Bank Marketing Effectiveness Prediction

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Business Context

The data is related to the marketing campaign(phone calls) of a portuguese banking institution. The marketing campaigns were based on phone calls. Often, more than one contact to the same client was required, in order to assess the product(bank term deposite) would be('Yes') or not('no') subscribed. The classification goal is to predict if the client will subscribe to the term deposite(Variable Y)

GitHub

[https://github.com/rahulinchal/Bank-Marketing-Effectiveness-prediction (https://github.com/rahulinchal/Bank-Marketing-Effectiveness-prediction)](https://github.com/rahulinchal/Bank-Marketing-Effectiveness-prediction)

Importing important Packages

In [1]:

```
import numpy as np
import pandas as pd
import seaborn as sns
from matplotlib import pyplot as plt
%matplotlib inline

# Filtering warnings
import warnings
warnings.filterwarnings('ignore')

# Displaying maximum columns
pd.set_option('display.max_columns', None)
```

In [2]:

```
# Loading the dataset
df = pd.read_csv("https://raw.githubusercontent.com/rahulinchal/Bank-Marketing-Effectiveness-predicti
                sep = ';')
```

Attribute Information:

Input variables:

bank client data:

1 - age (numeric)
2 - job : type of job (categorical: 'admin.','blue-collar','entrepreneur','housemaid','management','retired','self-employed','services','student','technician','unemployed','unknown')
3 - marital : marital status (categorical: 'divorced','married','single','unknown'; note: 'divorced' means divorced or widowed)
4 - education (categorical: basic.4y','basic.6y','basic.9y','high.school','illiterate','professional.course','university.degree','unknown')
5 - default: has credit in default? (categorical: 'no','yes','unknown')
6 - housing: has housing loan? (categorical: 'no','yes','unknown')
7 - loan: has personal loan? (categorical: 'no','yes','unknown')

related with the last contact of the current campaign:

8 - contact: contact communication type (categorical: 'cellular','telephone')
9 - month: last contact month of year (categorical: 'jan', 'feb', 'mar', ..., 'nov', 'dec')
10 - day_of_week: last contact day of the week (categorical: 'mon','tue','wed','thu','fri')
11 - duration: last contact duration, in seconds (numeric). Important note: this attribute highly affects the output target (e.g., if duration=0 then y='no'). Yet, the duration is not known before a call is performed. Also, after the end of the call y is obviously known. Thus, this input should only be included for benchmark purposes and should be discarded if the intention is to have a realistic predictive model.

other attributes:

12 - campaign: number of contacts performed during this campaign and for this client (numeric, includes last contact)
13 - pdays: number of days that passed by after the client was last contacted from a previous campaign (numeric; 999 means client was not previously contacted)
14 - previous: number of contacts performed before this campaign and for this client (numeric)
15 - poutcome: outcome of the previous marketing campaign (categorical: 'failure','nonexistent','success')

Output variable (desired target):

16 - y - has the client subscribed a term deposit? (binary: 'yes','no')

In [3]:
```python
# Getting the first 5 rows
df.head()
```

Out[3]:

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays
0	58	management	married	tertiary	no	2143	yes	no	unknown	5	may	261	1	-1
1	44	technician	single	secondary	no	29	yes	no	unknown	5	may	151	1	-1
2	33	entrepreneur	married	secondary	no	2	yes	yes	unknown	5	may	76	1	-1
3	47	blue-collar	married	unknown	no	1506	yes	no	unknown	5	may	92	1	-1
4	33	unknown	single	unknown	no	1	no	no	unknown	5	may	198	1	-1

As per the documentation, the Duration column has to be removed because this attribute highly affects the output target (e.g., if duration=0 then y='no'). Yet, the duration is not known before a call is performed. Also, after the end of the call y is obviously known. Thus, this input should only be included for benchmark purposes and should be discarded if the intention is to have a realistic predictive model.

In [4]:
```python
# Dropping the duration column
df.drop(['duration'], axis = 1, inplace = True)
```

In [5]:
```
# Getting the first 5 rows
df.head()
```

Out[5]:

	age	job	marital	education	default	balance	housing	loan	contact	day	month	campaign	pdays	previous
0	58	management	married	tertiary	no	2143	yes	no	unknown	5	may	1	-1	0
1	44	technician	single	secondary	no	29	yes	no	unknown	5	may	1	-1	0
2	33	entrepreneur	married	secondary	no	2	yes	yes	unknown	5	may	1	-1	0
3	47	blue-collar	married	unknown	no	1506	yes	no	unknown	5	may	1	-1	0
4	33	unknown	single	unknown	no	1	no	no	unknown	5	may	1	-1	0

Data Wrangling

In [6]:
```
# Getting the shape
df.shape
```

Out[6]: (45211, 16)

Finding if there are null values

In [7]:
```
df.isnull().sum()
```

Out[7]:
```
age          0
job          0
marital      0
education    0
default      0
balance      0
housing      0
loan         0
contact      0
day          0
month        0
campaign     0
pdays        0
previous     0
poutcome     0
y            0
dtype: int64
```

There are no null values

In [8]:
```
# Checking for duplicate values
df.duplicated().sum()
```

Out[8]: 16

In [9]:
```
# Dropping the null values
df = df.drop_duplicates()
```

In [10]:
```
# Getting the info of the columns
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 45195 entries, 0 to 45210
Data columns (total 16 columns):
 #   Column     Non-Null Count  Dtype 
---  ------     --------------  ----- 
 0   age        45195 non-null  int64 
 1   job        45195 non-null  object
 2   marital    45195 non-null  object
 3   education  45195 non-null  object
 4   default    45195 non-null  object
 5   balance    45195 non-null  int64 
 6   housing    45195 non-null  object
 7   loan       45195 non-null  object
 8   contact    45195 non-null  object
 9   day        45195 non-null  int64 
 10  month      45195 non-null  object
 11  campaign   45195 non-null  int64 
 12  pdays      45195 non-null  int64 
 13  previous   45195 non-null  int64 
 14  poutcome   45195 non-null  object
 15  y          45195 non-null  object
dtypes: int64(6), object(10)
memory usage: 5.9+ MB
```

In [11]:
```
df.head()
```

Out[11]:

	age	job	marital	education	default	balance	housing	loan	contact	day	month	campaign	pdays	previous
0	58	management	married	tertiary	no	2143	yes	no	unknown	5	may	1	-1	0
1	44	technician	single	secondary	no	29	yes	no	unknown	5	may	1	-1	0
2	33	entrepreneur	married	secondary	no	2	yes	yes	unknown	5	may	1	-1	0
3	47	blue-collar	married	unknown	no	1506	yes	no	unknown	5	may	1	-1	0
4	33	unknown	single	unknown	no	1	no	no	unknown	5	may	1	-1	0

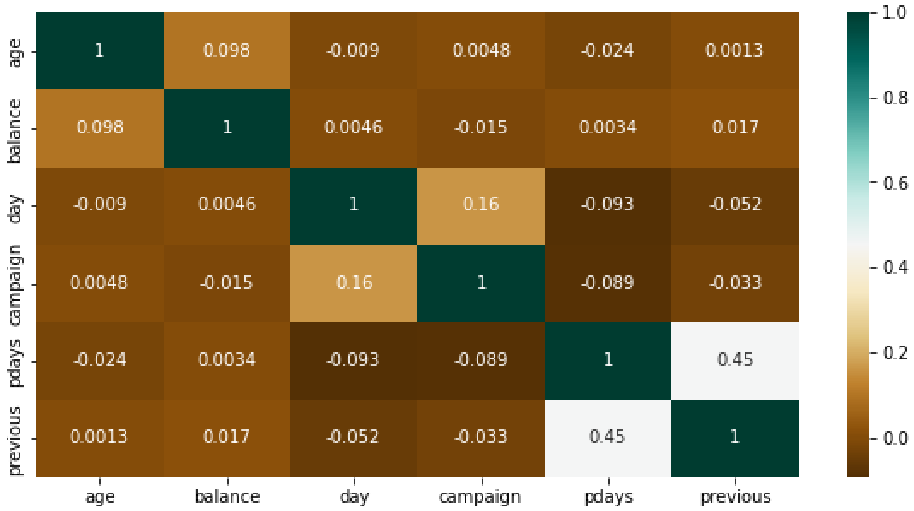
In [12]:
```
df.describe().T.style.background_gradient() # Getting the mathematical answers using Describe functio
```

