0.91      0.89     32931
```

In [134]:

```
lr_score_train = log_model.score(X_train_reduced,y_train)
lr_score_train
```

Out[134]:

0.9056208435820352

In [135]:

```
lr_score_test = log_model.score(X_test_reduced,y_test)
lr_score_test
```

Out[135]:

0.886675573909875

KNN Classifier

In [136]:

```
from sklearn import model_selection
from sklearn.neighbors import KNeighborsClassifier


neighbors = np.arange(0,25)

cv_scores = []
```

In [137]:

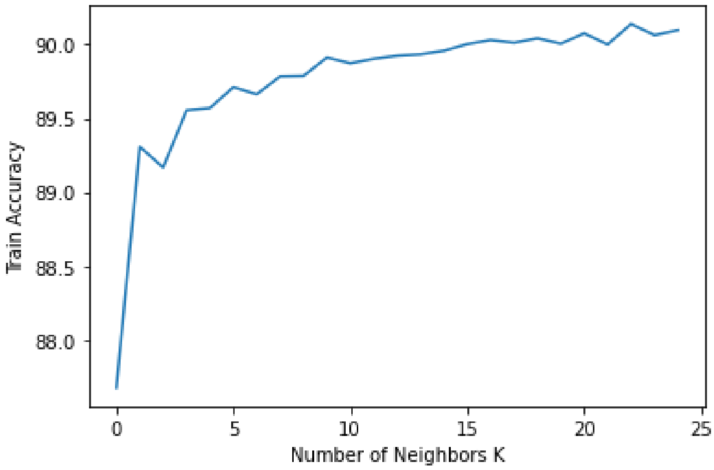
```
# To determine best k-value
for k in neighbors:
    k_val = k+1
    knn_clf = KNeighborsClassifier(n_neighbors = k_val, weights='uniform', p=2, metric='
euclidean')
    k_fold = model_selection.KFold(n_splits=10, random_state=123)
    cross_val_scores = model_selection.cross_val_score(knn_clf, X_train_reduced, y_train
, cv=k_fold, scoring='accuracy')
    cv_scores.append(cross_val_scores.mean()*100)
    print("k=%d %0.2f (+/- %0.2f)" % (k_val, cross_val_scores.mean()*100, cross_val_scor
es.std()*100))

optimal_kval = neighbors[cv_scores.index(max(cv_scores))]
print ("The optimal number of neighbors is %d with %0.1f%%" % (optimal_kval, cv_scores[o
ptimal_kval]))

plt.plot(neighbors, cv_scores)
plt.xlabel('Number of Neighbors K')
plt.ylabel('Train Accuracy')
plt.show()
```

```
k=1 87.67 (+/- 0.61)
k=2 89.31 (+/- 0.62)
k=3 89.17 (+/- 0.43)
k=4 89.55 (+/- 0.53)
k=5 89.57 (+/- 0.44)
k=6 89.71 (+/- 0.47)
k=7 89.66 (+/- 0.35)
k=8 89.78 (+/- 0.45)
k=9 89.79 (+/- 0.43)
k=10 89.91 (+/- 0.37)
k=11 89.87 (+/- 0.35)
k=12 89.90 (+/- 0.45)
k=13 89.92 (+/- 0.45)
k=14 89.93 (+/- 0.46)
k=15 89.96 (+/- 0.40)
k=16 90.00 (+/- 0.46)
k=17 90.03 (+/- 0.39)
k=18 90.01 (+/- 0.46)
k=19 90.04 (+/- 0.46)
k=20 90.01 (+/- 0.53)
k=21 90.08 (+/- 0.48)
k=22 90.00 (+/- 0.50)
k=23 90.14 (+/- 0.46)
k=24 90.06 (+/- 0.44)
```

k=25 90.10 (+/- 0.47)
The optimal number of neighbors is 22 with 90.1%



In [138]:

```
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier(n_neighbors=24)
knn.fit(X_train_reduced, y_train)
knn_pred = knn.predict(X_test_reduced)
```

In [139]:

