Bank Marketing Analysis

In [1]:
```
#importing the libery
import numpy as np
import pandas as pd
```

Data Collection

In [2]:
```
#data loading in panda
data=pd.read_csv('bank.csv')
```

In [3]:
```
#check first five rows of the dataset
data.head()
```

Out[3]:

	age	job	marital	education	default	balance	housing	loan	contact	day	mon
0	59	admin.	married	secondary	no	2343	yes	no	unknown	5	m
1	56	admin.	married	secondary	no	45	no	no	unknown	5	m
2	41	technician	married	secondary	no	1270	yes	no	unknown	5	m
3	55	services	married	secondary	no	2476	yes	no	unknown	5	m
4	54	admin.	married	tertiary	no	184	no	no	unknown	5	m

In [4]:
```
#check last five rows pf the dataset
data.tail()
```

Out[4]:

	age	job	marital	education	default	balance	housing	loan	contact	day
11157	33	blue-collar	single	primary	no	1	yes	no	cellular	20
11158	39	services	married	secondary	no	733	no	no	unknown	16
11159	32	technician	single	secondary	no	29	no	no	cellular	19
11160	43	technician	married	secondary	no	0	no	yes	cellular	8
11161	34	technician	married	secondary	no	0	no	no	cellular	9

In [3]:
```
#check basic infomation of the dataset
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11162 entries, 0 to 11161
Data columns (total 17 columns):
 #   Column     Non-Null Count  Dtype 
---  ------     --------------  ----- 
 0   age        11162 non-null  int64 
 1   job        11162 non-null  object
 2   marital    11162 non-null  object
 3   education  11162 non-null  object
 4   default    11162 non-null  object
 5   balance    11162 non-null  int64 
 6   housing    11162 non-null  object
 7   loan       11162 non-null  object
 8   contact    11162 non-null  object
 9   day        11162 non-null  int64 
 10  month      11162 non-null  object
 11  duration   11162 non-null  int64 
 12  campaign   11162 non-null  int64 
 13  pdays      11162 non-null  int64 
 14  previous   11162 non-null  int64 
 15  poutcome   11162 non-null  object
 16  deposit    11162 non-null  object
dtypes: int64(7), object(10)
memory usage: 1.4+ MB
```

In [4]:
```
#check columns name of the dataset
data.columns
```

Out[4]:
```
Index(['age', 'job', 'marital', 'education', 'default', 'balance',
'housing',
       'loan', 'contact', 'day', 'month', 'duration', 'campaign',
'pdays',
       'previous', 'poutcome', 'deposit'],
      dtype='object')
```

In [5]:
```
data.head(10)
```

Out[5]:

	age	job	marital	education	default	balance	housing	loan	contact	day
0	59	admin.	married	secondary	no	2343	yes	no	unknown	5
1	56	admin.	married	secondary	no	45	no	no	unknown	5
2	41	technician	married	secondary	no	1270	yes	no	unknown	5
3	55	services	married	secondary	no	2476	yes	no	unknown	5
4	54	admin.	married	tertiary	no	184	no	no	unknown	5
5	42	management	single	tertiary	no	0	yes	yes	unknown	5
6	56	management	married	tertiary	no	830	yes	yes	unknown	6
7	60	retired	divorced	secondary	no	545	yes	no	unknown	6
8	37	technician	married	secondary	no	1	yes	no	unknown	6
9	28	services	single	secondary	no	5090	yes	no	unknown	6

In [6]:
```
#check mathamatic realtionship of the dataset
data.describe()
```

Out[6]:

	age	balance	day	duration	campaign	pdays
count	11162.000000	11162.000000	11162.000000	11162.000000	11162.000000	11162.00000
mean	41.231948	1528.538524	15.658036	371.993818	2.508421	51.33040
std	11.913369	3225.413326	8.420740	347.128386	2.722077	108.75828
min	18.000000	-6847.000000	1.000000	2.000000	1.000000	-1.00000
25%	32.000000	122.000000	8.000000	138.000000	1.000000	-1.00000
50%	39.000000	550.000000	15.000000	255.000000	2.000000	-1.00000
75%	49.000000	1708.000000	22.000000	496.000000	3.000000	20.75000
max	95.000000	81204.000000	31.000000	3881.000000	63.000000	854.00000

1. Age / Age
2. Job / Job
3. Marital Status / Marital Status
4. Education / Education Level
5. Default / Having a previously broken credit
6. Housing / home loan?
7. Loan / Personal Loan?
8. Contact / Was the customer contacted on his home or mobile phone?
9. Month: Last month of contact
10. Day: The day of the contacted.
11. Duration: Talk time on last call
12. Campaign: The number of contacts reaching the customer during the current campaign (including the last contact)
13. Pdays: The number of days since the previous campaign, if reached (-1 if it was never reached before)
14. Previous: The number of contacts that reached the customer before this campaign
15. Poutcome: Previous campaign success, failure or failure

Univariate Variable Analysis

- Categorical Variables:job,marital, default, education,housing,loan,contact,poutcome,mounth,deposit,day
- Numerical Variables: age, campaign,duration, pdays,balance,previous