Out[12]:

	count	mean	std	min	25%	50%	75%	max
age	45195.000000	40.937604	10.619108	18.000000	33.000000	39.000000	48.000000	95.000000
balance	45195.000000	1362.754331	3045.196838	-8019.000000	72.000000	449.000000	1428.000000	102127.000000
day	45195.000000	15.804824	8.322816	1.000000	8.000000	16.000000	21.000000	31.000000
campaign	45195.000000	2.763978	3.098304	1.000000	1.000000	2.000000	3.000000	63.000000
pdays	45195.000000	40.212413	100.143468	-1.000000	-1.000000	-1.000000	-1.000000	871.000000
previous	45195.000000	0.580529	2.303823	0.000000	0.000000	0.000000	0.000000	275.000000

In [13]:
```python
# Plotting a heat map
plt.figure(figsize=(10,5))
sns.heatmap(df.corr(),cmap="BrBG",annot=True)
```

Out[13]: <AxesSubplot:>



Data Visualization

In [14]:
```python
df.head() # FInding the head
```

Out[14]:

	age	job	marital	education	default	balance	housing	loan	contact	day	month	campaign	pdays	previous
0	58	management	married	tertiary	no	2143	yes	no	unknown	5	may	1	-1	0
1	44	technician	single	secondary	no	29	yes	no	unknown	5	may	1	-1	0
2	33	entrepreneur	married	secondary	no	2	yes	yes	unknown	5	may	1	-1	0
3	47	blue-collar	married	unknown	no	1506	yes	no	unknown	5	may	1	-1	0
4	33	unknown	single	unknown	no	1	no	no	unknown	5	may	1	-1	0

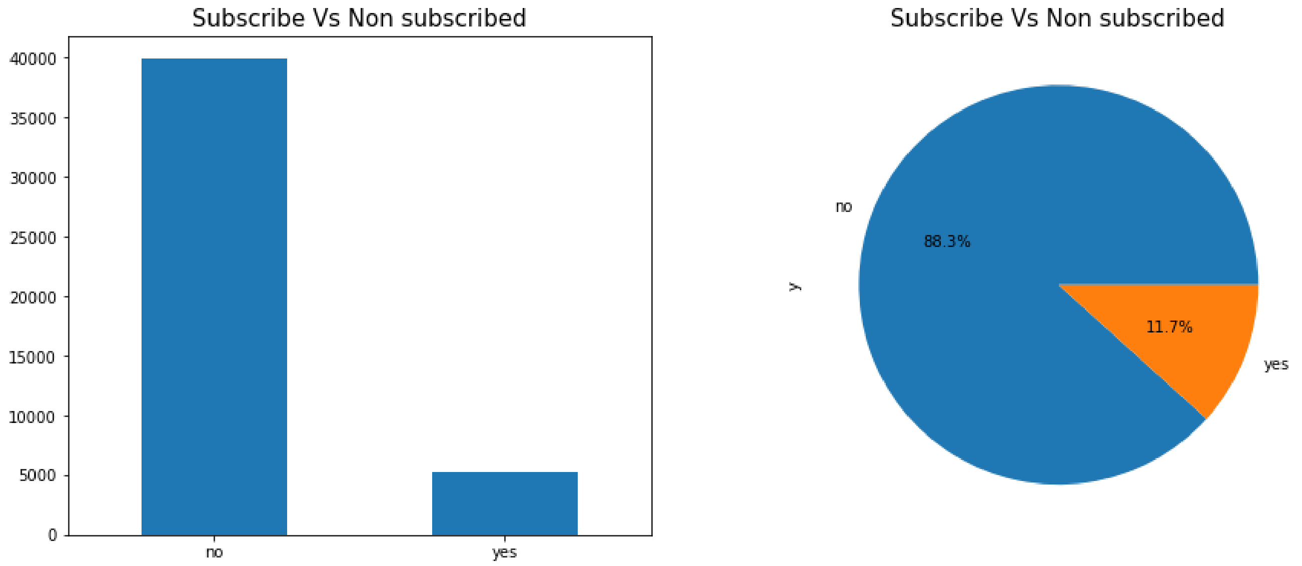
In [15]:
```python
df['y'].value_counts() # Calculating the value counts
```

Out[15]:
```
no     39906
yes     5289
Name: y, dtype: int64
```

In [16]:
```
plt.figure(figsize = (15,6))

plt.subplot(1,2,1)
df['y'].value_counts().plot(kind = 'bar')  # Plotting the bar graph
plt.title("Subscribe Vs Non subscribed", fontsize = 15)
plt.xticks(rotation = 360)

plt.subplot(1,2,2)
df['y'].value_counts().plot(kind = 'pie', autopct = '%1.1f%%') #plotting the pie chart for the same
plt.title("Subscribe Vs Non subscribed", fontsize = 15)
plt.show()
```



Observation

From this data we can see that 88% customers did not subscribed for Term deposit

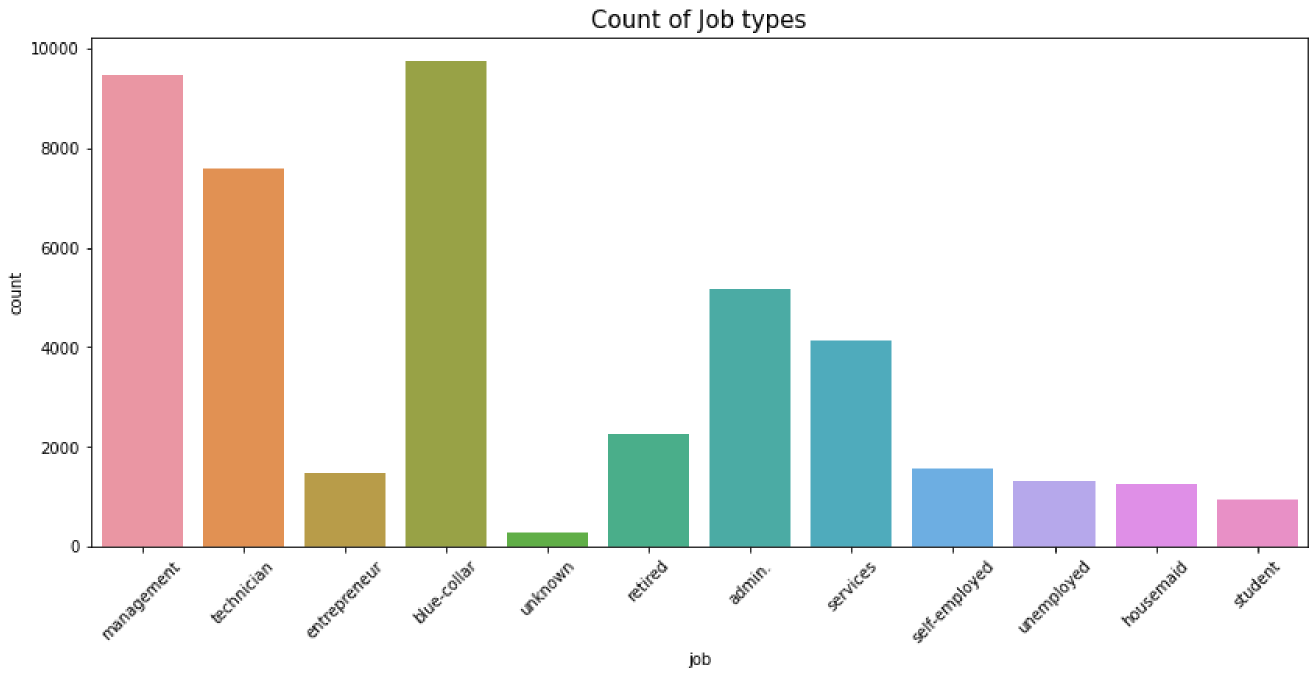
From the above plot we can observe that our dataset is highly imbalanced. Majority of the data points belong to no class. Ratio of No class to yes class is 8:1.

