Inital data processing

In [245]:
```
import os
import pandas as pd
import matplotlib
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
import pickle
from sklearn.manifold import TSNE
from sklearn import preprocessing
```

In [246]:
```
data=pd.read_csv("C://Users//sthakal//OneDrive - George Weston Limited-6469347-MTCAD//Ps
nal//Ryerson_Big_Data Certification_Final_Project//Data Set//bank-additional-full.csv",s
ep = ";")
data.head(15)
```

Out[246]:

	age	job	marital	education	default	housing	loan	contact	month	day_of_w
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	45	services	married	basic.9y	unknown	no	no	telephone	may	mon
6	59	admin.	married	professional.course	no	no	no	telephone	may	mon
7	41	blue-collar	married	unknown	unknown	no	no	telephone	may	mon
8	24	technician	single	professional.course	no	yes	no	telephone	may	mon
9	25	services	single	high.school	no	yes	no	telephone	may	mon
10	41	blue-collar	married	unknown	unknown	no	no	telephone	may	mon
11	25	services	single	high.school	no	yes	no	telephone	may	mon
12	29	blue-collar	single	high.school	no	no	yes	telephone	may	mon
13	57	housemaid	divorced	basic.4y	no	yes	no	telephone	may	mon
14	35	blue-collar	married	basic.6y	no	yes	no	telephone	may	mon

15 rows × 21 columns

In [247]:
```
# see what type of data it contains
data.dtypes
```

Out[247]:
```
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 [248]:
```
data.isna().count()
# CHECKING missing values
```

Out[248]:
```
age               41188
job               41188
marital           41188
education         41188
default           41188
housing           41188
loan              41188
contact           41188
month             41188
day_of_week       41188
duration          41188
campaign          41188
pdays             41188
previous          41188
poutcome          41188
emp.var.rate      41188
cons.price.idx    41188
cons.conf.idx     41188
euribor3m         41188
nr.employed       41188
y                 41188
dtype: int64
```

In [249]:
```
data.shape
#rows and columns
```

Out[249]:
```
(41188, 21)
```

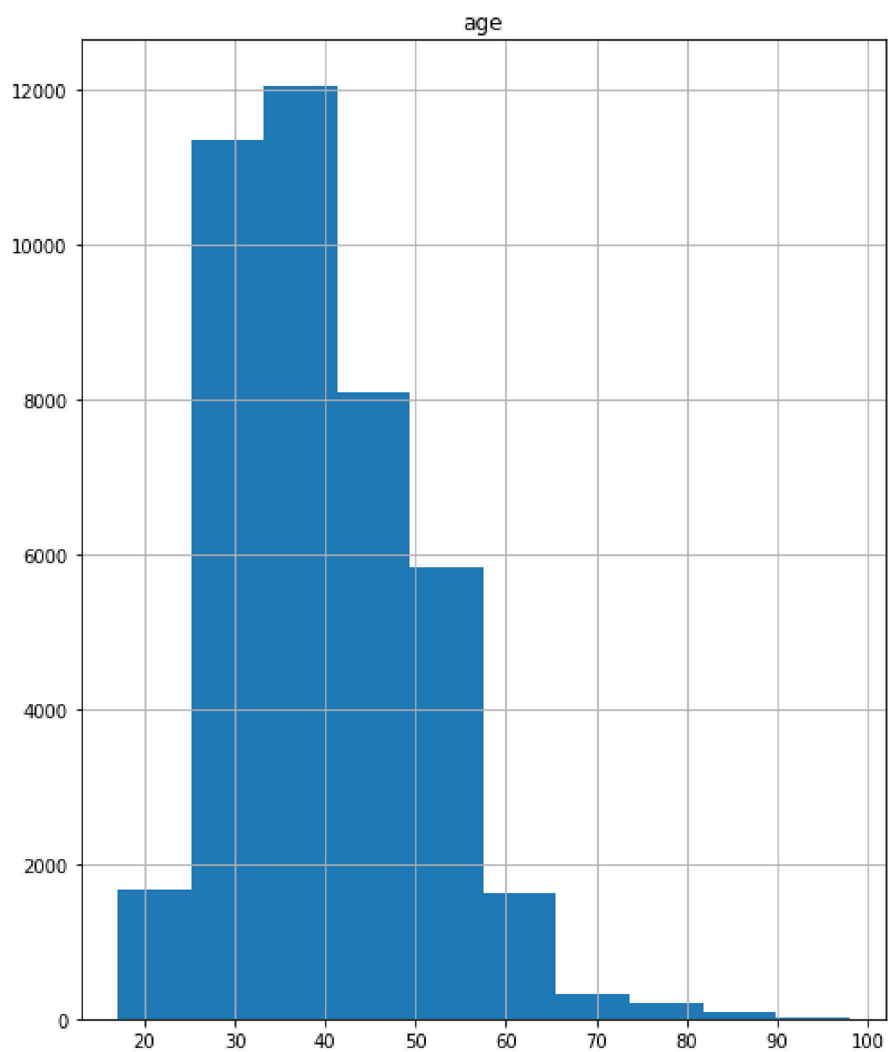
In [250]:
```
data.describe()
#Checking the stats of numerical variable
```

Out[250]:

	age	duration	campaign	pdays	previous	emp.var.rate	cons.pri
count	41188.00000	41188.000000	41188.000000	41188.000000	41188.000000	41188.000000	41188.00
mean	40.02406	258.285010	2.567593	962.475454	0.172963	0.081886	93.5756
std	10.42125	259.279249	2.770014	186.910907	0.494901	1.570960	0.57884
min	17.00000	0.000000	1.000000	0.000000	0.000000	-3.400000	92.2010
25%	32.00000	102.000000	1.000000	999.000000	0.000000	-1.800000	93.0750
50%	38.00000	180.000000	2.000000	999.000000	0.000000	1.100000	93.7490
75%	47.00000	319.000000	3.000000	999.000000	0.000000	1.400000	93.9940
max	98.00000	4918.000000	56.000000	999.000000	7.000000	1.400000	94.7670

In [251]:
```
data.hist('age')
#Age histograms
```

Out[251]:
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x0000024E928BCA58>]],
      dtype=object)
```



Checking the counts of Categorical variables

In [252]:
```
#we are now seeing the counts of the categorical variable one by one to see the values
#Checking the counts of categorical variables to see what value they are concentrated in

job_cnt=data['job'].value_counts()
print(job_cnt)
```

```
admin.           10422
blue-collar       9254
technician        6743
services          3969
management        2924
retired           1720
entrepreneur      1456
self-employed     1421
housemaid         1060
unemployed        1014
student            875
unknown            330
Name: job, dtype: int64
```

In [253]:
```
data['marital'].value_counts()
```

Out[253]:
```
married     24928
single      11568
divorced     4612
unknown        80
Name: marital, dtype: int64
```

In [254]:
```
data['education'].value_counts()
```

Out[254]:
```
university.degree      12168
high.school             9515
basic.9y                6045
professional.course     5243
basic.4y                4176
basic.6y                2292
unknown                 1731
illiterate                18
Name: education, dtype: int64
```

In [255]:
```
data['marital'].value_counts()
```

Out[255]:
```
married     24928
single      11568
divorced     4612
unknown        80
Name: marital, dtype: int64
```

In [256]:
```
data['education'].value_counts()
```

Out[256]:
```
university.degree      12168
high.school             9515
basic.9y                6045
professional.course     5243
basic.4y                4176
basic.6y                2292
unknown                 1731
illiterate                18
Name: education, dtype: int64
```

In [257]:
```
data['housing'].value_counts()
```

Out[257]:
```
yes        21576
no         18622
unknown      990
Name: housing, dtype: int64
```

In [258]:
```
data['loan'].value_counts()
```

Out[258]:
```
no         33950
yes         6248
unknown      990
Name: loan, dtype: int64
```

In [259]:
```
data['contact'].value_counts()
```

Out[259]:
```
cellular     26144
telephone    15044
Name: contact, dtype: int64
```

In [260]:
```
data['month'].value_counts()
```

Out[260]:
```
may    13769
jul     7174
aug     6178
jun     5318
nov     4101
apr     2632
oct      718
sep      570
mar      546
dec      182
Name: month, dtype: int64
```