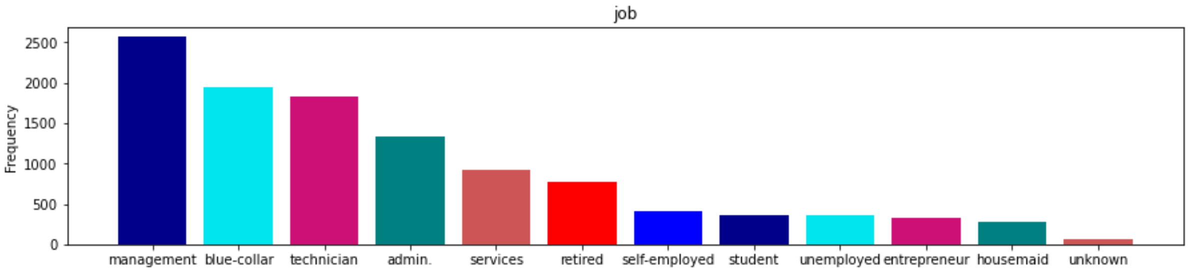
Categorical Variable

In [7]:
```
import matplotlib.pyplot as plt
```

In [8]:
```
def bar_plot(variable):
    var =data[variable]
    varValue = var.value_counts()
    plt.figure(figsize=(15,3))
    plt.bar(varValue.index, varValue,color=['#00008b','#00e5ee','#c
    plt.xticks(varValue.index, varValue.index.values)
    plt.ylabel("Frequency")
    plt.title(variable)

    plt.show()
    print("{}: \n {}".format(variable,varValue))
```

In [9]:
```
categoryc = ["job","marital","education", "housing", "loan","contac
for c in categoryc:
    bar_plot(c)
```

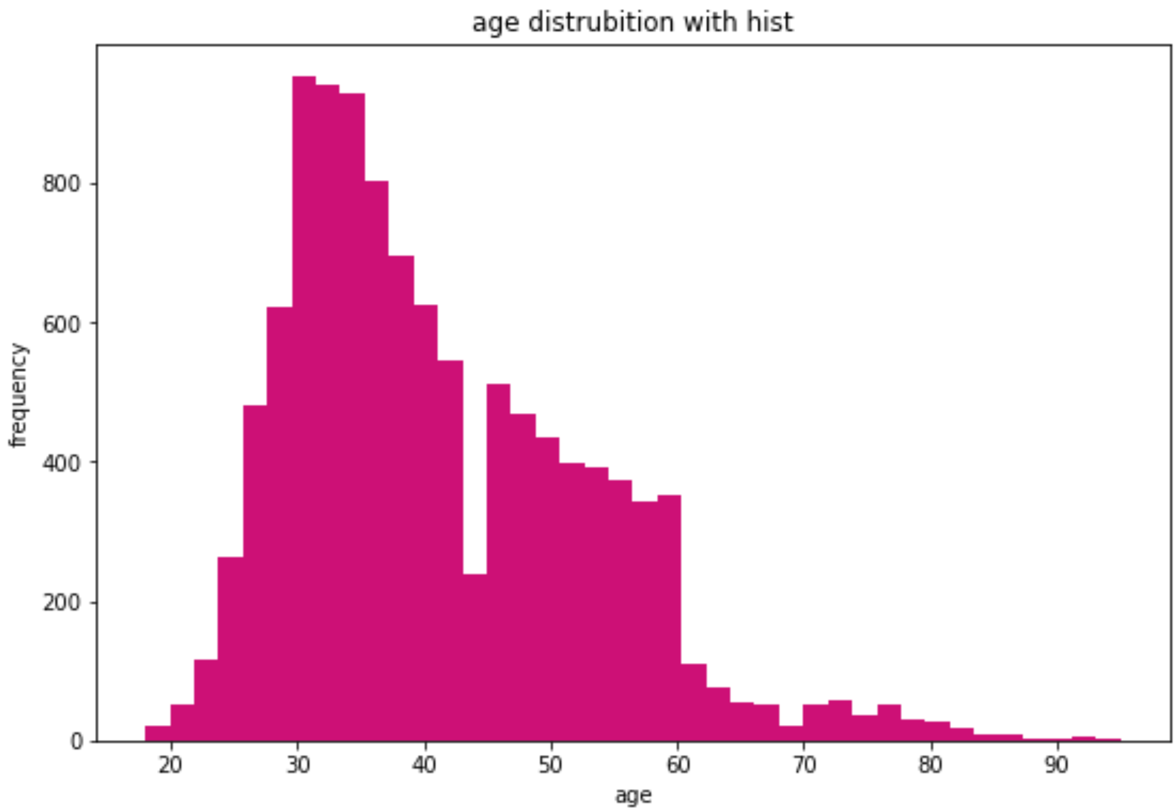


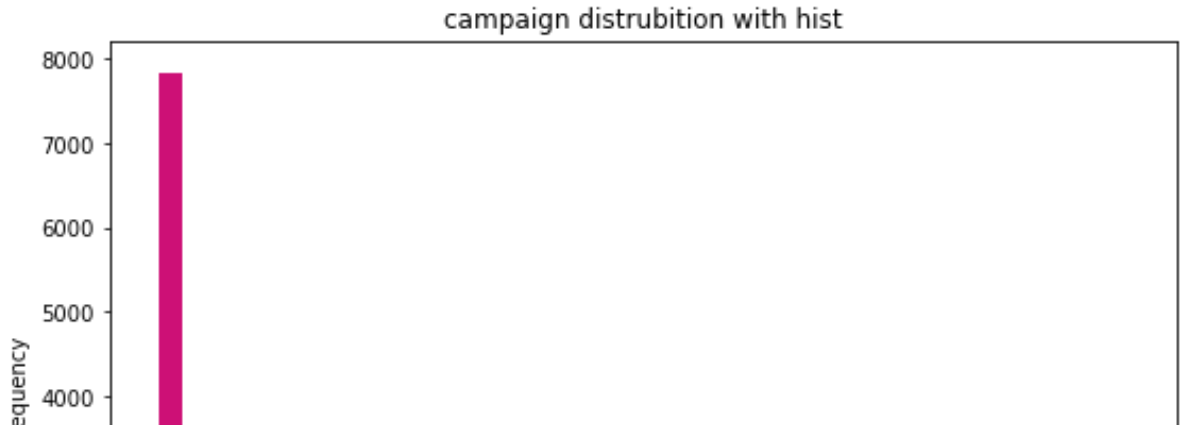

```
job:
 management       2566
blue-collar      1944
technician       1823
admin.           1334
services          923
retired           778
self-employed     405
student           360
unemployed        357
entrepreneur      328
```