In [17]:
```
df.head()
```

Out[17]:

	age	job	marital	education	default	balance	housing	loan	contact	day	month	campaign	pdays	previous
0	58	management	married	tertiary	no	2143	yes	no	unknown	5	may	1	-1	0
1	44	technician	single	secondary	no	29	yes	no	unknown	5	may	1	-1	0
2	33	entrepreneur	married	secondary	no	2	yes	yes	unknown	5	may	1	-1	0
3	47	blue-collar	married	unknown	no	1506	yes	no	unknown	5	may	1	-1	0
4	33	unknown	single	unknown	no	1	no	no	unknown	5	may	1	-1	0

In [18]:
```
plt.figure(figsize = (14,6))
sns.countplot(data = df, x = df['job'])
plt.xticks(rotation = 45)
plt.title("Count of Job types", fontsize = 15)
plt.show()
```



Observation

we can see that most of the customers have jobs as "management", "blue-collar" or "technician".

In [19]:
```
df.head()
```

Out[19]:

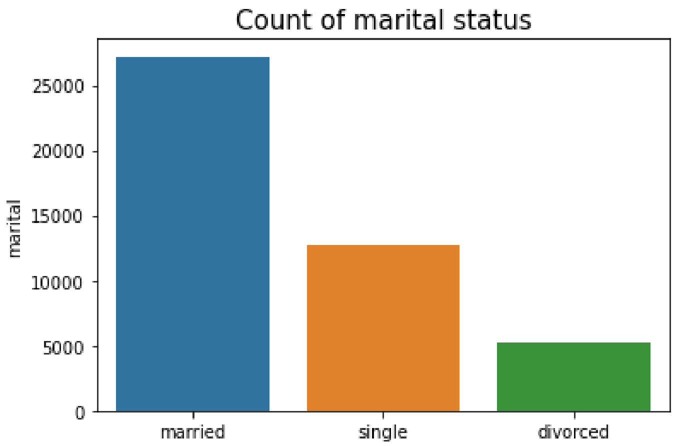
	age	job	marital	education	default	balance	housing	loan	contact	day	month	campaign	pdays	previous
0	58	management	married	tertiary	no	2143	yes	no	unknown	5	may	1	-1	0
1	44	technician	single	secondary	no	29	yes	no	unknown	5	may	1	-1	0
2	33	entrepreneur	married	secondary	no	2	yes	yes	unknown	5	may	1	-1	0
3	47	blue-collar	married	unknown	no	1506	yes	no	unknown	5	may	1	-1	0
4	33	unknown	single	unknown	no	1	no	no	unknown	5	may	1	-1	0

In [20]:
```
df['marital'].value_counts()
```

Out[20]:
```
married     27208
single      12780
divorced     5207
Name: marital, dtype: int64
```

In [21]:

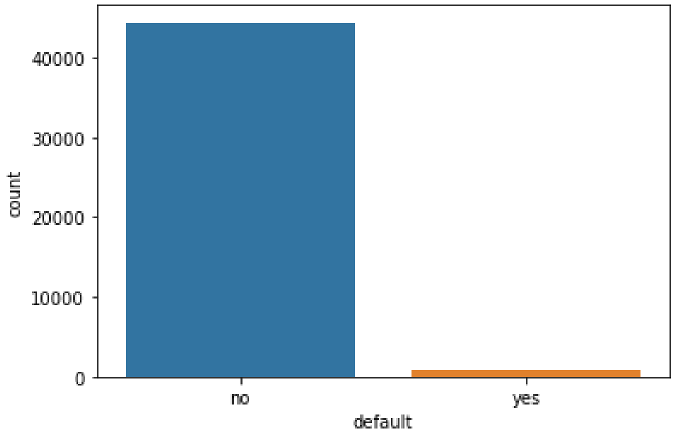
```
sns.barplot(data = df, x = df['marital'].value_counts().keys(), y = df['marital'].value_counts())
plt.title("Count of marital status", fontsize = 15)
plt.show()
```



Client who married are high in records in given dataset and divorced are less

In [22]:

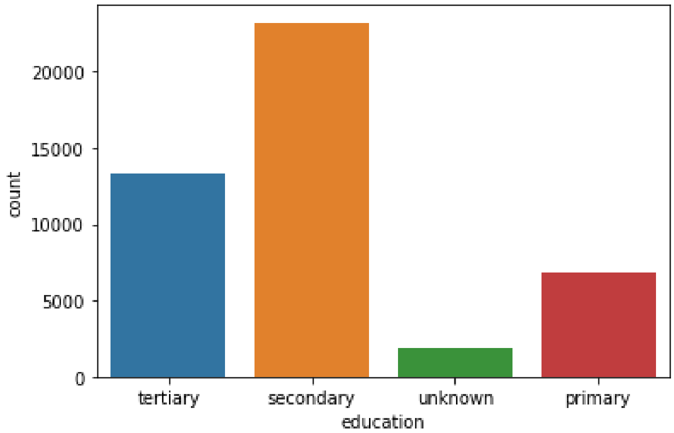
```
sns.countplot(x='default', data=df)
plt.show()
```



defualt feature seems to be does not play important role as it has value of no at high ratio to value yes which can drop###

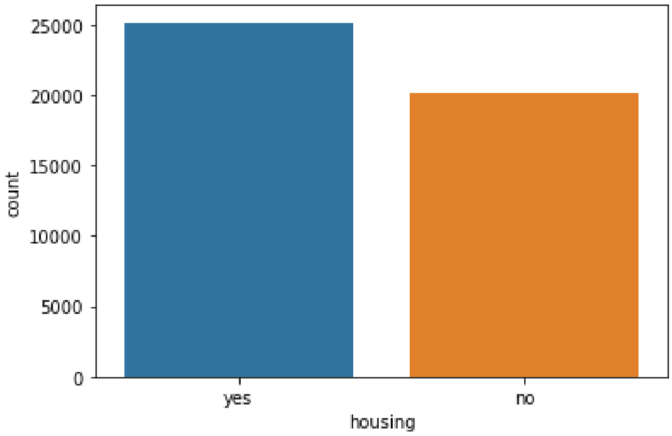
In [23]:

```
sns.countplot(x='education', data=df)
plt.show()
```



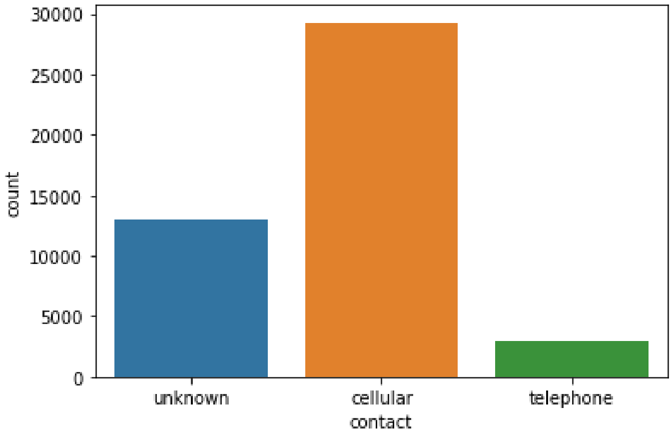
education background is secondary are in high numbers in given dataset