In [261]:
```
data['day_of_week'].value_counts()
```

Out[261]:
```
thu    8623
mon    8514
wed    8134
tue    8090
fri    7827
Name: day_of_week, dtype: int64
```

In [262]:
```
data['poutcome'].value_counts()
```

Out[262]:
```
nonexistent    35563
failure         4252
success         1373
Name: poutcome, dtype: int64
```

In [263]:
```
data['month'].value_counts()
```

Out[263]:
```
may    13769
jul     7174
aug     6178
jun     5318
nov     4101
apr     2632
oct      718
sep      570
mar      546
dec      182
Name: month, dtype: int64
```

In [264]:
```
data['y'].value_counts()
#understanding the count of the Predictor variable
```

Out[264]:
```
no     36548
yes     4640
Name: y, dtype: int64
```

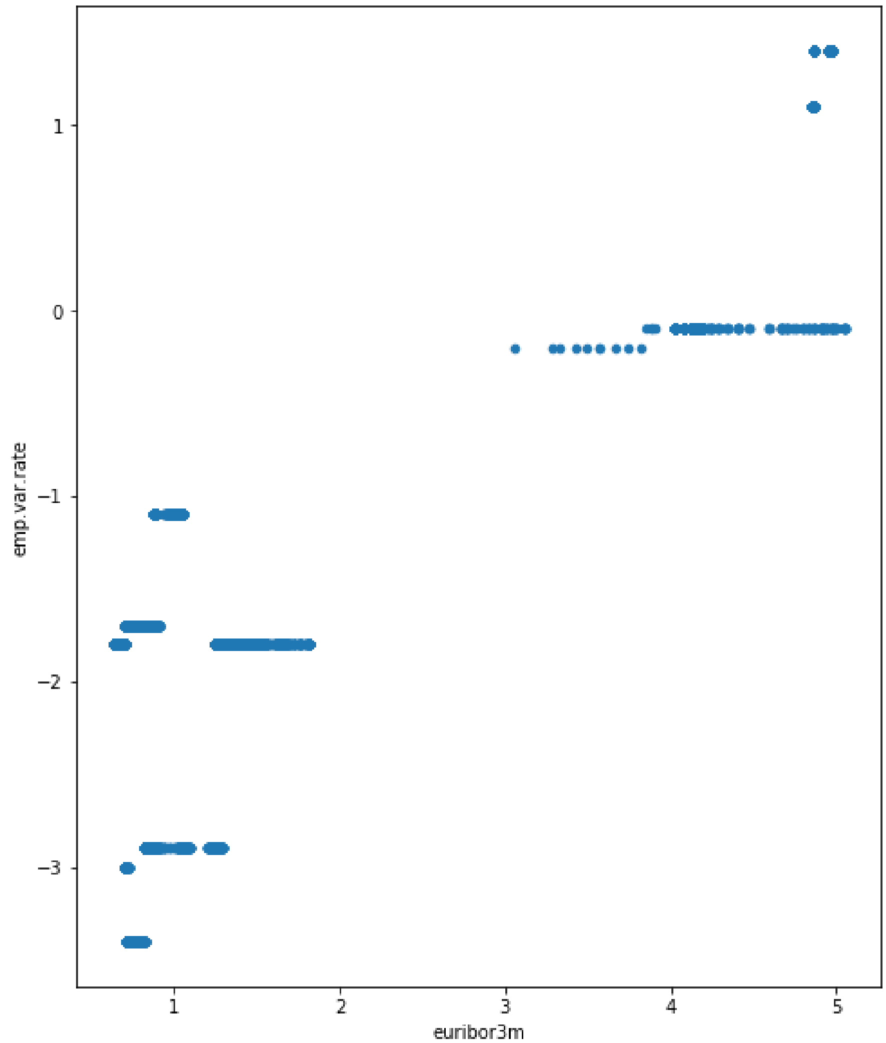
In [265]:
```
data['default'].value_counts()
```

Out[265]:
```
no         32588
unknown     8597
yes            3
Name: default, dtype: int64
```

Bivarate Analysis

In [266]:
```
data.plot.scatter('euribor3m', 'emp.var.rate',)
```

Out[266]: <matplotlib.axes._subplots.AxesSubplot at 0x24e8e4b25c0>



In [267]:
```
data.corr()
#Checking numerical correlation
```

Out[267]:

	age	duration	campaign	pdays	previous	emp.var.rate	cons.price.idx	co
age	1.000000	-0.000866	0.004594	-0.034369	0.024365	-0.000371	0.000857	0.1
duration	-0.000866	1.000000	-0.071699	-0.047577	0.020640	-0.027968	0.005312	-0.
campaign	0.004594	-0.071699	1.000000	0.052584	-0.079141	0.150754	0.127836	-0.
pdays	-0.034369	-0.047577	0.052584	1.000000	-0.587514	0.271004	0.078889	-0.
previous	0.024365	0.020640	-0.079141	-0.587514	1.000000	-0.420489	-0.203130	-0.
emp.var.rate	-0.000371	-0.027968	0.150754	0.271004	-0.420489	1.000000	0.775334	0.1
cons.price.idx	0.000857	0.005312	0.127836	0.078889	-0.203130	0.775334	1.000000	0.0
cons.conf.idx	0.129372	-0.008173	-0.013733	-0.091342	-0.050936	0.196041	0.058986	1.0
euribor3m	0.010767	-0.032897	0.135133	0.296899	-0.454494	0.972245	0.688230	0.2
nr.employed	-0.017725	-0.044703	0.144095	0.372605	-0.501333	0.906970	0.522034	0.1

Some preprocessing for Bivarate

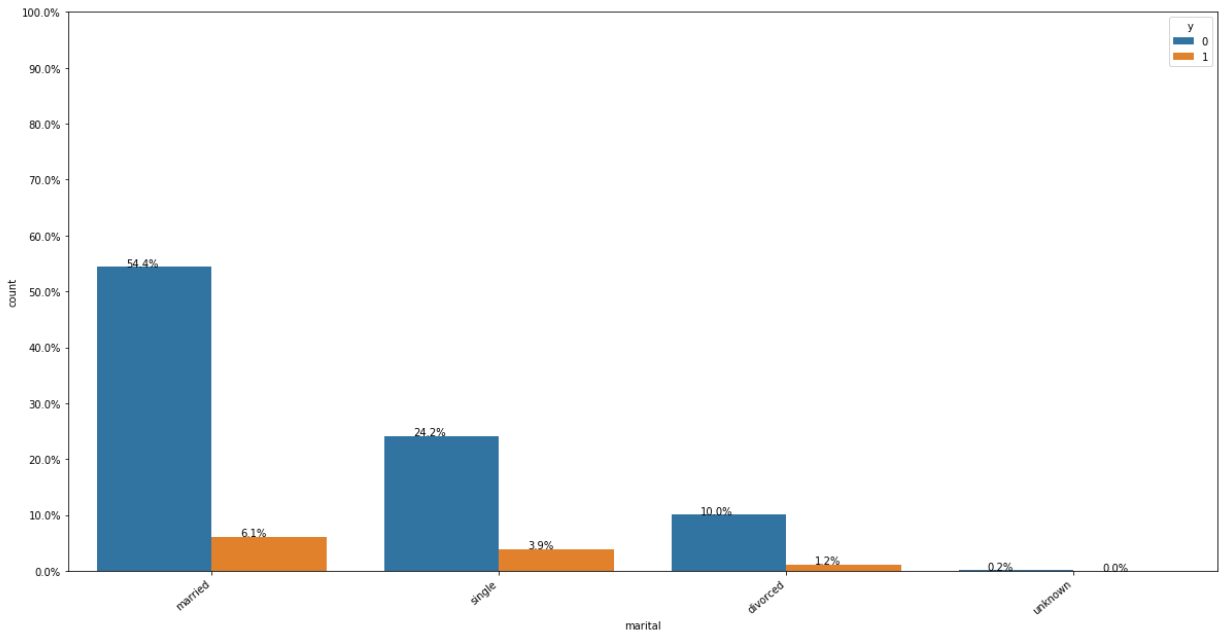
In [268]:
```
#Clubbing all basic eduction in one
data['education']=np.where(data['education'] =='basic.9y', 'Basic', data['education'])
data['education']=np.where(data['education'] =='basic.6y', 'Basic', data['education'])
data['education']=np.where(data['education'] =='basic.4y', 'Basic', data['education'])
```