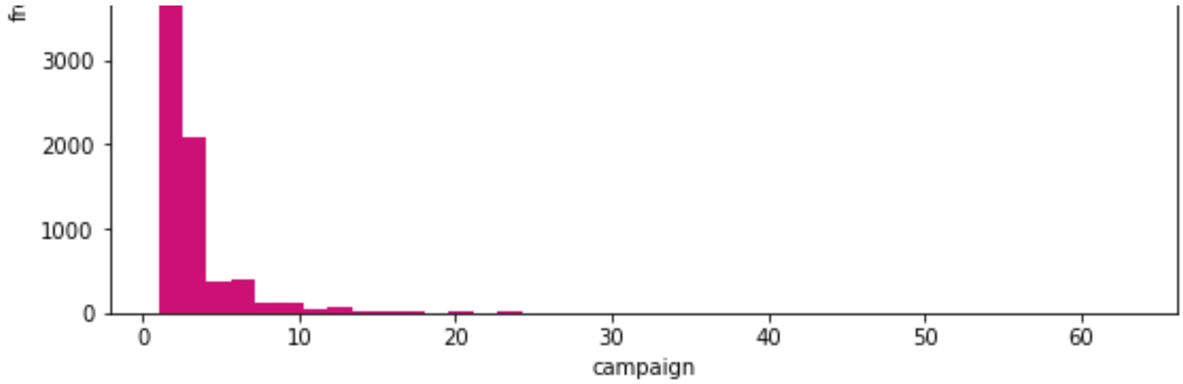
Numerical Variable

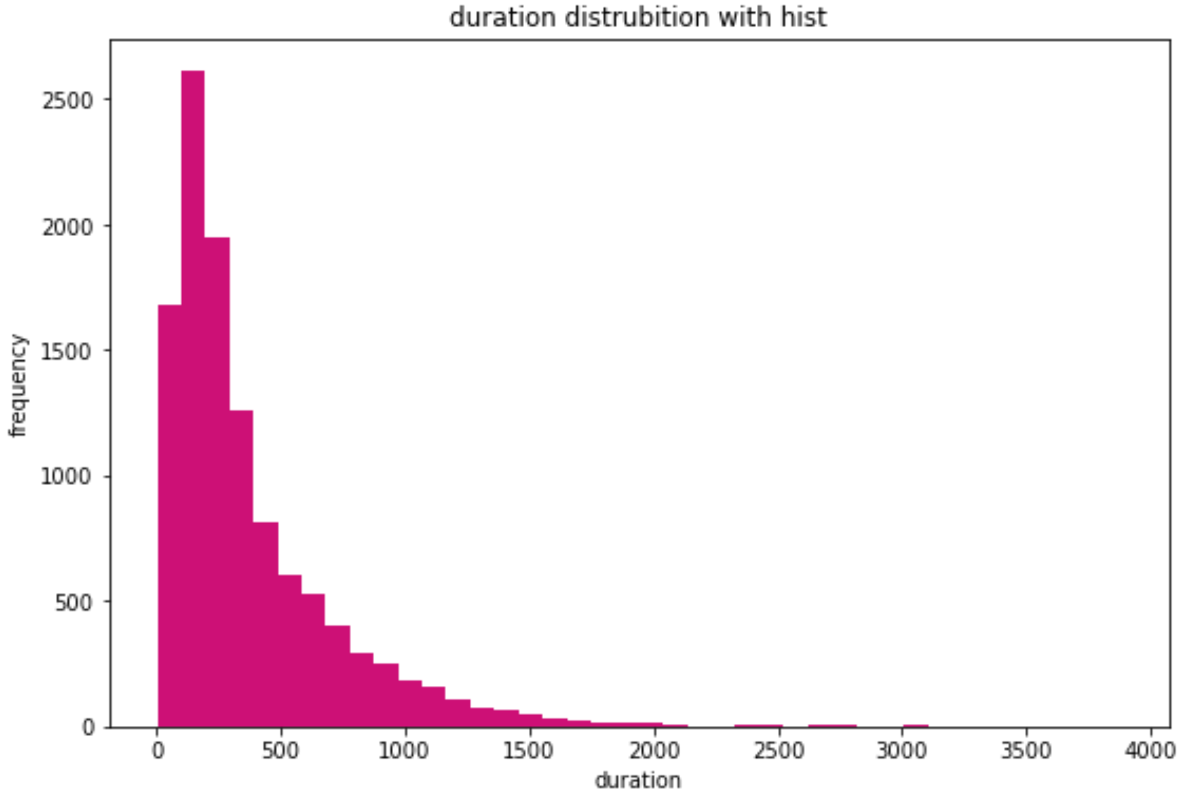
In [10]:
```
def plot_hist(variable):
    plt.figure(figsize=(9,6))
    plt.hist(data[variable], bins=40,color='#cd1076')
    plt.xlabel(variable)
    plt.ylabel("frequency")
    plt.title("{} distrubition with hist".format(variable))
    plt.show()
```