In [24]:
```
sns.countplot(x='housing', data=df)
plt.show()
```



People with housing loan are the most ones

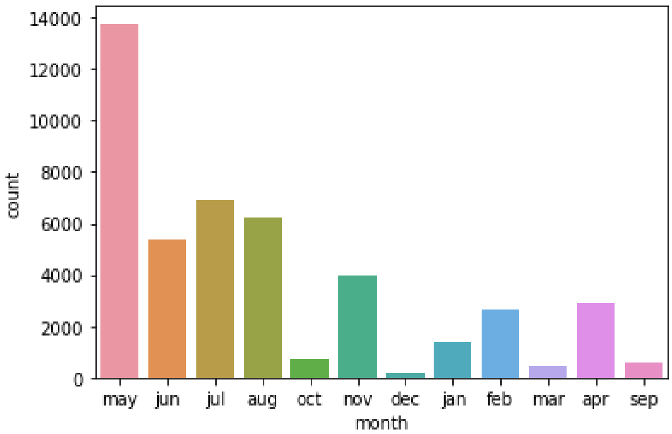
In [25]:
```
sns.countplot(x='contact', data=df)
plt.show()
```



Cellular contacts are more compared to telphone

In [26]:
```
sns.countplot(x='month', data=df)
```

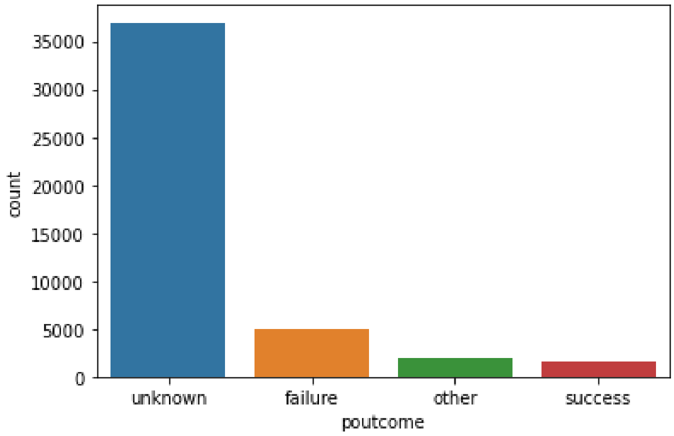
Out[26]: <AxesSubplot:xlabel='month', ylabel='count'>



May has the most last contact month of year

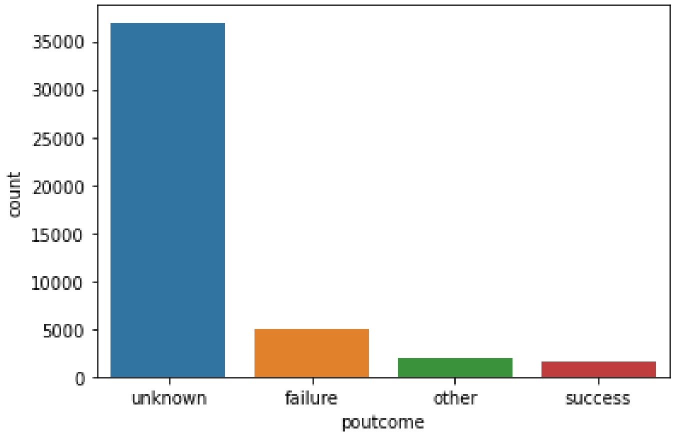
In [27]:
```
sns.countplot(x='poutcome', data=df)
```

Out[27]: <AxesSubplot:xlabel='poutcome', ylabel='count'>



In [28]:
```
sns.countplot(x='poutcome', data=df)
```

Out[28]: <AxesSubplot:xlabel='poutcome', ylabel='count'>



This feature indicates the outcome of the previous marketing campaign

Majority of the outcome of the previous campaign is Non-Existent. Very few people counts who successfully subscribed from previous marketing strategy.

The visualization is being done. Now we head to model building

One hot encoding

What is meant by one-hot encoding?
One-hot encoding in machine learning is the conversion of categorical information into a format that may be fed into machine learning algorithms to improve prediction accuracy. One-hot encoding is a common method for dealing with categorical data in machine learning.

In [29]:
```
# One hot encoding
df = pd.get_dummies(df, columns = ['job', 'marital', 'education', 'default', 'housing', 'loan', 'cont
                                    'poutcome'])
```

In [30]:
```
# Finding head of the data after one hot encoding
df.head()
```

Out[30]:

	age	balance	day	campaign	pdays	previous	y	job_admin.	job_blue-collar	job_entrepreneur	job_housemaid	job_managem
0	58	2143	5	1	-1	0	no	0	0	0	0	
1	44	29	5	1	-1	0	no	0	0	0	0	
2	33	2	5	1	-1	0	no	0	0	1	0	
3	47	1506	5	1	-1	0	no	0	1	0	0	
4	33	1	5	1	-1	0	no	0	0	0	0	

In [31]:
```
# Finding shape
df.shape
```

Out[31]: (45195, 51)

In [32]:
```
# Replacing the dependent variable with 0 and 1
df['y'].replace({'no': 0, 'yes': 1}, inplace = True)
```

In [33]:
```
df['y'].value_counts() # FInding the value counts
```

Out[33]:
```
0    39906
1     5289
Name: y, dtype: int64
```

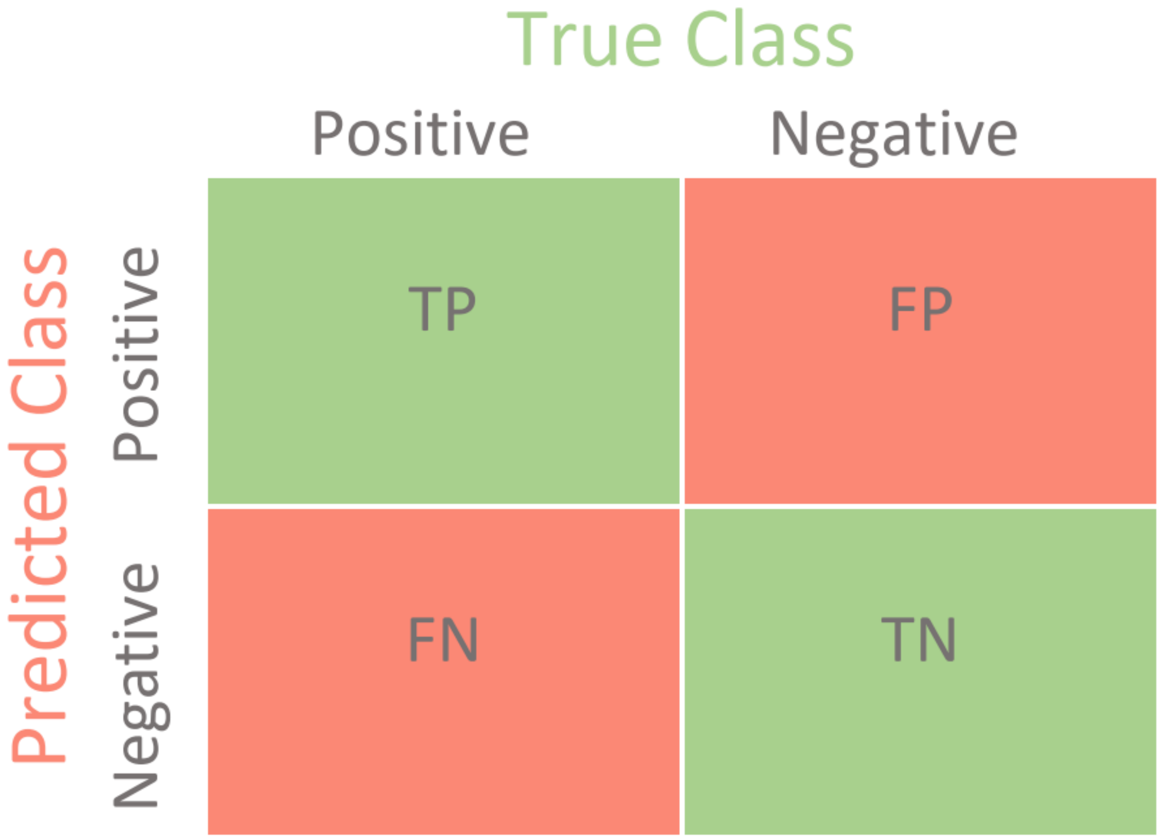
Defining X and Y

In [34]:
```
x = df.drop(['y'], axis = 1).values # Set of independent variable
y = df['y'].values # Dependent valriable
```

Splitting the data into train test split

In [35]:
```
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x,y,shuffle = True, test_size=0.2, random_state=1
```

Modelling



To evaluate our model we will use the confusion matrix as our base for the evaluation.