In [269]:
```
data['y']=np.where(data['y'] =='yes',1, data['y'])# changing into binary/
data['y']=np.where(data['y'] =='no',0, data['y'])
```

In [270]:
```
#Checking how the categorical variable is related to the Response variable
%matplotlib inline

def countplot_withY(label, dataset):
  plt.figure(figsize=(20,10))
  Y = data[label]
  total = len(Y)*1.
  ax=sns.countplot(x=label, data=dataset, hue="y")
  for p in ax.patches:
    ax.annotate('{:.1f}%'.format(100*p.get_height()/total), (p.get_x()+0.1, p.get_height
()+5))

  #put 11 ticks (therefore 10 steps), from 0 to the total number of rows in the datafram
e
  ax.yaxis.set_ticks(np.linspace(0, total, 11))
  #adjust the ticklabel to the desired format, without changing the position of the tick
s.
  ax.set_yticklabels(map('{:.1f}%'.format, 100*ax.yaxis.get_majorticklocs()/total))
  ax.set_xticklabels(ax.get_xticklabels(), rotation=40, ha="right")
  # ax.legend(labels=["no","yes"])
  plt.show()
```

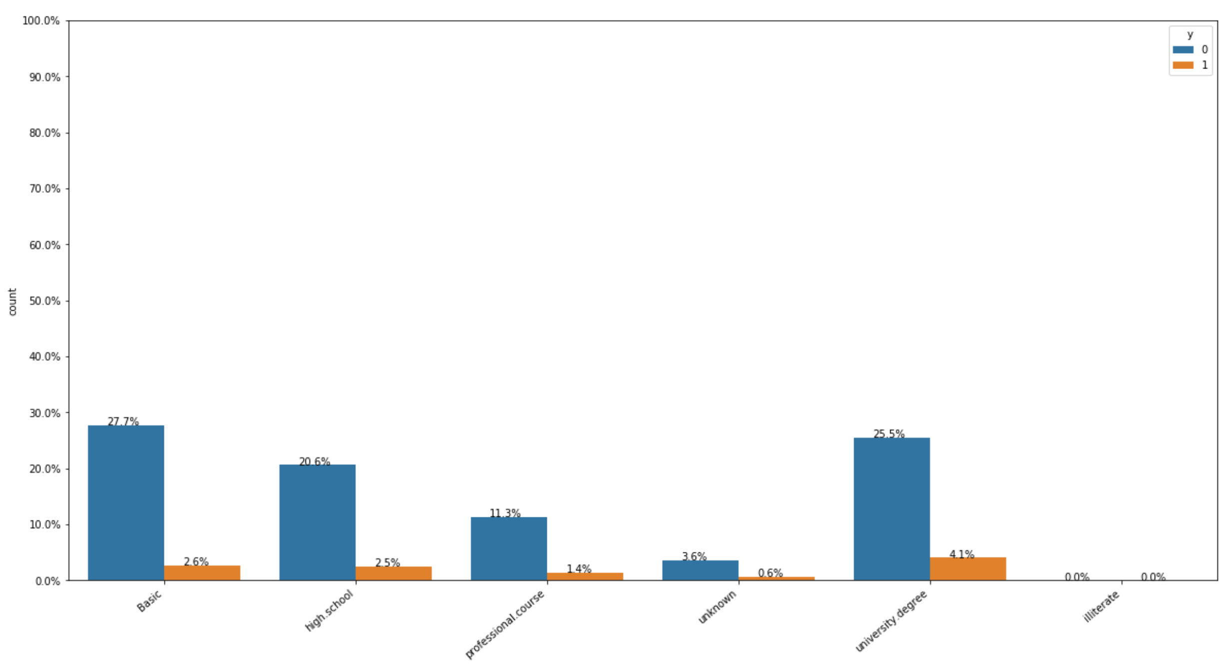
Seeing the relationship of categorical variables with Response Variable

In [271]:
```
countplot_withY("marital",data)
```

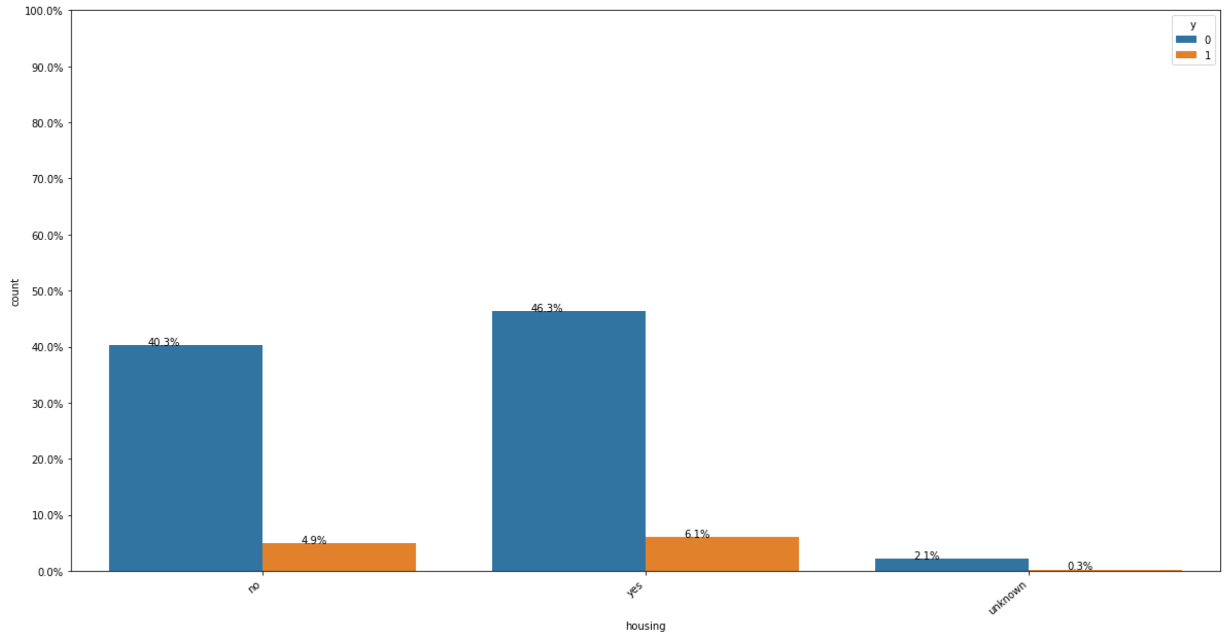


In [272]:
```
countplot_withY?
```

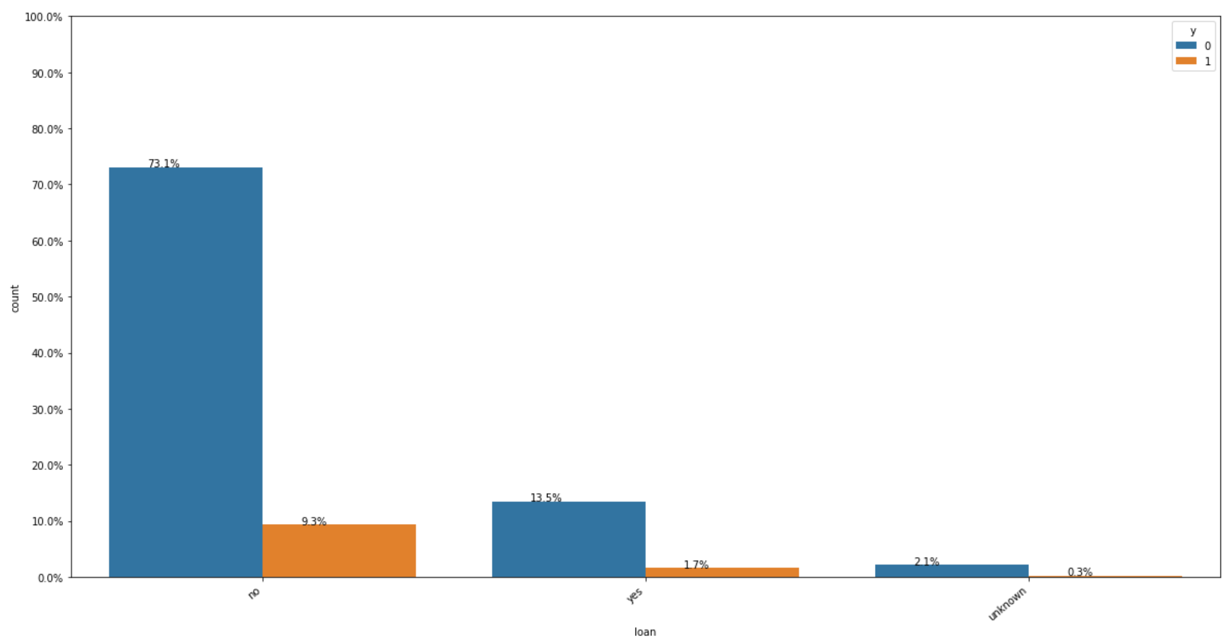
In [273]:
```
countplot_withY("education",data)
```