In [11]:
```
numericVar = ["age","campaign","duration"]
for n in numericVar:
    plot_hist(n)
```

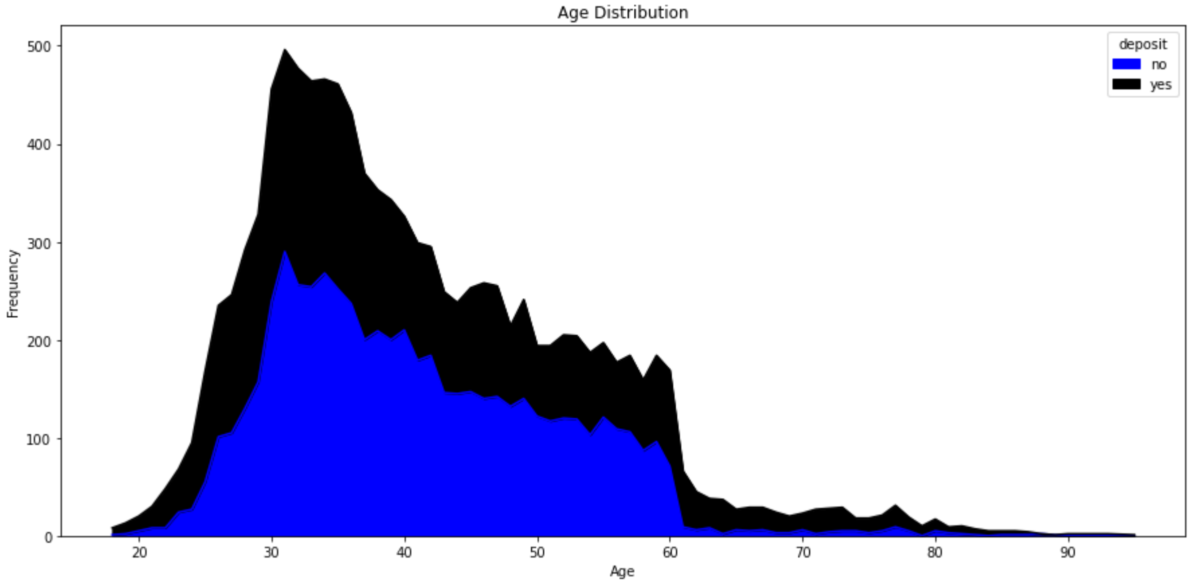





fr
3000
2000
1000
0
0
10
20
30
40
50
60
campaign

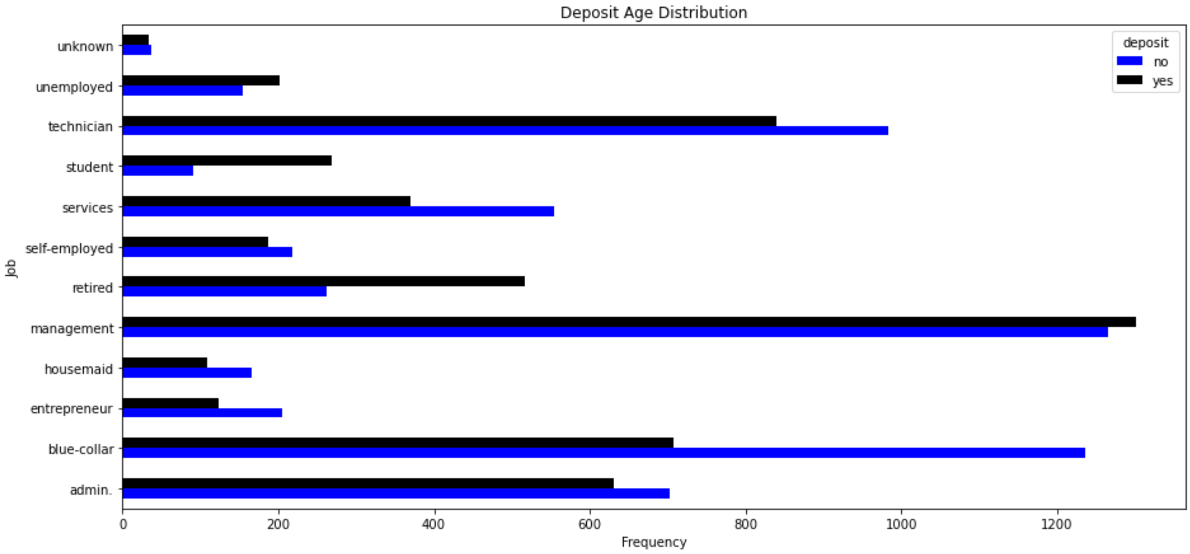

duration distrubition with hist
frequency
2500
2000
1500
1000
500
0
0
500
1000
1500
2000
2500
3000
3500
4000
duration

In [12]:
```
pd.crosstab(data.age,data.deposit).plot(kind="area",figsize=(15,7),
plt.title('Age Distribution')
plt.xlabel('Age')
plt.ylabel('Frequency')
plt.show()
```



The number of people who are 25 to 40 years old with a time deposit account is high.

In [13]:
```
pd.crosstab(data.job,data.deposit).plot(kind="barh",figsize=(15,7),
plt.title('Deposit Age Distribution')
plt.xlabel('Frequency')
plt.ylabel('Job')
plt.show()
```



In people at the executive level have more deposit accounts.