There are 6 metrics use to evaluate models:

1. Accuracy: the proportion of true results among the total number of cases examined.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$$

Where: TP = True Positive; FP = False Positive; TN = True Negative; FN = False Negative.

2. Precision: used to calculate how much proportion of all data that was predicted positive was actually positive.
$$Precision = \frac{TP}{TP+FP}$$
3. Recall: used to calculate how much proportion of actual positives is correctly classified.
$$Recall = \frac{TP}{TP+FN}$$
4. F1 score: a number between 0 and 1 and is the harmonic mean of precision and recall.
$$F1 = \frac{2TP}{2TP+FP+FN}$$
5. Cohen Kappa Score: Cohen's kappa measures the agreement between two raters who each classify N items into C mutually exclusive categories.
$$\kappa = \frac{p_o - p_e}{1 - p_e}$$
where p_o is the empirical probability of agreement on the label assigned to any sample (the observed agreement ratio), and p_e is the expected agreement when both annotators assign labels randomly. p_e is estimated using a per-annotator empirical prior over the class labels.
6. Area Under Curve (AUC): indicates how well the probabilities from the positive classes are separated from the negative classes

In [36]:

```python
# function to evaluate and calculate accuracy, precision, recall, F1-score and kappa score
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)*100
    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)

    # Visualization of Confusion matrix
    plt.figure(figsize = (10,8))
    sns.heatmap(cm/np.sum(cm), annot=True, fmt='.2%', cmap='Blues')

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

Feature Scaling

What is Feature Scaling?

Feature scaling is a method used to normalize the range of independent variables or features of data. In data processing, it is also known as data normalization and is generally performed during the data preprocessing step. Just to give you an example — if you have multiple independent variables like age, salary, and height; With their range as (18–100 Years), (25,000–75,000 Euros), and (1–2 Meters) respectively, feature scaling would help them all to be in the same range, for example- centered around 0 or in the range (0,1) depending on the scaling technique.

In order to visualize the above, let us take an example of the independent variables of alcohol and Malic Acid content in the wine dataset from the “Wine Dataset” that is deposited on the UCI machine learning repository. Below you can see the impact of the two most common scaling techniques (Normalization and Standardization) on the dataset.

Normalization

Also known as min-max scaling or min-max normalization, it is the simplest method and consists of rescaling the range of features to scale the range in [0, 1]. The general formula for normalization is given as:

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)}$$

Here, max(x) and min(x) are the maximum and the minimum values of the feature respectively.

Standardization

Feature standardization makes the values of each feature in the data have zero mean and unit variance. The general method of calculation is to determine the distribution mean and standard deviation for each feature and calculate the new data point by the following formula:

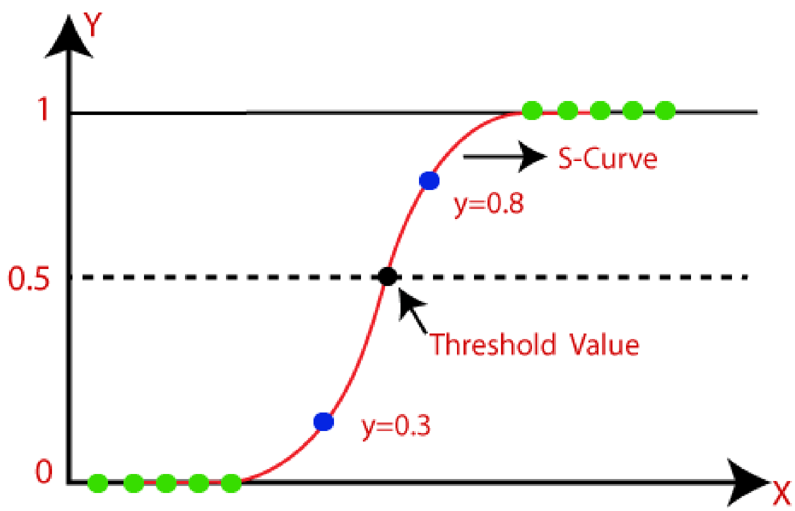
$$x' = \frac{x - \bar{x}}{}$$

In [37]:
```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
x_train = sc.fit_transform(x_train)
x_test = sc.transform(x_test)
```

Logistic Regression

Logistic Regression in Machine Learning

- Logistic regression is one of the most popular Machine Learning algorithms, which comes under the Supervised Learning technique. It is used for predicting the categorical dependent variable using a given set of independent variables.
- Logistic regression predicts the output of a categorical dependent variable. Therefore the outcome must be a categorical or discrete value. It can be either Yes or No, 0 or 1, true or False, etc. but instead of giving the exact value as 0 and 1, it gives the probabilistic values which lie between 0 and 1.
- Logistic Regression is much similar to the Linear Regression except that how they are used. Linear Regression is used for solving Regression problems, whereas Logistic regression is used for solving the classification problems.
- In Logistic regression, instead of fitting a regression line, we fit an "S" shaped logistic function, which predicts two maximum values (0 or 1).
- The curve from the logistic function indicates the likelihood of something such as whether the cells are cancerous or not, a mouse is obese or not based on its weight, etc.
- Logistic Regression is a significant machine learning algorithm because it has the ability to provide probabilities and classify new data using continuous and discrete datasets.
- Logistic Regression can be used to classify the observations using different types of data and can easily determine the most effective variables used for the classification. The below image is showing the logistic function:



In [38]:
```
# Importing Logistic Regression from linear model
from sklearn.linear_model import LogisticRegression
logreg = LogisticRegression(random_state = 0)
```

Fitting the model in training data

In [39]:
```
logreg.fit(x_train,y_train) # Fitting the model
```

Out[39]:
```
LogisticRegression(random_state=0)
```

Predicting the results

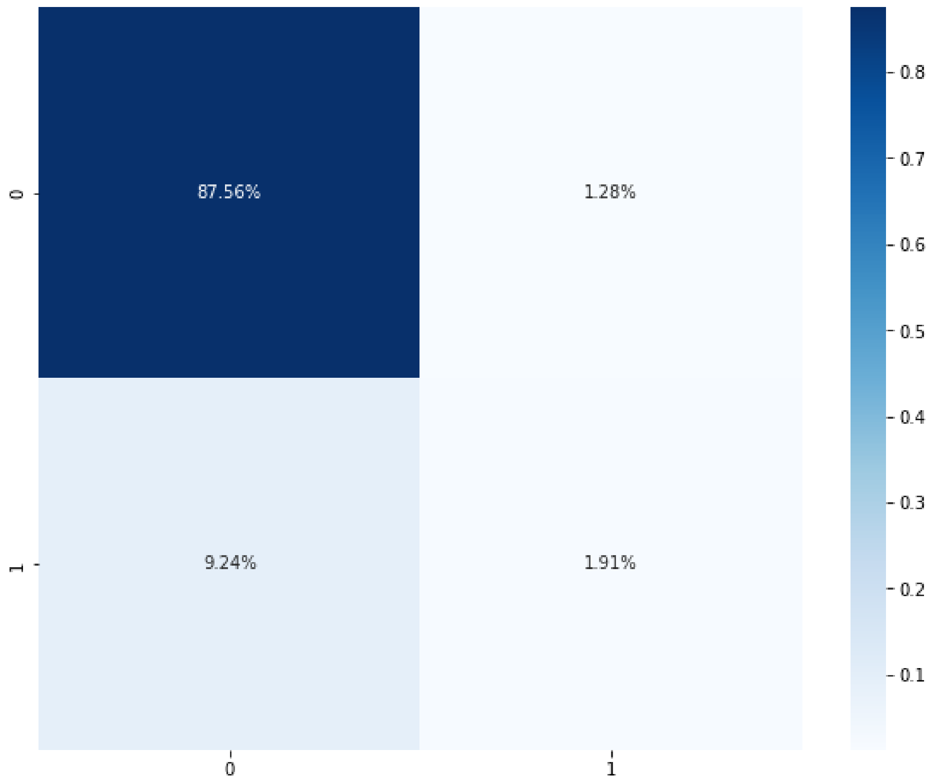
In [40]:
```
y_pred_lr = logreg.predict(x_test) # Predicting the results
```

Caluculating confusion matrics

In [41]:
```python
# Evaluate Decision Tree Model
logreg_score = evaluate_model(logreg, x_test, y_test)