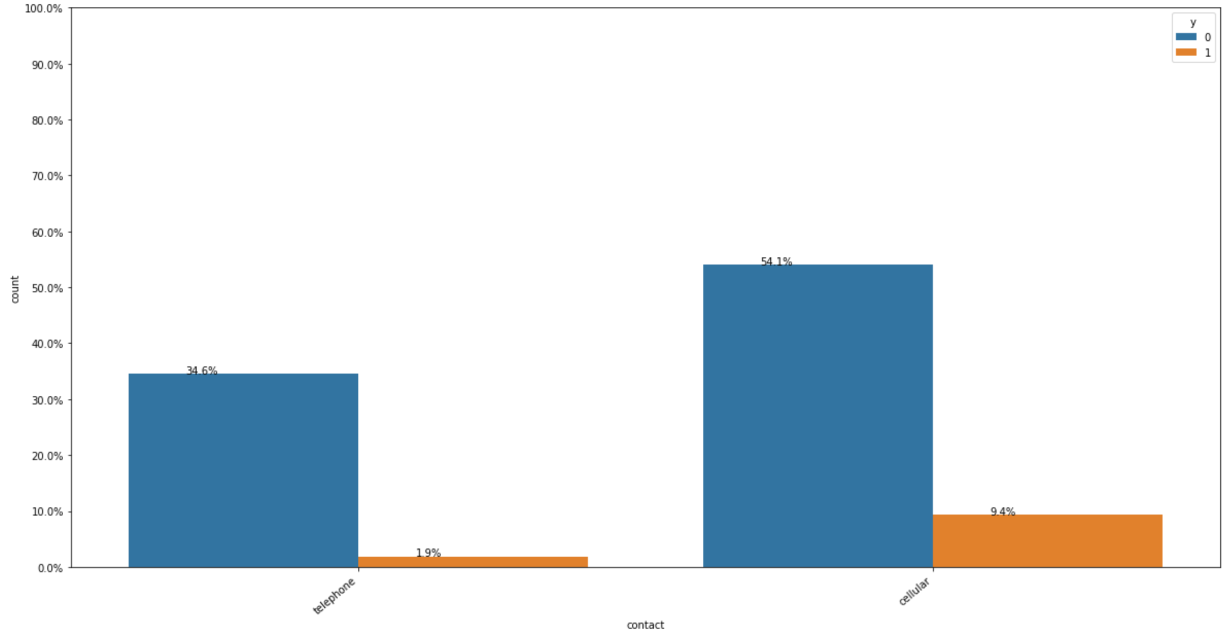
In [274]:
```
countplot_withY("housing",data)
```



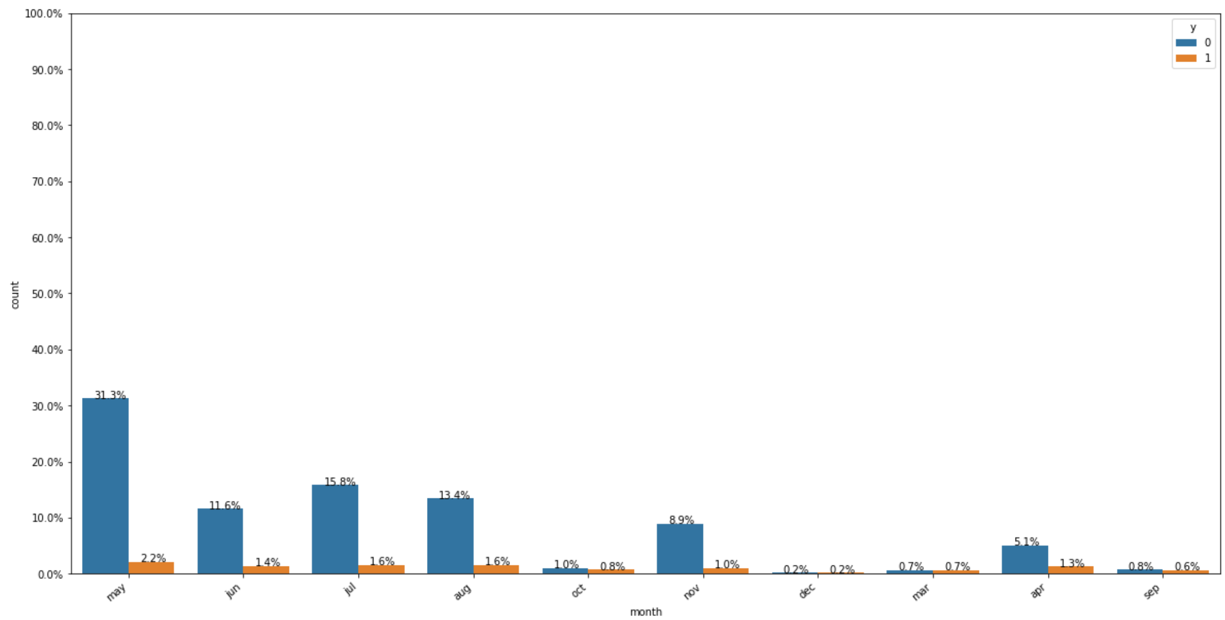
In [275]:
```
countplot_withY("loan",data)
```



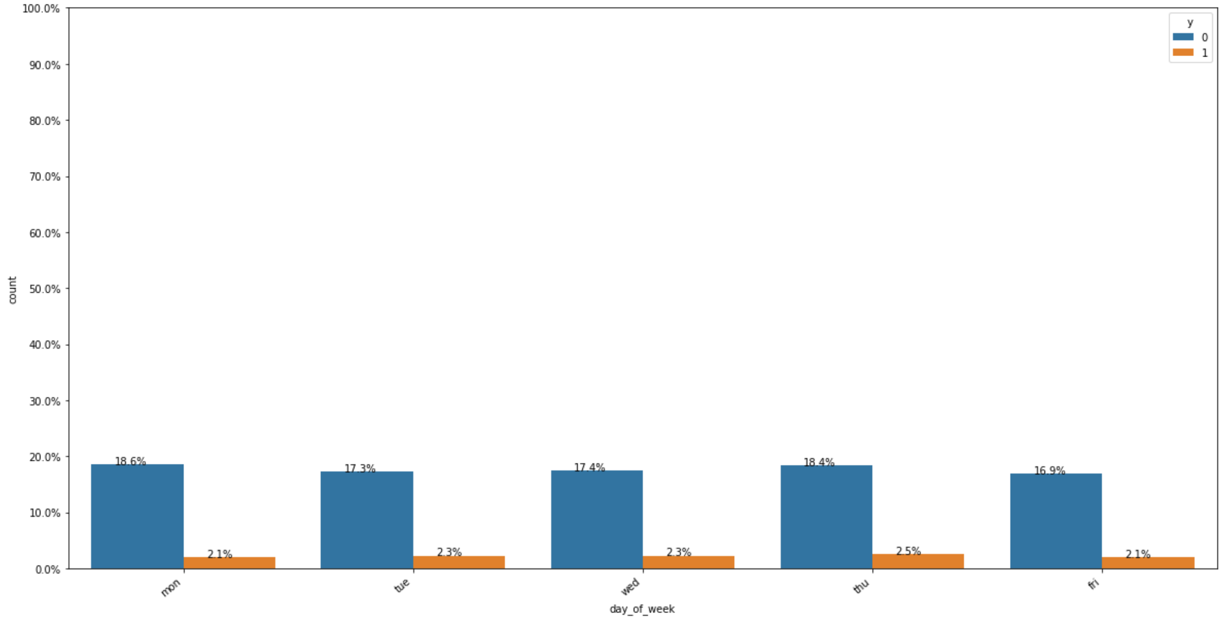
In [276]:
```
countplot_withY("contact",data)
```