Outlier Detection

In [14]:
```
from collections import Counter
def detect_outliers(data,features):
    outlier_indices = []
    for c in features:
        # 1st quartile
        Q1 = np.percentile(data[c],25)
        # 3rd quartile
        Q3 = np.percentile(data[c],75)
        # IQR
        IQR = Q3 - Q1
        # Outlier step
        outlier_step = IQR * 1.5
        # detect outlier and their indeces
        outlier_list_col = data[(data[c] < Q1 - outlier_step) | (da
        # store indeces
        outlier_indices.extend(outlier_list_col)

    outlier_indices = Counter(outlier_indices)
    multiple_outliers = list(i for i, v in outlier_indices.items()

    return multiple_outliers
```

In [15]:
```
data.loc[detect_outliers(data,['age',
                               'day','duration','campaign','previou
```

Out[15]:

	age	job	marital	education	default	balance	housing	loan	contact	day	mo
3945	84	retired	married	tertiary	no	4761	no	no	telephone	9	s

I do not include this row

In [16]:
```
data = data.drop([3945], axis=0)
```

Missing Value

In [17]:
```
data.isnull().sum()
```

Out[17]:
```
age          0
job          0
marital      0
education    0
default      0
balance      0
housing      0
loan         0
contact      0
day          0
month        0
duration     0
campaign     0
pdays        0
previous     0
poutcome     0
deposit      0
dtype: int64
```

No missing value..

Correlation matrix

In [18]:
```python
import seaborn as sns
fig, ax = plt.subplots(figsize=(13,13))         # Sample figsize in
sns.heatmap(data.corr(), annot=True, linewidths=.5, ax=ax)
```

Out[18]: <matplotlib.axes._subplots.AxesSubplot at 0x7f705038d390>

* Calculated correlation between two variables (r) gets a value between -1 and 1.

- No correlaiton r=0
- Very weak correlation: r<20
- Weak correlation: between 0.20-0.49
- Moderate correlation: between 0.5-0.79
- Strong correlation: between 0.8-0.99
- Perfect correlation: r=1

Looking at it, there is a moderate correlation between the *days* and the *previous* ones. (r=0.51)

Data Manipulation

I do not include the *Duration column* in the dataset, as it is unknown data at the time of the prediction.

duration: Talk Time on Last Call

In [19]:
```
data=data.drop(['duration'],axis=1)
```

In [20]:
```
data.head()
```

Out[20]:

	age	job	marital	education	default	balance	housing	loan	contact	day	mon
0	59	admin.	married	secondary	no	2343	yes	no	unknown	5	m
1	56	admin.	married	secondary	no	45	no	no	unknown	5	m
2	41	technician	married	secondary	no	1270	yes	no	unknown	5	m
3	55	services	married	secondary	no	2476	yes	no	unknown	5	m
4	54	admin.	married	tertiary	no	184	no	no	unknown	5	m

One-Hot Encoding

One Hot Encoding means that categorical variables are represented as binary.

In [21]:
```
columns=data.select_dtypes(include=[object]).columns
data=pd.concat([data,pd.get_dummies(data[columns])],axis=1)
data=data.drop(['job','marital','education','default','housing','lo
data.info()
data.head()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 11161 entries, 0 to 11161
Data columns (total 52 columns):
 #   Column               Non-Null Count  Dtype 
---  ------               --------------  ----- 
 0   age                  11161 non-null  int64 
 1   balance              11161 non-null  int64 
 2   campaign             11161 non-null  int64 
 3   pdays                11161 non-null  int64 
 4   previous             11161 non-null  int64 
 5   deposit              11161 non-null  object
 6   job_admin.           11161 non-null  uint8 
 7   job_blue-collar      11161 non-null  uint8 
 8   job_entrepreneur     11161 non-null  uint8 
 9   job_housemaid        11161 non-null  uint8 
 10  job_management       11161 non-null  uint8 
 11  job_retired          11161 non-null  uint8 
 12  job_self-employed    11161 non-null  uint8 
 13  job_services         11161 non-null  uint8 
 14  job_student          11161 non-null  uint8 
 15  job_technician       11161 non-null  uint8 
 16  job_unemployed       11161 non-null  uint8 
 17  job_unknown          11161 non-null  uint8 
 18  marital_divorced     11161 non-null  uint8 
 19  marital_married      11161 non-null  uint8 
 20  marital_single       11161 non-null  uint8 
 21  education_primary    11161 non-null  uint8 
 22  education_secondary  11161 non-null  uint8 
 23  education_tertiary   11161 non-null  uint8 
 24  education_unknown    11161 non-null  uint8 
 25  default_no           11161 non-null  uint8 
 26  default_yes          11161 non-null  uint8 
 27  housing_no           11161 non-null  uint8 
 28  housing_yes          11161 non-null  uint8 
 29  loan_no              11161 non-null  uint8 
 30  loan_yes             11161 non-null  uint8 
 31  contact_cellular     11161 non-null  uint8 
 32  contact_telephone    11161 non-null  uint8 
 33  contact_unknown      11161 non-null  uint8 
 34  month_apr            11161 non-null  uint8 
 35  month_aug            11161 non-null  uint8 
 36  month_dec            11161 non-null  uint8 
```

```
 37  month_feb            11161 non-null  uint8
 38  month_jan            11161 non-null  uint8
 39  month_jul            11161 non-null  uint8
 40  month_jun            11161 non-null  uint8
 41  month_mar            11161 non-null  uint8
 42  month_may            11161 non-null  uint8
 43  month_nov            11161 non-null  uint8
 44  month_oct            11161 non-null  uint8
 45  month_sep            11161 non-null  uint8
 46  poutcome_failure     11161 non-null  uint8
 47  poutcome_other       11161 non-null  uint8
 48  poutcome_success     11161 non-null  uint8
 49  poutcome_unknown     11161 non-null  uint8
 50  deposit_no           11161 non-null  uint8
 51  deposit_yes          11161 non-null  uint8
dtypes: int64(5), object(1), uint8(46)
memory usage: 1.1+ MB
```