```
# for train data
from sklearn.metrics import classification_report
print(classification_report(y_train, knn.predict(X_train_reduced)))
```

```
              precision    recall  f1-score   support

           0       0.91      0.99      0.95     29218
           1       0.71      0.25      0.37      3713

    accuracy                           0.90     32931
   macro avg       0.81      0.62      0.66     32931
weighted avg       0.89      0.90      0.88     32931
```

In [140]:

```
# for test data
confusion_matrix(y_test, knn.predict(X_test_reduced))
```

Out[140]:

```
array([[7249,   59],
       [ 875,   50]], dtype=int64)
```

In [141]:

```
print(classification_report(y_test, knn.predict(X_test_reduced)))
```

```
              precision    recall  f1-score   support

           0       0.89      0.99      0.94      7308
           1       0.46      0.05      0.10       925

    accuracy                           0.89      8233
   macro avg       0.68      0.52      0.52      8233
weighted avg       0.84      0.89      0.84      8233
```

In [142]:

```
knn_score_test = knn.score(X_test_reduced,y_test)
knn_score_test
```

Out[142]:

0.88655411150249

Linear SVM

In [143]:

```
from sklearn.svm import LinearSVC

svm = LinearSVC()
svm.fit(X_train_reduced,y_train)
svc_pred = svm.predict(X_test_reduced)
```

In [144]:

```
# for train set
from sklearn.metrics import classification_report
print(classification_report(y_train, svm.predict(X_train_reduced)))
```

```
              precision    recall  f1-score   support

           0       0.92      0.98      0.95     29218
           1       0.67      0.31      0.42      3713

    accuracy                           0.90     32931
   macro avg       0.79      0.64      0.68     32931
weighted avg       0.89      0.90      0.89     32931
```

In [145]:

```
#for test set
from sklearn.metrics import classification_report
print(classification_report(y_test, svm.predict(X_test_reduced)))
```

```
              precision    recall  f1-score   support

           0       0.90      0.98      0.94      7308
           1       0.48      0.17      0.25       925

    accuracy                           0.89      8233
   macro avg       0.69      0.57      0.59      8233
weighted avg       0.86      0.89      0.86      8233
```

In [146]:

```
svm_score_train = svm.score(X_train_reduced,y_train)
svm_score_train
```

Out[146]:

0.904588381767939

In [147]:

```
svm_score_test = svm.score(X_test_reduced,y_test)
svm_score_test
```

Out[147]:

0.8860682618729503

Decision Tree Classifier

In [148]:

```
d_tree = DecisionTreeClassifier(criterion='entropy', random_state=0)
d_tree.fit(X_train_reduced, y_train)
```

```
d_tree_pred = d_tree.predict(X_test_reduced)
```

In [149]:

```
print(classification_report(y_test, d_tree.predict(X_test_reduced)))
```

```
              precision    recall  f1-score   support

           0       0.91      0.88      0.89      7308
           1       0.23      0.28      0.26       925

    accuracy                           0.81      8233
   macro avg       0.57      0.58      0.57      8233
weighted avg       0.83      0.81      0.82      8233
```

In [150]:

```
print(classification_report(y_train, d_tree.predict(X_train_reduced)))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     29218
           1       1.00      1.00      1.00      3713

    accuracy                           1.00     32931
   macro avg       1.00      1.00      1.00     32931
weighted avg       1.00      1.00      1.00     32931
```

In [151]:

```
d_tree_score_train = d_tree.score(X_train_reduced,y_train)
d_tree_score_train
```

Out[151]:

```
0.9999696334760559
```

In [152]:

```
d_tree_score_test = d_tree.score(X_test_reduced,y_test)
d_tree_score_test
```

Out[152]:

```
0.814283979108466
```

Kernalized SVM(linear, rbf, poly)

In [153]:

```
from sklearn.svm import SVC
from sklearn.model_selection import GridSearchCV

tuned_parameters = [{'kernel': ['rbf'], 'gamma': [0.1],
                     'C': [1]},
                    {'kernel': ['linear'], 'C': [1]},
                   {'kernel' : ['poly'], 'degree':[3], 'C':[10] }]
```

In [154]:

```
clf = GridSearchCV(SVC(), tuned_parameters, cv=5, scoring='precision')
clf.fit(X_train, y_train)

print(clf.cv_results_)
```

```
{'mean_fit_time': array([91.10583048, 70.27198591, 80.00121274]), 'std_fit_time': array([
1.04248985, 7.38563372, 1.80327034]), 'mean_score_time': array([5.95953856, 2.66312752, 2
.90309567]), 'std_score_time': array([0.01897421, 0.03878049, 0.03692636]), 'param_C': ma
sked_array(data=[1, 1, 10],
```

```
             mask=[False, False, False],
       fill_value='?',
            dtype=object), 'param_gamma': masked_array(data=[0.1, --, --],
             mask=[False,  True,  True],
       fill_value='?',
            dtype=object), 'param_kernel': masked_array(data=['rbf', 'linear', 'poly'],
             mask=[False, False, False],
       fill_value='?',
            dtype=object), 'param_degree': masked_array(data=[--, --, 3],
             mask=[ True,  True, False],
       fill_value='?',
            dtype=object), 'params': [{'C': 1, 'gamma': 0.1, 'kernel': 'rbf'}, {'C': 1, '
kernel': 'linear'}, {'C': 10, 'degree': 3, 'kernel': 'poly'}], 'split0_test_score': array
([0.67412141, 0.63099631, 0.60408163]), 'split1_test_score': array([0.63467492, 0.6293929
7, 0.53682171]), 'split2_test_score': array([0.62170088, 0.65116279, 0.56097561]), 'split
3_test_score': array([0.63276836, 0.64312268, 0.59578544]), 'split4_test_score': array([0
.59744409, 0.62666667, 0.5462963 ]), 'mean_test_score': array([0.63214193, 0.63626828, 0.
56879214]), 'std_test_score': array([0.02482757, 0.00933899, 0.02669553]), 'rank_test_sco
re': array([2, 1, 3])}
```

In [155]:

```
print('The best model is: ', clf.best_params_)
print('This model produces a mean cross-validated score (precision) of', clf.best_score_)
```

```
The best model is:  {'C': 1, 'kernel': 'linear'}
This model produces a mean cross-validated score (precision) of 0.6362682830306745
```

In [156]:

```
svm_ker_lin = SVC(kernel='linear', C=1)
svm_ker_rbf = SVC(kernel='rbf', gamma=0.1, C=1)
svm_ker_poly = SVC(kernel='poly', degree=3, C=10)
```

In [157]:

```
svm_ker_lin.fit(X_train_reduced, y_train)
svm_ker_rbf.fit(X_train_reduced, y_train)
svm_ker_poly.fit(X_train_reduced, y_train)

ker_lin_pred = svm.predict(X_test_reduced)
ker_rbf_pred = svm.predict(X_test_reduced)
ker_poly_pred = svm.predict(X_test_reduced)
```

In [158]:

```
print(classification_report(y_train, svm_ker_lin.predict(X_train_reduced)))
```

```
              precision    recall  f1-score   support

           0       0.92      0.98      0.95     29218
           1       0.65      0.29      0.41      3713

    accuracy                           0.90     32931
   macro avg       0.79      0.64      0.68     32931
weighted avg       0.89      0.90      0.89     32931
```

In [159]:

```
print(classification_report(y_train, svm_ker_rbf.predict(X_train_reduced)))
```

```
              precision    recall  f1-score   support

           0       0.94      0.99      0.97     29218
           1       0.89      0.52      0.66      3713

    accuracy                           0.94     32931
   macro avg       0.92      0.76      0.81     32931
weighted avg       0.94      0.94      0.93     32931
```

In [160]:

```
print(classification_report(y_train, svm_ker_poly.predict(X_train_reduced)))
```