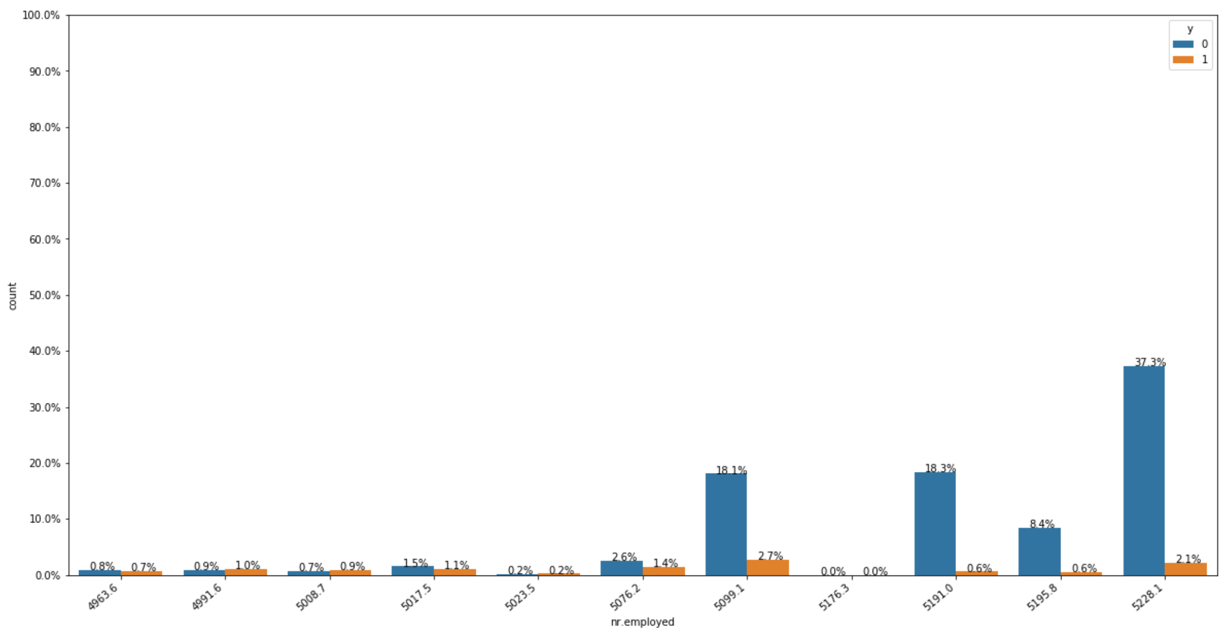
In [277]:
```
countplot_withY("month",data)
```



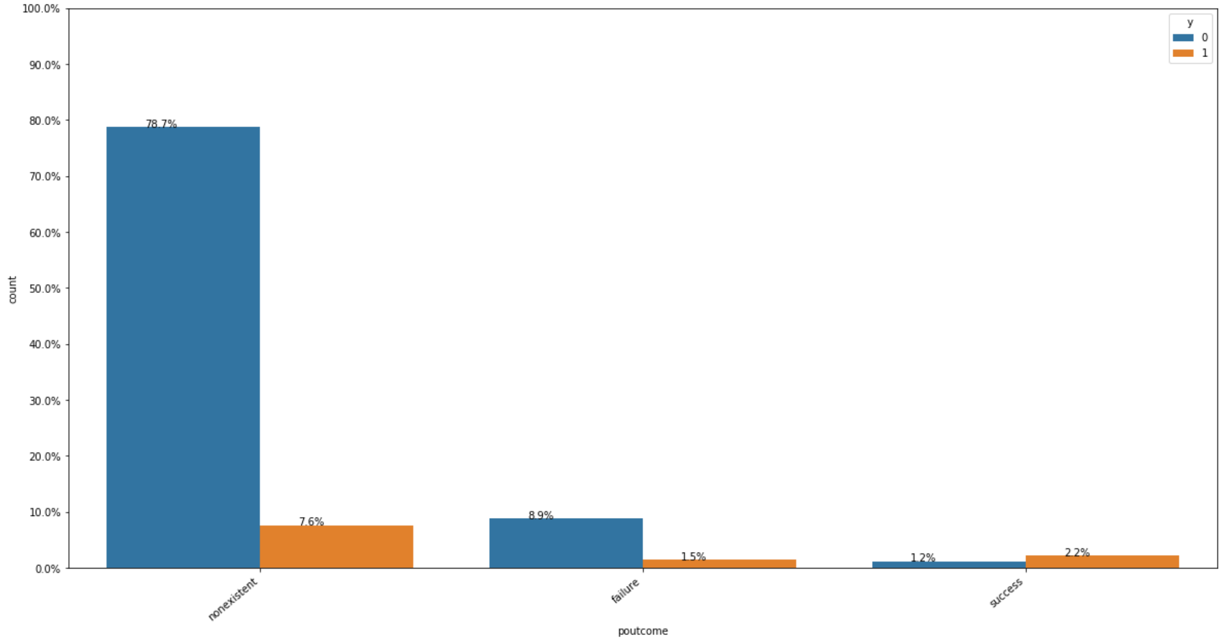
In [278]:
```
countplot_withY("day_of_week",data)
```



In [279]:
```
countplot_withY("nr.employed",data)
```



In [280]:
```
countplot_withY("poutcome",data)
```



In [281]:
```
data_response_yes=data[data['y']==1]
#only selecting those dataset where response is yes
```

In [282]:
```
data_response_yes.describe()
#Just checking how the numerical variable of success looks like
```

Out[282]:

	age	duration	campaign	pdays	previous	emp.var.rate	cons.price.id
count	4640.000000	4640.000000	4640.000000	4640.000000	4640.000000	4640.000000	4640.000000
mean	40.913147	553.191164	2.051724	792.035560	0.492672	-1.233448	93.354386
std	13.837476	401.171871	1.666245	403.407181	0.860344	1.623626	0.676644
min	17.000000	37.000000	1.000000	0.000000	0.000000	-3.400000	92.201000
25%	31.000000	253.000000	1.000000	999.000000	0.000000	-1.800000	92.893000
50%	37.000000	449.000000	2.000000	999.000000	0.000000	-1.800000	93.200000
75%	50.000000	741.250000	2.000000	999.000000	1.000000	-0.100000	93.918000
max	98.000000	4199.000000	23.000000	999.000000	6.000000	1.400000	94.767000

Some preprocessing for model building

In [283]:
```
#Create dummy variables
data_x = data.iloc[:, :-1]
print("Shape of X:", data_x.shape)
data_y = data["y"]
print("Shape of Y:", data_y.shape)
```

```
Shape of X: (41188, 20)
Shape of Y: (41188,)
```

In [284]:
```
from sklearn.model_selection import train_test_split

X_rest, X_test, y_rest, y_test = train_test_split(data_x, data_y, test_size=0.2)
X_train, X_cv, y_train, y_cv = train_test_split(X_rest, y_rest, test_size=0.2)

print("X Train:", X_train.shape)
print("X CV:", X_cv.shape)
print("X Test:", X_test.shape)
print("Y Train:", y_train.shape)
print("Y CV:", y_cv.shape)
print("Y Test:", y_test.shape)
```

```
X Train: (26360, 20)
X CV: (6590, 20)
X Test: (8238, 20)
Y Train: (26360,)
Y CV: (6590,)
Y Test: (8238,)
```

In [285]:
```
y_train.replace({"no":0, "yes":1}, inplace=True)
y_cv.replace({"no":0, "yes":1}, inplace=True)
y_test.replace({"no":0, "yes":1}, inplace=True)
```