Out[21]:

	age	balance	campaign	pdays	previous	deposit	job_admin.	job_blue-collar	job_entrepren
0	59	2343	1	-1	0	yes	1	0	
1	56	45	1	-1	0	yes	1	0	
2	41	1270	1	-1	0	yes	0	0	
3	55	2476	1	-1	0	yes	0	0	
4	54	184	2	-1	0	yes	1	0	

5 rows × 52 columns

Others..

1. The *pdays* data indicates how many times the customer has been contacted before.

Updated as follows.

if the **pdays = 0**, it indicates that it has not been contacted before

if the **pdays = 1**, it indicates that it was contacted earlier

In [22]:
```
def pdayswork(pdays):
    if(pdays == -1):
        return(0)
    elif(pdays >= 0):
        return(1)
data['pdays2'] = data['pdays'].apply(pdayswork)
```

2. For a single target column

In [23]:
```
data=data.drop(['deposit_no', 'deposit_yes'],axis=1)
```

In [24]:
```
def deposit1(deposit):
    if(deposit=='yes'):
        return(1)
    elif(deposit=='no'):
        return(0)
data['depositNew'] = data['deposit'].apply(deposit1)
```

In [25]:
```
data=data.drop(['deposit'],axis=1)
```

In this way, our target column, whose data type is object, turned into numerical values. And new target column name is *depositNew*. Also as this is a classification problem, the target column can remain as an object. But I chose to convert it to int data type.

the current state of our data set.

In [26]:
```
data.head()
```

Out[26]:

	age	balance	campaign	pdays	previous	job_admin.	job_blue-collar	job_entrepreneur	job_l
0	59	2343	1	-1	0	1	0	0	
1	56	45	1	-1	0	1	0	0	
2	41	1270	1	-1	0	0	0	0	
3	55	2476	1	-1	0	0	0	0	
4	54	184	2	-1	0	1	0	0	

5 rows × 51 columns

In [27]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 11161 entries, 0 to 11161
Data columns (total 51 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   age                  11161 non-null  int64
 1   balance              11161 non-null  int64
 2   campaign             11161 non-null  int64
 3   pdays                11161 non-null  int64
 4   previous             11161 non-null  int64
 5   job_admin.           11161 non-null  uint8
 6   job_blue-collar      11161 non-null  uint8
 7   job_entrepreneur     11161 non-null  uint8
 8   job_housemaid        11161 non-null  uint8
 9   job_management       11161 non-null  uint8
 10  job_retired          11161 non-null  uint8
 11  job_self-employed    11161 non-null  uint8
 12  job_services         11161 non-null  uint8
 13  job_student          11161 non-null  uint8
 14  job_technician       11161 non-null  uint8
 15  job_unemployed       11161 non-null  uint8
 16  job_unknown          11161 non-null  uint8
 17  marital_divorced     11161 non-null  uint8
 18  marital_married      11161 non-null  uint8
 19  marital_single       11161 non-null  uint8
 20  education_primary    11161 non-null  uint8
 21  education_secondary  11161 non-null  uint8
 22  education_tertiary   11161 non-null  uint8
 23  education_unknown    11161 non-null  uint8
 24  default_no           11161 non-null  uint8
 25  default_yes          11161 non-null  uint8
 26  housing_no           11161 non-null  uint8
 27  housing_yes          11161 non-null  uint8
 28  loan_no              11161 non-null  uint8
 29  loan_yes             11161 non-null  uint8
 30  contact_cellular     11161 non-null  uint8
 31  contact_telephone    11161 non-null  uint8
 32  contact_unknown      11161 non-null  uint8
 33  month_apr            11161 non-null  uint8
 34  month_aug            11161 non-null  uint8
 35  month_dec            11161 non-null  uint8
 36  month_feb            11161 non-null  uint8
 37  month_jan            11161 non-null  uint8
 38  month_jul            11161 non-null  uint8
 39  month_jun            11161 non-null  uint8
 40  month_mar            11161 non-null  uint8
 41  month_may            11161 non-null  uint8
 42  month_nov            11161 non-null  uint8
 43  month_oct            11161 non-null  uint8
 44  month_sep            11161 non-null  uint8
 45  poutcome_failure     11161 non-null  uint8
```

```
 46  poutcome_other       11161 non-null  uint8
 47  poutcome_success     11161 non-null  uint8
 48  poutcome_unknown     11161 non-null  uint8
 49  pdays2               11161 non-null  int64
 50  depositNew           11161 non-null  int64
dtypes: int64(7), uint8(44)
memory usage: 1.1 MB
```

Data Normalization

StandartScaler, normalizes the data with a standard deviation of 1 with an average of 0.

The target column is not normalized.

In [28]:

```
from sklearn.preprocessing import StandardScaler
X = data.iloc[:, 0:50]
Y = data.iloc[:, 50]
nd = StandardScaler()
nd.fit(X)
X =nd.transform(X)
print(X)
```