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

```
Accuracy: 89.4789246598075
Precision: 0.5986159169550173
Recall: 0.17162698412698413
F1 Score: 0.26676946800308404
Cohens Kappa Score: 0.2284246804965353
Area Under Curve: 0.7538832658369454
Confusion Matrix:
 [[7915  116]
 [ 835  173]]
```



Decision tree classifier

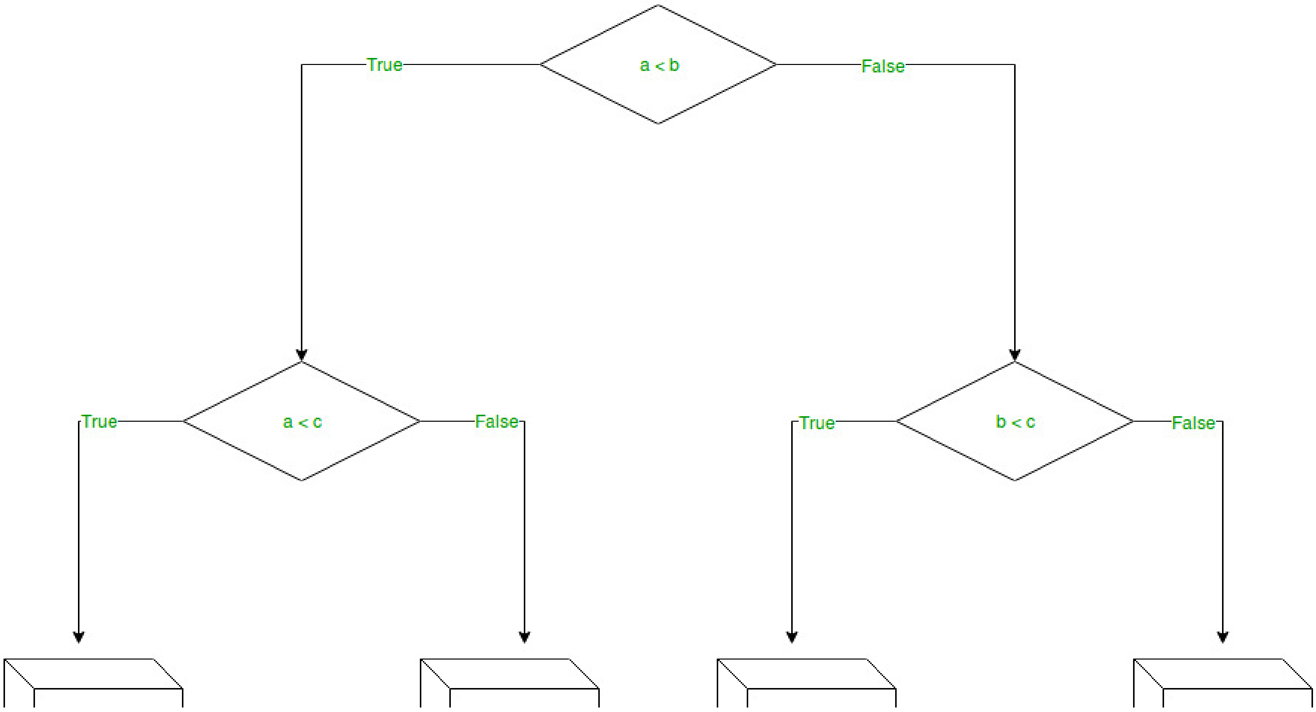
Decision Tree

Decision Tree is a decision-making tool that uses a flowchart-like tree structure or is a model of decisions and all of their possible results, including outcomes, input costs, and utility. Decision-tree algorithm falls under the category of supervised learning algorithms. It works for both continuous as well as categorical output variables.

The branches/edges represent the result of the node and the nodes have either:

1. Conditions [Decision Nodes]
2. Result [End Nodes]

The branches/edges represent the truth/falsity of the statement and take makes a decision based on that in the example below which shows a decision tree that evaluates the smallest of three numbers:



In [42]:
```
from sklearn.tree import DecisionTreeClassifier # Importing the decision tree model from tree
dtc = DecisionTreeClassifier()
```

In [43]:
```
dtc.fit(x_train, y_train) # FItting the trianing data
```

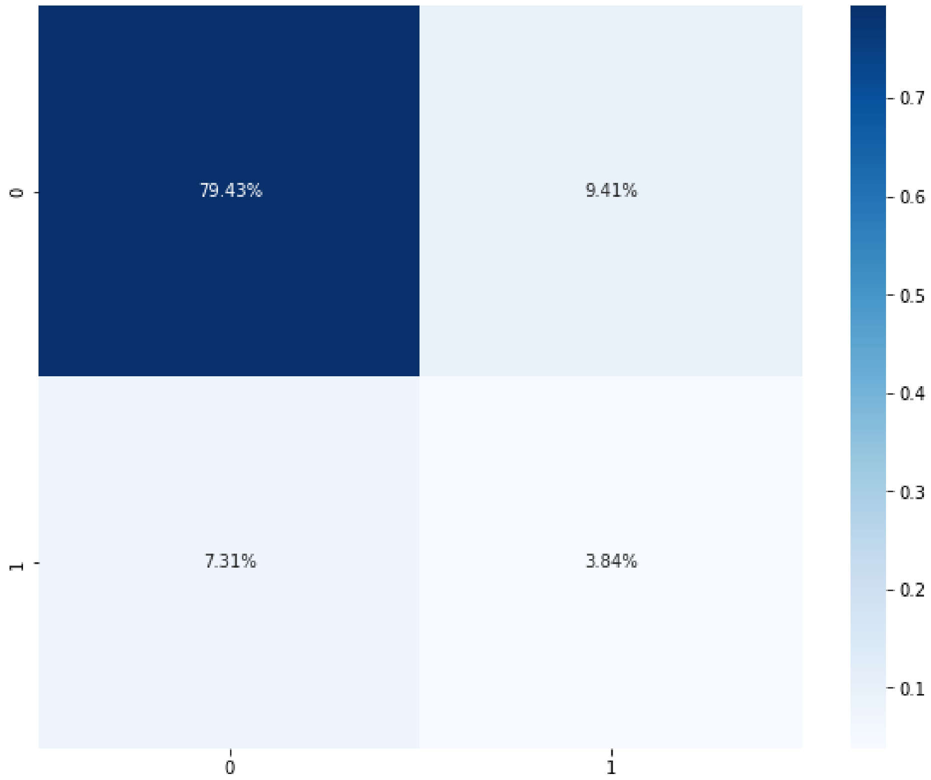
Out[43]: DecisionTreeClassifier()

In [44]:
```
y_pred_dtc = dtc.predict(x_test) #predicting the data
```

In [45]:
```python
# Evaluate Decision Tree Model
dtc_eval = evaluate_model(dtc, x_test, y_test)

# 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'])
```

```
Accuracy: 83.27248589445735
Precision: 0.2896494156928214
Recall: 0.34424603174603174
F1 Score: 0.31459655485040794
Cohens Kappa Score: 0.22013851632303494
Area Under Curve: 0.619140821874759
Confusion Matrix:
 [[7180  851]
 [ 661  347]]
```



Random Forest

Random Forest Regression is a supervised learning algorithm that uses ensemble learning method for regression. Ensemble learning method is a technique that combines predictions from multiple machine learning algorithms to make a more accurate prediction than a single model.