In [286]:
```
# without "duration" column
# As this column is after the fact

#From Train
X_train = X_train.drop("duration", axis=1)
print("The shape of the train dataset: ", X_train.shape)

# From CV
X_cv = X_cv.drop("duration", axis=1)
print("The shape of the cv dataset: ", X_cv.shape)

# From Test
X_test = X_test.drop("duration", axis=1)
print("The shape of the test dataset: ", X_test.shape)
```

```
The shape of the train dataset:  (26360, 19)
The shape of the cv dataset:  (6590, 19)
The shape of the test dataset:  (8238, 19)
```

In [287]:
```
# Categorical boolean mask
categorical_feature_mask = data_x.dtypes==object

# filter categorical columns using mask and turn it into a list
categorical_cols = data_x.columns[categorical_feature_mask].tolist()
```

In [288]:
```
from sklearn.feature_extraction.text import CountVectorizer

def add_onehot_to_dataframe(sparse, df, vectorizer, name):
  '''
      This function will add the one hot encoded to the dataframe.

  '''
  for i, col in enumerate(vectorizer.get_feature_names()):
    colname = name+"_"+col
    # df[colname] = pd.SparseSeries(sparse[:, i].toarray().flatten(), fill_value=0)
    df[colname] = sparse[:, i].toarray().ravel().tolist()

  return df

def OneHotEncoder(categorical_cols, X_train, X_test, X_cv=None, include_cv=False):
  '''
    This function takes categorical column names as inputs. The objective
    of this function is to take the column names iteratively and encode the
    features using One hot Encoding mechanism and also adding the encoded feature
    to the respective dataframe.

    The include_cv parameter indicates whether we should include CV dataset or not.
    This is added specifically because when using GridSearchCV or RandomizedSearchCV,
    we only split the dataset into train and test to give more data to training purpose
s.
    This is done because GridSearchCV splits the data internally anyway.
  '''

  for i in categorical_cols:
    Vectorizer = CountVectorizer(token_pattern="[A-Za-z0-9-.]+")
    print("Encoding for feature: ", i)
    # Encoding training dataset
    temp_cols = Vectorizer.fit_transform(X_train[i])
    X_train = add_onehot_to_dataframe(temp_cols, X_train, Vectorizer, i)

    # Encoding Cross validation dataset
    if include_cv:
      temp_cols = Vectorizer.transform(X_cv[i])
      X_cv = add_onehot_to_dataframe(temp_cols, X_cv, Vectorizer, i)

    # Encoding Test dataset
    temp_cols = Vectorizer.transform(X_test[i])
    X_test = add_onehot_to_dataframe(temp_cols, X_test, Vectorizer, i)
```

In [289]:
```
OneHotEncoder(categorical_cols, X_train, X_test, X_cv, True)

# Drop the categorical features as the one hot encoded representation is present
X_train = X_train.drop(categorical_cols, axis=1)
X_cv = X_cv.drop(categorical_cols, axis=1)
X_test = X_test.drop(categorical_cols, axis=1)

print("Shape of train: ", X_train.shape)
print("Shape of CV: ", X_cv.shape)
print("Shape of test: ", X_test.shape)
```

```
Encoding for feature:  job
Encoding for feature:  marital
Encoding for feature:  education
Encoding for feature:  default
Encoding for feature:  housing
Encoding for feature:  loan
Encoding for feature:  contact
Encoding for feature:  month
Encoding for feature:  day_of_week
Encoding for feature:  poutcome
Shape of train:  (26360, 60)
Shape of CV:  (6590, 60)
Shape of test:  (8238, 60)
```

In [290]:
```
data['job'].value_counts()
```

Out[290]:
```
admin.           10422
blue-collar       9254
technician        6743
services          3969
management        2924
retired           1720
entrepreneur      1456
self-employed     1421
housemaid         1060
unemployed        1014
student            875
unknown            330
Name: job, dtype: int64
```

In [291]:
```
X_train.head()
```

Out[291]:

	age	campaign	pdays	previous	emp.var.rate	cons.price.idx	cons.conf.idx	euribor3m	nr.en
9368	31	2	999	0	1.4	94.465	-41.8	4.967	5228
6113	37	1	999	0	1.1	93.994	-36.4	4.857	5191
2719	41	1	999	0	1.1	93.994	-36.4	4.859	5191
21296	30	1	999	0	1.4	93.444	-36.1	4.963	5228
15163	39	2	999	0	1.4	93.918	-42.7	4.958	5228

5 rows × 60 columns

In [292]:
```
# Running the Logistic Regression model
from sklearn.metrics import roc_auc_score
from sklearn.linear_model import LogisticRegression
import time

start = time.time()

# insert some code to do something here


model = LogisticRegression(class_weight='balanced',max_iter=1000)
model.fit(X_train, y_train)
y_pred = model.predict_proba(X_test)

print("AUC score: ", roc_auc_score(y_test, y_pred[:,1]))
end = time.time()
print("Run time [s]: ",end-start)
```

```
AUC score:  0.7874636635959017
Run time [s]:  1.0059287548065186
```

In [293]:
```
# import the class
from sklearn.linear_model import LogisticRegression

# instantiate the model (using the default parameters)
logreg = LogisticRegression(max_iter=500)

# fit the model with data
logreg.fit(X_train,y_train)

#
y_pred=logreg.predict(X_test)

print("Accuracy:",metrics.accuracy_score(y_test, y_pred))
print("Precision:",metrics.precision_score(y_test, y_pred))
print("Recall:",metrics.recall_score(y_test, y_pred))
```

```
Accuracy: 0.8997329448895363
Precision: 0.6861538461538461
Recall: 0.235480464625132
```

In [294]:
```
from sklearn.model_selection import cross_val_score
```

In [295]:
```
Logestic_Regression_Model=LogisticRegression(class_weight='balanced',max_iter=1000)
```

In [296]:
```
#Using cross validation for the data we seperated for the purpose
#run 1

import time
start = time.time()
print(cross_val_score(Logestic_Regression_Model,X_cv, y_cv, cv=10))
# insert some code to do something here

end = time.time()
print("Run time [s]: ",end-start)
```

```
[0.84066768 0.80576631 0.79817906 0.82549317 0.83459788 0.83308042
 0.82852807 0.81942337 0.83915023 0.82094082]
Run time [s]:  6.635006427764893
```

In [297]:
```
#run2

import time
start = time.time()
print(cross_val_score(Logestic_Regression_Model,X_test, y_test, cv=10))
end = time.time()
print("Run time [s]: ",end-start)
```

```
[0.80461165 0.82645631 0.81553398 0.8276699  0.8118932  0.83616505
 0.80703883 0.82524272 0.83232078 0.79100851]
Run time [s]:  4.5913002490997314
```

In [305]:
```
start = time.time()

mean_cross_val_score_logistic= np.mean(cross_val_score(Logestic_Regression_Model,X_cv, y
_cv, cv=10))
std_cross_val_score_logistic=np.std(cross_val_score(Logestic_Regression_Model,X_cv, y_cv
, cv=10))
print("The mean cross val score of Logistic Regression is:"+ str(np.round_(mean_cross_va
l_score_logistic,3)))
print("The Standard Deviation of  Logistic Regression is:"+str(np.round_(std_cross_val_s
core_logistic,3)))

end = time.time()
print("Run time [s]: ",end-start)
```

```
The mean cross val score of Logistic Regression is:0.825
The Standard Deviation of  Logistic Regression is:0.013
Run time [s]:  12.48766303062439
```