```
[[ 1.4926218   0.25261499 -0.55420079 ... -0.32579855  0.58352347
  -0.58379938]
 [ 1.24065834 -0.4598839  -0.55420079 ... -0.32579855  0.58352347
  -0.58379938]
 [-0.01915895 -0.08007052 -0.55420079 ... -0.32579855  0.58352347
  -0.58379938]
 ...
 [-0.77504932 -0.46484473 -0.18682923 ... -0.32579855  0.58352347
  -0.58379938]
 [ 0.14881669 -0.47383623 -0.18682923 ... -0.32579855 -1.71372713
   1.71291719]
 [-0.60707368 -0.47383623 -0.55420079 ... -0.32579855  0.58352347
  -0.58379938]]
```

Algorithm Works

In [29]:
```
from sklearn.model_selection import train_test_split
from sklearn.metrics import cohen_kappa_score
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import ConfusionMatrixDisplay
from sklearn.metrics import f1_score
X = data.iloc[:, 0:50]
Y = data.iloc[:, 50]
X_train, X_test, y_train, y_test = train_test_split( X, Y, test_siz

accuracies = {}
kappaScores= {}
f1scores={}
```

Logistic Regression

Logistic regression is a predictive linear model that aims to explain the relationship between a dependent binary variable and one or more independent variables. The output of Logistic Regression is a number between *0 and 1* which you can think about as being the probability that a given class is true or not.

In [30]:
```
from sklearn.linear_model import LogisticRegression
lr=LogisticRegression(random_state=101,multi_class='ovr',solver='li
lr.fit(X_train,y_train)
prediction = lr.predict(X_test)
```

In [31]:
```
print(classification_report(y_test,prediction))
acc = accuracy_score(y_test,prediction)*100
print("Logistic Regression accuracy:",acc)
accuracies['Logistic Regression']=acc

f1=f1_score(y_test,prediction)*100
print("F1-Score: ",f1)
f1scores['Logistic Regression']=f1


cohen_kappa = cohen_kappa_score(y_test, prediction)*100
print('Cohen Kappa score: ',cohen_kappa)
kappaScores['Logistic Regression']=cohen_kappa
```

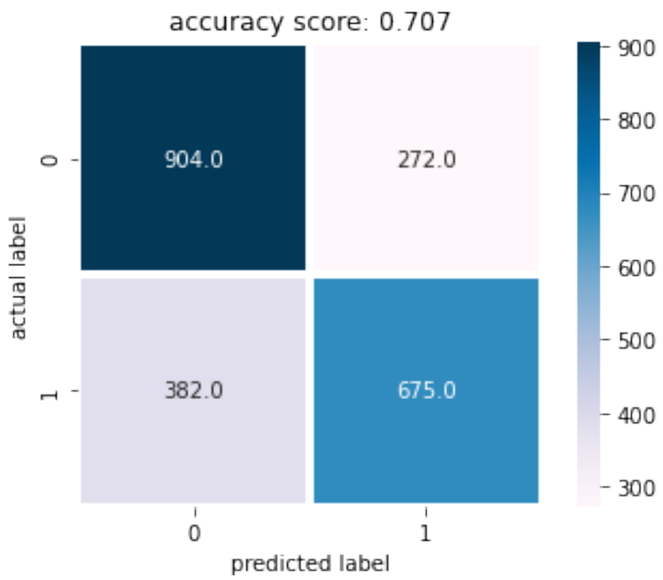
```
              precision    recall  f1-score   support

           0       0.70      0.77      0.73      1176
           1       0.71      0.64      0.67      1057

    accuracy                           0.71      2233
   macro avg       0.71      0.70      0.70      2233
weighted avg       0.71      0.71      0.71      2233

Logistic Regression accuracy: 70.71204657411553
F1-Score:  67.36526946107784
Cohen Kappa score:  40.94632616436728
```

In [32]:
```
score=round(accuracy_score(y_test,prediction),3)
cm= confusion_matrix
cm1=cm(y_test,prediction)
sns.heatmap(cm1, annot=True,fmt=".1f",linewidths=3,square=True, cma
plt.ylabel('actual label')
plt.xlabel('predicted label')
plt.title('accuracy score: {0}'.format(score),size=12)
plt.show()
```



Random Forest

In [33]:
```
from sklearn.ensemble import RandomForestClassifier
```

In [34]:
```
clf = RandomForestClassifier(n_estimators=100, max_depth=12,
                             random_state=50)

clf.fit(X_train,y_train)

prediction = clf.predict(X_test)
```

In [35]:
```
acc = accuracy_score(y_test,prediction)*100
print("Random Forest accuracy:",acc)
accuracies['Random Forest']=acc

f1=f1_score(y_test,prediction)*100
print("F1-Score: ",f1)
f1scores['Random Forest']=f1

cohen_kappa = cohen_kappa_score(y_test, prediction)*100
print('Cohen Kappa score: ',cohen_kappa)
kappaScores['Random Forest']=cohen_kappa
```

```
Random Forest accuracy: 72.05553067622034
F1-Score:  66.5236051502146
Cohen Kappa score:  43.27305059532291
```

Naive Bayes

In [36]:
```
from sklearn.naive_bayes import GaussianNB
```

In [37]:
```
nb=GaussianNB()
nb.fit(X_train,y_train)
naiveb=nb.predict(X_test)
prediction= nb.predict(X_test)
```

In [38]:
```
acc = accuracy_score(y_test,prediction)*100
print("Naive Bayes accuracy:",acc)
accuracies['Naive Bayes']=acc

f1=f1_score(y_test,prediction)*100
print("F1-Score: ",f1)
f1scores['Naive Bayes']=f1

cohen_kappa = cohen_kappa_score(y_test, prediction)*100
print('Cohen Kappa score: ',cohen_kappa)
kappaScores['Naive Bayes']=cohen_kappa
```