In [46]:
```python
from sklearn.ensemble import RandomForestClassifier # Importing the random forest from ensemble
rfc = RandomForestClassifier()
```

In [47]:
```python
rfc.fit(x_train, y_train) # Fitting the model
```

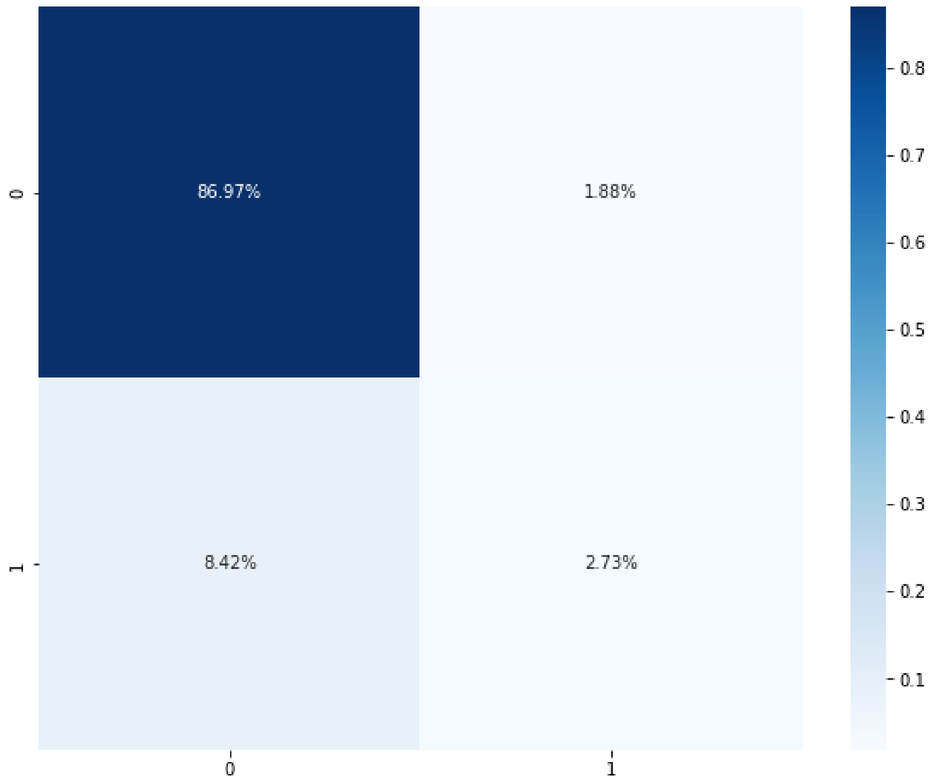
Out[47]:
```
RandomForestClassifier()
```

In [48]:
```python
y_pred_rfc = rfc.predict(x_test) # Predicting the model
```

In [49]:
```python
# Evaluate Decision Tree Model
rfc_eval = evaluate_model(rfc, x_test, y_test)

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

```
Accuracy: 89.70018807390197
Precision: 0.592326139088729
Recall: 0.24503968253968253
F1 Score: 0.3466666666666666
Cohens Kappa Score: 0.30104843867928166
Area Under Curve: 0.7650296198461122
Confusion Matrix:
 [[7861  170]
 [ 761  247]]
```



gradient boosting classifier

In [50]:
```python
from sklearn.ensemble import GradientBoostingClassifier # Importing the gradient booster from ensembl
gbc = GradientBoostingClassifier()
```

In [51]:
```python
gbc.fit(x_train, y_train)# Fitting the model
```

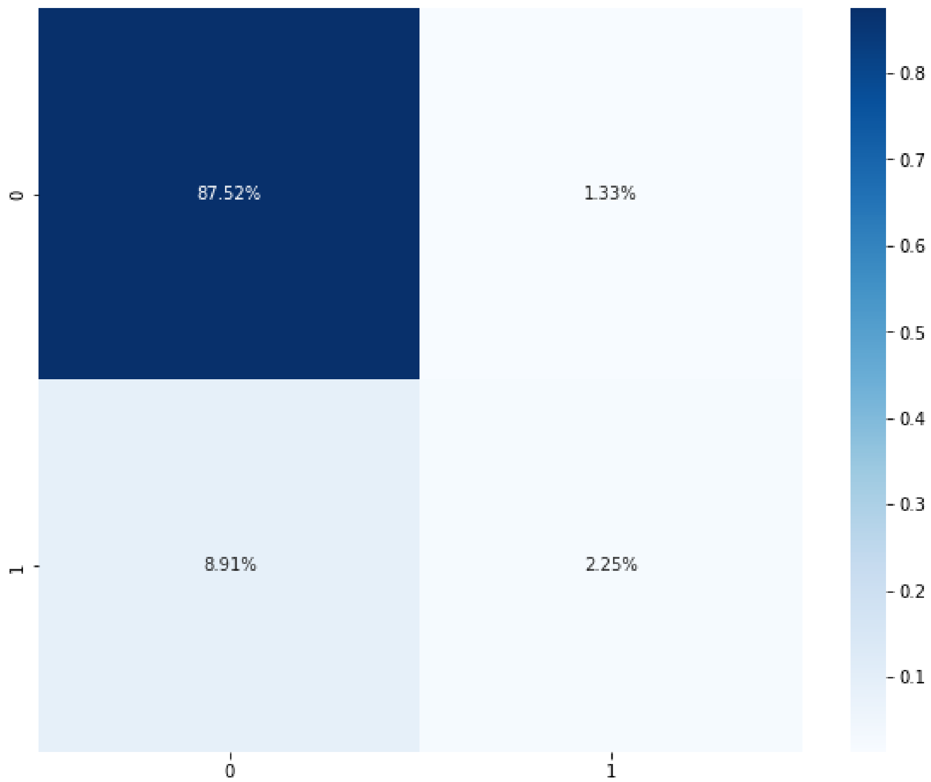
Out[51]:
```
GradientBoostingClassifier()
```

In [52]:
```python
y_pred_gbc = gbc.predict(x_test)# Predicting the model
```

In [53]:
```python
# Evaluate Decision Tree Model
gbc_eval = evaluate_model(gbc, x_test, y_test)

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

```
Accuracy: 89.76656709813032
Precision: 0.628482972136223
Recall: 0.2013888888888889
F1 Score: 0.30503380916604056
Cohens Kappa Score: 0.2652666699532089
Area Under Curve: 0.780273686488666
Confusion Matrix:
 [[7911  120]
 [ 805  203]]
```



XG boost

In [54]:
```python
from xgboost.sklearn import XGBClassifier # Importing the xgb classifier from sklearn
xgb = XGBClassifier(learning_rate = 0.1, max_depth = 6, min_child_weight = 5, gamma = 0,
                    subsample = 0.9, colsample_bytree = 0.9, scale_pos_weight = 1)
```

In [55]:
```python
xgb.fit(x_train, y_train)# Fitting the model
```

```
[11:59:58] WARNING: ..\src\learner.cc:1115: Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed from 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
```