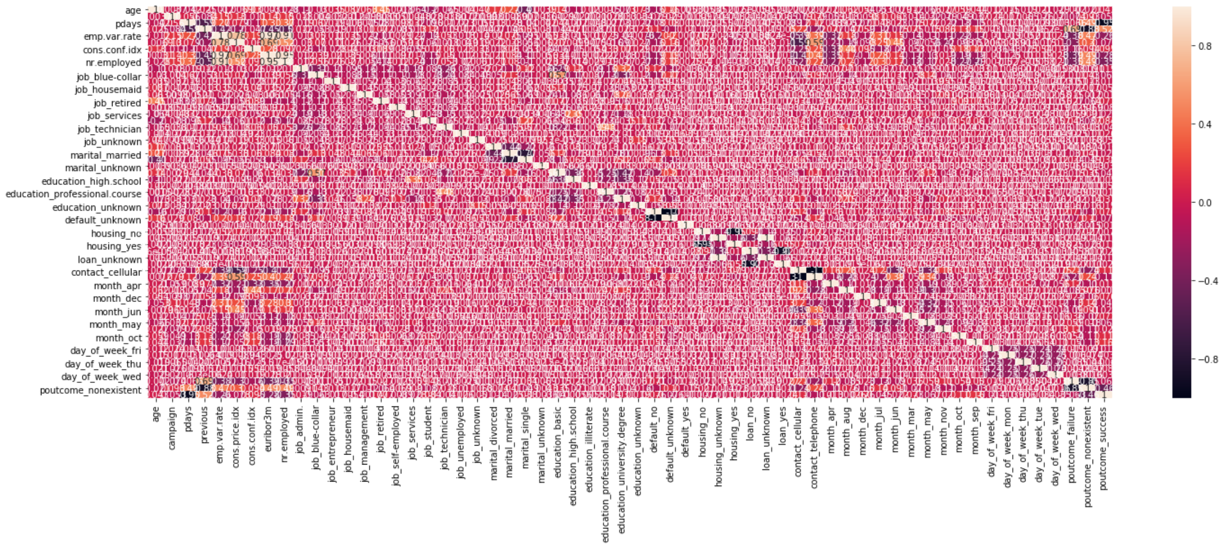
In [306]:
```
### neural network method
```

In [307]:
```
from sklearn.neural_network import MLPRegressor
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
```

In [308]:
```
sc_X = StandardScaler()
sc_X.fit(X_train)
X_trainscaled=sc_X.fit_transform(X_train)
X_testscaled=sc_X.transform(X_test)
```

In [309]:
```
columns_value_new=X_train.columns
test_X_Scaled_Except = pd.DataFrame(X_trainscaled, columns=columns_value_new)
```

In [310]:
```
import seaborn as sns
plt.rcParams["figure.figsize"] = (24, 8)
sns.heatmap(test_X_Scaled_Except.corr(),annot=True);
```



In [312]:
```
from sklearn.decomposition import PCA
PCA_data_train =X_trainscaled
PCA_data_test =X_testscaled
pca = PCA(n_components=15)
pca.fit(PCA_data_train)
X_pca_train= pca.fit_transform(PCA_data_train)
X_pca_test= pca.fit_transform(PCA_data_test)
principalDf_train = pd.DataFrame(data = X_pca_train)
principalDf_test = pd.DataFrame(data = X_pca_test)
```

In [313]:
```
principalDf_train.head(10)
```

Out[313]:

	0	1	2	3	4	5	6	7	8	
0	-2.497043	0.046395	2.210257	0.807705	-0.486997	-1.257356	0.493053	-1.012544	-1.158545	-(
1	-1.778482	0.149128	2.042176	0.223557	-0.875591	-1.706006	0.314094	-0.564023	0.199450	-(
2	-2.183393	2.292706	0.700497	-0.099743	-0.929288	-1.476292	0.236782	0.535660	0.465353	-(
3	-0.973170	-2.266912	-1.226679	1.199715	0.088081	1.507342	-0.637140	1.426862	0.969482	2
4	-1.356171	0.206941	-2.257548	-0.402906	-0.488603	1.910939	0.279471	0.327530	-1.062663	-(
5	3.840331	1.874349	-0.387108	-1.711629	-0.982290	0.560890	-0.850451	-0.064931	-1.403221	-(
6	-1.051397	-1.245991	-1.091416	1.681713	-0.157401	-1.058452	1.422463	-0.171194	-0.115636	-(
7	4.865399	-1.230331	0.301805	-1.972052	-0.854190	0.930516	-0.377125	-1.412174	-1.305806	0
8	2.471014	-0.078277	-1.439621	0.809316	-0.202708	1.113854	-0.440478	0.261209	-2.760368	-2
9	-1.562321	-0.023942	1.037075	0.404993	1.844372	-1.120324	-2.936820	-2.563323	1.262887	-(

In [314]:
```
import time
start = time.time()

from sklearn.neural_network import MLPClassifier
clf = MLPClassifier(hidden_layer_sizes=(256,128,64,32),activation="relu",random_state=1,
max_iter=500).fit(principalDf_train, y_train)
y_pred=clf.predict(principalDf_test)
print(clf.score(principalDf_test, y_test))


end = time.time()
print("Run time [s]: ",end-start)
```

```
0.7847778587035689
Run time [s]:  182.91237878799438
```

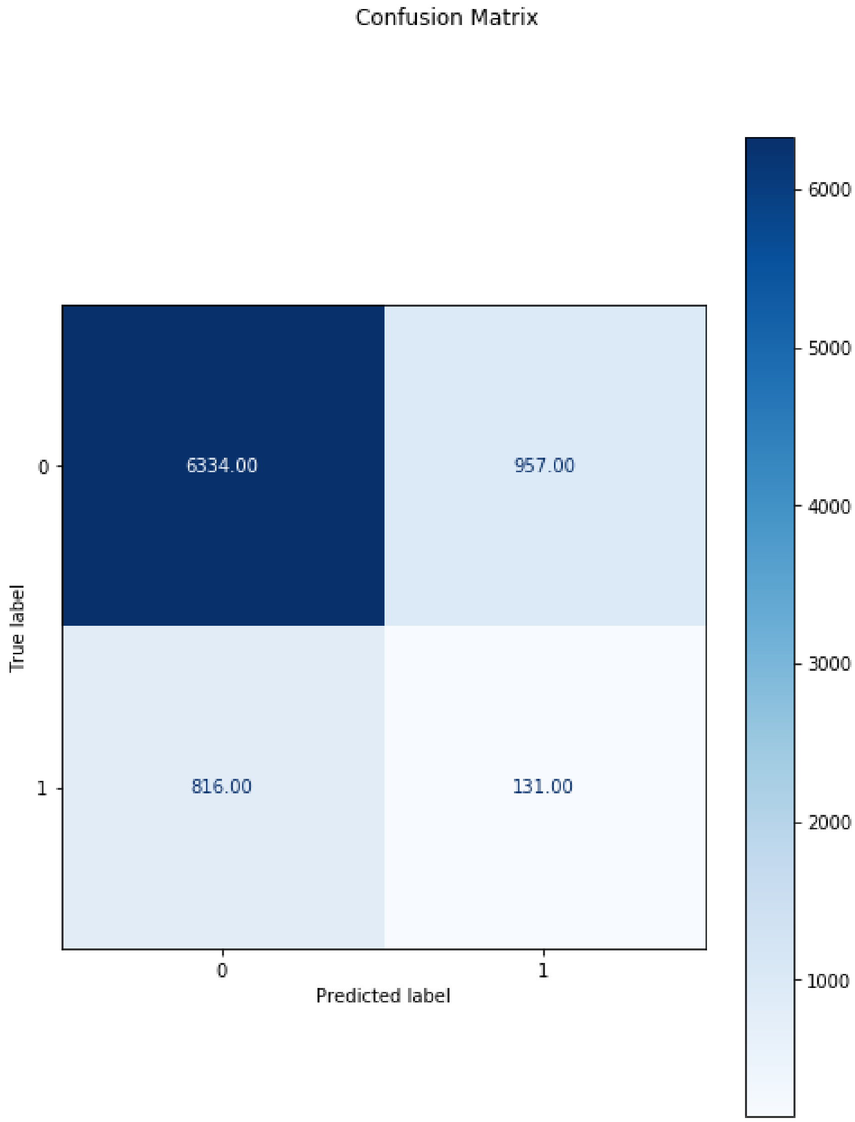
In [315]:
```
start = time.time()
mean_cross_val_score_NN= np.mean(cross_val_score(clf,X_cv, y_cv, cv=10))
std_cross_val_score_NN=np.std(cross_val_score(clf,X_cv, y_cv, cv=10))

print("The mean cross val score of Neural Network is:"+ str(np.round_(mean_cross_val_sco
re_NN,3)))
print("The Standard Deviation of  cross val score of Neural Network is:"+str(np.round_(s
td_cross_val_score_NN,3)))

end = time.time()
print("Run time [s]: ",end-start)
```

```
The mean cross val score of Neural Network is:0.896
The Standard Deviation of  cross val score of Neural Network is:0.008
Run time [s]:  200.81286001205444
```