```
              precision    recall  f1-score   support

           0       0.94      0.98      0.96     29218
           1       0.80      0.50      0.62      3713

    accuracy                           0.93     32931
   macro avg       0.87      0.74      0.79     32931
weighted avg       0.92      0.93      0.92     32931
```

In [161]:

```
print(classification_report(y_test, svm_ker_poly.predict(X_test_reduced)))
```

```
              precision    recall  f1-score   support

           0       0.91      0.91      0.91      7308
           1       0.30      0.32      0.31       925

    accuracy                           0.84      8233
   macro avg       0.61      0.61      0.61      8233
weighted avg       0.84      0.84      0.84      8233
```

In [162]:

```
print(classification_report(y_test, svm_ker_lin.predict(X_test_reduced)))
```

```
              precision    recall  f1-score   support

           0       0.90      0.98      0.94      7308
           1       0.53      0.15      0.24       925

    accuracy                           0.89      8233
   macro avg       0.72      0.57      0.59      8233
weighted avg       0.86      0.89      0.86      8233
```

In [163]:

```
print(classification_report(y_test, svm_ker_rbf.predict(X_test_reduced)))
```

```
              precision    recall  f1-score   support

           0       0.89      0.99      0.94      7308
           1       0.31      0.02      0.04       925

    accuracy                           0.88      8233
   macro avg       0.60      0.51      0.49      8233
weighted avg       0.82      0.88      0.84      8233
```

In [164]:

```
# Since linear kernel is our best model, we will consider it's train and test scores.
#test score
svm_ker_lin_score_test = svm_ker_lin.score(X_test_reduced,y_test)
svm_ker_lin_score_test
```

Out[164]:

```
0.8895906716871128
```

In [165]:

```
#train score
svm_ker_lin_score_train = svm_ker_lin.score(X_train_reduced,y_train)
```

```
svm_ker_lin_score_train
```

Out[165]:

```
0.9028574899031307
```

Results from Project 1 for all models :

Train scores for our models are as follows :

Logistic Regression : 0.9092951929792596

KNN Classification : 0.9031915216665148

Linear SVM : 0.9085056633567156

Kernalized SVM : 0.8997904709847864

Decision Tree Classifier : 0.9999696334760559

Test scores for our models are as follows :

Logistic Regression : 0.9086602696465444

KNN Classification : 0.9001579011296004

Linear SVM : 0.9069597959431556

Kernalized SVM : 0.9086602696465444

Decision Tree Classifier : 0.8933560063160452

As we can see from our train and test scores from Project 1 and our train and test scores when using our PCA reduced dataset, the scores have dropped. Hence, we can say that the dimensionally reduced dataset results in a poorer score compared to the original dataset. Although, PCA did help in saving computational time by reducing the features to 29 from 38.

In [166]:

```
import numpy
from keras.models import Sequential
from keras.layers import Dense
from keras.wrappers.scikit_learn import KerasClassifier

# create model
clf_model = Sequential()
clf_model.add(Dense(12, input_dim=45, activation='relu'))
clf_model.add(Dense(8, activation='relu'))
clf_model.add(Dense(1, activation='sigmoid'))

# Compile model
clf_model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
return model

# Fit the model
clf_model.fit(X_train, y_train, epochs=150, batch_size=10)

# evaluate the model
clf_model_scores = clf_model.evaluate(X_test, y_test)
print("\n%s: %.2f%%" % (clf_model.metrics_names[1], scores[1]*100))
```

```
---------------------------------------------------------------------------
ModuleNotFoundError                       Traceback (most recent call last)
<ipython-input-166-2a2fa6886b37> in <module>
```

```
      1 import numpy
----> 2 from keras.models import Sequential
      3 from keras.layers import Dense
      4 from keras.wrappers.scikit_learn import KerasClassifier
      5

ModuleNotFoundError: No module named 'keras'
```

In [ ]:

```
y_predict = clf_model.predict(X_test)
y_predict
```

In [ ]:

```

```