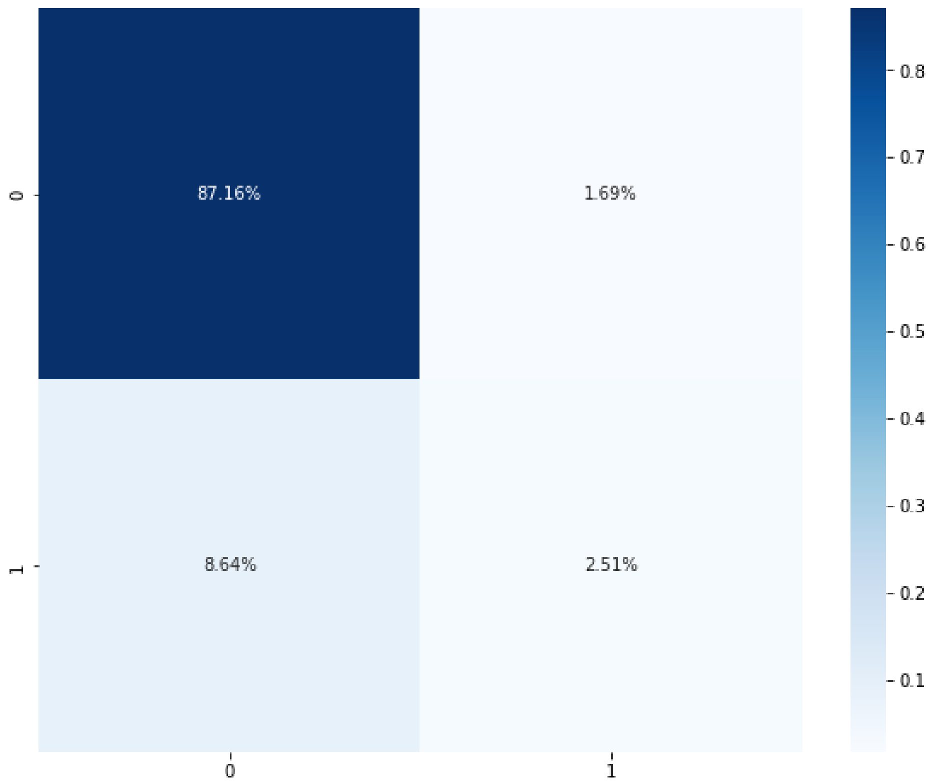
Out[55]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=0.9,
              enable_categorical=False, gamma=0, gpu_id=-1,
              importance_type=None, interaction_constraints='',
              learning_rate=0.1, max_delta_step=0, max_depth=6,
              min_child_weight=5, missing=nan, monotone_constraints='()',
              n_estimators=100, n_jobs=4, num_parallel_tree=1, predictor='auto',
              random_state=0, reg_alpha=0, reg_lambda=1, scale_pos_weight=1,
              subsample=0.9, tree_method='exact', validate_parameters=1,
              verbosity=None)
```

In [56]:
```python
y_pred_xgb = xgb.predict(x_test)# Predicting the model
```

In [57]:
```python
# Evaluate Decision Tree Model
xgb_eval = evaluate_model(xgb, x_test, y_test)

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

```
Accuracy: 89.6669985617878
Precision: 0.5973684210526315
Recall: 0.2251984126984127
F1 Score: 0.32708933717579247
Cohens Kappa Score: 0.28332863046784507
Area Under Curve: 0.788092038687388
Confusion Matrix:
 [[7878  153]
 [ 781  227]]
```



SVC

In [58]:
```
from sklearn.svm import SVC # Importing svc from svm
svc = SVC()
```

In [59]:
```
svc.fit(x_train, y_train)# Fitting the model
```

Out[59]:
```
SVC()
```

In [60]:
```
y_pred_svc = svc.predict(x_test)# Predicting the model
```

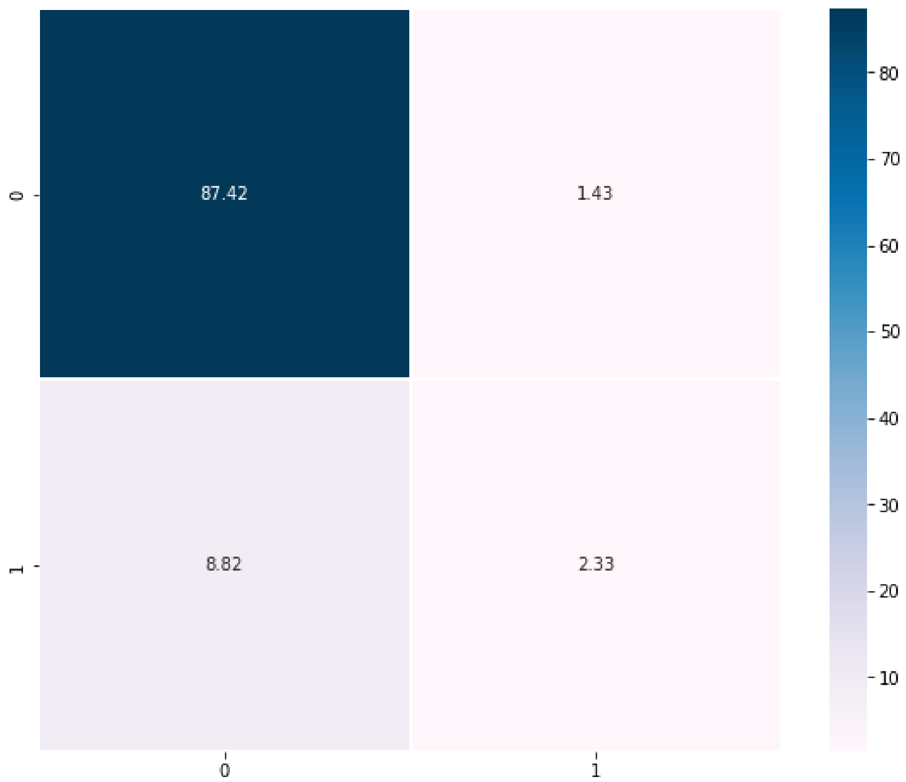
In [61]:
```
#Importing precision recall, recall score, accuracy score and f1 score
from sklearn.metrics import precision_score,recall_score,accuracy_score,f1_score
from sklearn import metrics
from sklearn.metrics import confusion_matrix
```

In [62]:
```
# Printing the evaluation matrics
print("Accuracy = " , accuracy_score(y_test, y_pred_svc)*100)
print("Precision = " ,precision_score(y_test, y_pred_svc))
print("Recall = " ,recall_score(y_test, y_pred_svc))
print("F1 Score = " ,f1_score(y_test, y_pred_svc))

plt.figure(figsize = (10,8))
cm = confusion_matrix(y_test,y_pred_svc)
sns.heatmap((cm/np.sum(cm))*100, annot=True, fmt=".2f", linewidths=.3,
        square = True, cmap = 'PuBu')
```

```
Accuracy =  89.7555039274256
Precision =  0.6205882352941177
Recall =  0.20932539682539683
F1 Score =  0.31305637982195844
```

Out[62]:
```
<AxesSubplot:>
```



In [63]:

```
overall_scores = pd.DataFrame({'Logistic Regression': (logreg_score['acc']),
                               'Decision Tree Classifier': (dtc_eval['acc']),
                               'Random Forest Classifer': (rfc_eval['acc']),
                               'Gradient Boosting Classifier': (gbc_eval['acc']),
                               'XGBoost': (xgb_eval['acc']),
                               'SVC': (accuracy_score(y_test, y_pred_svc))*100}, index = [0])
overall_scores.T.rename(columns = {0:'Accuracy Scores'})
```

Out[63]:

	Accuracy Scores
Logistic Regression	89.478925
Decision Tree Classifier	83.272486
Random Forest Classifer	89.700188
Gradient Boosting Classifier	89.766567
XGBoost	89.666999
SVC	89.755504

In terms of accuracy, Classifier like Logisitic Regression, Random Forest, Gradient Boosting classifier, XGB and SVC gives almost the same score i.e., 89%.