In [316]:
```
from sklearn.metrics import classification_report
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.89      0.87      0.88      7291
           1       0.12      0.14      0.13       947

    accuracy                           0.78      8238
   macro avg       0.50      0.50      0.50      8238
weighted avg       0.80      0.78      0.79      8238
```

In [317]:
```
from sklearn.metrics import plot_confusion_matrix
plt.rcParams["figure.figsize"] = (8, 10)
fig=plot_confusion_matrix(clf, principalDf_test, y_test,display_labels=["0",'1'],cmap=pl
t.cm.Blues,values_format = '.2f')
fig.figure_.suptitle("Confusion Matrix ")
plt.show()
```



In [318]:
```
from sklearn import metrics
from sklearn.metrics import confusion_matrix
```

In [319]:
```
Decison_tree_model=dtc.fit(X_train, y_train)
```

In [320]:
```
def evaluate_model(model, x_test, y_test):
    from sklearn import metrics

    # Predict Test Data
    y_pred = model.predict(x_test)

    # Calculate accuracy, precision, recall, f1-score, and kappa score
    acc = metrics.accuracy_score(y_test, y_pred)
    prec = metrics.precision_score(y_test, y_pred)
    rec = metrics.recall_score(y_test, y_pred)
    f1 = metrics.f1_score(y_test, y_pred)
    kappa = metrics.cohen_kappa_score(y_test, y_pred)

    # Calculate area under curve (AUC)
    y_pred_proba = model.predict_proba(x_test)[::,1]
    fpr, tpr, _ = metrics.roc_curve(y_test, y_pred_proba)
    auc = metrics.roc_auc_score(y_test, y_pred_proba)

    # Display confussion matrix
    cm = metrics.confusion_matrix(y_test, y_pred)

    return {'acc': acc, 'prec': prec, 'rec': rec, 'f1': f1, 'kappa': kappa,
            'fpr': fpr, 'tpr': tpr, 'auc': auc, 'cm': cm}
```

In [321]:
```
 evaluate_model(Decison_tree_model, X_test, y_test)
```

Out[321]:
```
{'acc': 0.8352755523185239,
 'prec': 0.30438931297709926,
 'rec': 0.3368532206969377,
 'f1': 0.3197994987468672,
 'kappa': 0.2263636739857956,
 'fpr': array([0.        , 0.09998628, 0.10656974, 0.10725552, 0.10752983,
        1.        ]),
 'tpr': array([0.        , 0.33685322, 0.34002112, 0.34002112, 0.34002112,
        1.        ]),
 'auc': 0.6173593255604217,
 'cm': array([[6562,  729],
        [ 628,  319]], dtype=int64)}
```

In [322]:
```
###decison trees
from sklearn import tree

# Building Decision Tree model
dtc = tree.DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None, criterion='gini',
                       max_depth=None, max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0,
                       random_state=0, splitter='best')
dtc.fit(X_train, y_train)
```

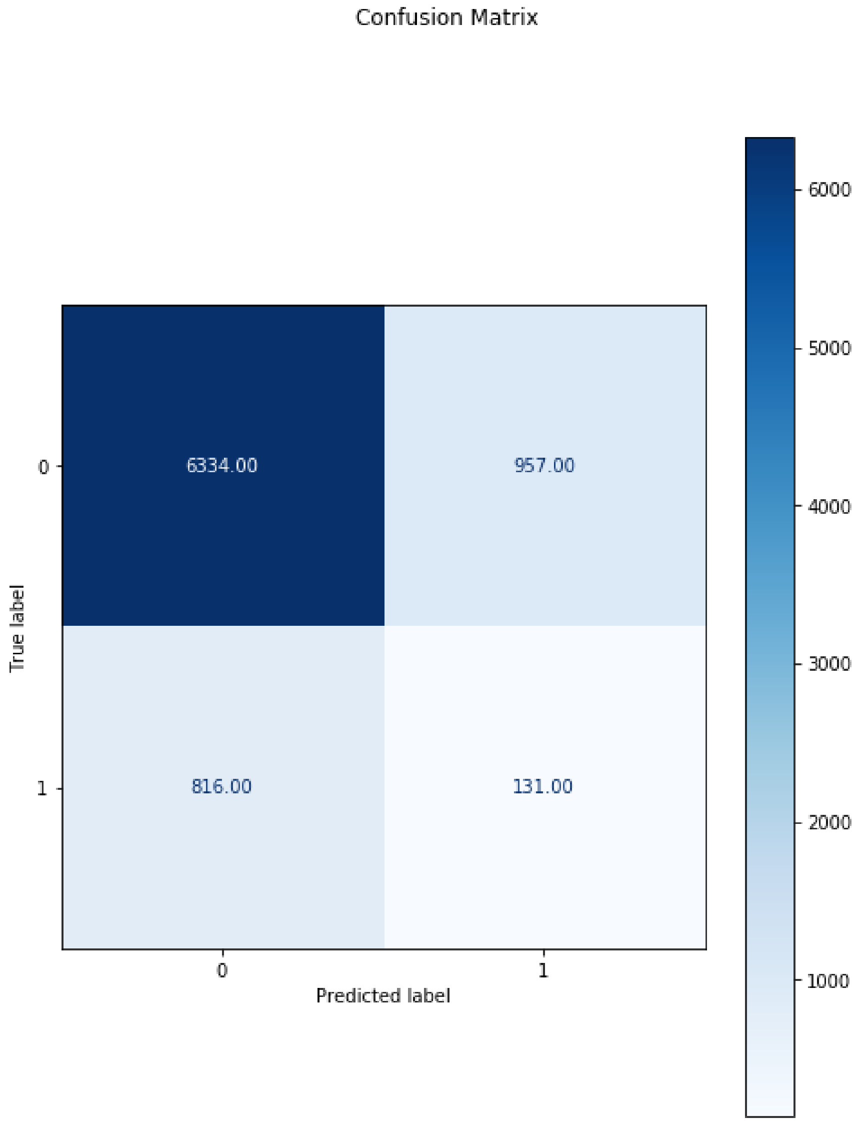
Out[322]:
```
DecisionTreeClassifier(random_state=0)
```

In [323]:
```
Decison_tree_model=dtc.fit(X_train, y_train) #training the model
```

In [324]:
```
# Evaluate Model

import time
start = time.time()



dtc_eval = evaluate_model(Decison_tree_model, X_cv, y_cv)

# Print result
print('Accuracy:', dtc_eval['acc'])
print('Precision:', dtc_eval['prec'])
print('Recall:', dtc_eval['rec'])
print('F1 Score:', dtc_eval['f1'])
print('Cohens Kappa Score:', dtc_eval['kappa'])
print('Area Under Curve:', dtc_eval['auc'])
print('Confusion Matrix:\n', dtc_eval['cm'])


end = time.time()
print("Run time [s]: ",end-start)
```

```
Accuracy: 0.8423368740515933
Precision: 0.30562659846547313
Recall: 0.3251700680272109
F1 Score: 0.31509558338826626
Cohens Kappa Score: 0.22610706539368797
Area Under Curve: 0.6192481569912337
Confusion Matrix:
 [[5312  543]
 [ 496  239]]
Run time [s]:  0.06317543983459473
```

In [325]:
```
from sklearn.metrics import plot_confusion_matrix
plt.rcParams["figure.figsize"] = (8, 10)
fig=plot_confusion_matrix(clf, principalDf_test, y_test,display_labels=["0",'1'],cmap=pl
t.cm.Blues,values_format = '.2f')
fig.figure_.suptitle("Confusion Matrix ")
plt.show()
```



In [326]:
```
import time
start = time.time()

mean_cross_val_score= np.mean(cross_val_score(Decison_tree_model,X_cv, y_cv, cv=10))
std_cross_val_score=np.std(cross_val_score(dtc,X_cv, y_cv, cv=10))
print("The mean cross val score of Decison Tree is:"+ str(np.round_(mean_cross_val_score
,3)))
print("The Standard Deviation of Decison Tree is:"+str(np.round_(std_cross_val_score)))

end = time.time()
print("Run time [s]: ",end-start)
```

```
The mean cross val score of Decison Tree is:0.84
The Standard Deviation of Decison Tree is:0.0
Run time [s]:  1.9679393768310547
```