```
Naive Bayes accuracy: 68.3833407971339
F1-Score:  62.08378088077337
Cohen Kappa score:  35.812328283001015
```

Stochastic Gradient Descent Classifier

In [39]:
```
from sklearn.linear_model import SGDClassifier
```

In [40]:
```
sgd=SGDClassifier(loss='modified_huber',shuffle=True,random_state=1
                  ,max_iter=100,eta0=0.2,learning_rate='optimal')
sgd.fit(X_train,y_train)
prediction=sgd.predict(X_test)
```

In [41]:
```
acc = accuracy_score(y_test,prediction)*100
print("SGD Classifier accuracy:",acc)
accuracies['SGDC']=acc

f1=f1_score(y_test,prediction)*100
print("F1-Score: ",f1)
f1scores['SGDC']=f1

cohen_kappa = cohen_kappa_score(y_test, prediction)*100
print('Cohen Kappa score: ',cohen_kappa)
kappaScores['SGDC']=cohen_kappa
```

```
SGD Classifier accuracy: 65.42767577250336
F1-Score:  61.361361361361354
Cohen Kappa score:  30.271249787643693
```

KNN

In [42]:
```
from sklearn.neighbors import KNeighborsClassifier
```

In [43]:
```
knn= KNeighborsClassifier(n_neighbors = 4,algorithm='ball_tree')
knn.fit(X_train, y_train)
prediction=knn.predict(X_test)
```

In [44]:
```
acc = accuracy_score(y_test,prediction)*100
print("Knn accuracy:",acc)
accuracies['KNN']=acc

f1=f1_score(y_test,prediction)*100
print("F1-Score: ",f1)
f1scores['KNN']=f1

cohen_kappa = cohen_kappa_score(y_test, prediction)*100
print('Cohen Kappa score: ',cohen_kappa)
kappaScores['KNN']=cohen_kappa
```

```
Knn accuracy: 61.12852664576802
F1-Score:  49.651972157772626
Cohen Kappa score:  20.55250457646862
```

Decision Tree

In [45]:
```
from sklearn.tree import DecisionTreeClassifier
```

In [46]:
```
dtree= DecisionTreeClassifier(criterion='gini',max_depth=10,random_
dtree.fit(X_train, y_train)
prediction=dtree.predict(X_test)
```

In [47]:
```
acc = accuracy_score(y_test,prediction)*100
print("Decision Tree accuracy:",acc)
accuracies['Decision Tree']=acc

f1=f1_score(y_test,prediction)*100
print("F1-Score: ",f1)
f1scores['Decision Tree']=f1

cohen_kappa = cohen_kappa_score(y_test, prediction)*100
print('Cohen Kappa score: ',cohen_kappa)
kappaScores['Decision Tree']=cohen_kappa
```

```
Decision Tree accuracy: 70.53291536050156
F1-Score:  62.61363636363636
Cohen Kappa score:  39.879244072476475
```

Neural Network - Perceptron

In [48]:
```
from sklearn.linear_model import Perceptron
```

In [49]:
```
pr = Perceptron(alpha=0.07,max_iter=100, random_state=100,penalty='
pr.fit(X_train, y_train)
prediction = pr.predict(X_test)
```

In [50]:
```
acc = accuracy_score(y_test, prediction)*100
print("Perceptron accuracy:",acc)
accuracies['Perceptron']=acc

f1=f1_score(y_test,prediction)*100
print("F1-Score: ",f1)
f1scores['Perceptron']=f1

cohen_kappa = cohen_kappa_score(y_test, prediction)*100
print('Cohen Kappa score: ',cohen_kappa)
kappaScores['Perceptron']=cohen_kappa
```

```
Perceptron accuracy: 61.262875055978505
F1-Score:  47.41641337386018
Cohen Kappa score:  20.520826432474315
```

Gradient Boosting Classifier

In [51]:
```
from sklearn.ensemble import GradientBoostingClassifier
```

In [52]:
```
clf = GradientBoostingClassifier(n_estimators=100, learning_rate=0.
    max_depth=2, random_state=0)
clf.fit(X_train, y_train)
prediction = clf.predict(X_test)
```

In [53]:
```
acc = accuracy_score(y_test, prediction)*100
print("Gradient Boosting Classifier accuracy:",acc)
accuracies['Gradient Boosting']=acc

f1=f1_score(y_test,prediction)*100
print("F1-Score: ",f1)
f1scores['Gradient Boosted']=f1

cohen_kappa = cohen_kappa_score(y_test, prediction)*100
print('Cohen Kappa score: ',cohen_kappa)
kappaScores['Gradient Boosting']=cohen_kappa
```

```
Gradient Boosting Classifier accuracy: 70.98074339453649
F1-Score:  66.14420062695925
Cohen Kappa score:  41.23359639746186
```

Xgboost Classifier

In [54]:
```
from xgboost import XGBClassifier
```

In [55]:
```
xgb =XGBClassifier(n_estimators=100, learning_rate=0.08, gamma=0, s
                           colsample_bytree=1, max_depth=7)
xgb.fit(X_train,y_train)
prediction = xgb.predict(X_test)
```

In [56]:
```
acc = accuracy_score(y_test, prediction)*100
print("Xgboost Classifier accuracy:",acc)
accuracies['Xgboost Classifier']=acc

f1=f1_score(y_test,prediction)*100
print("F1 Score: ",f1)
f1scores['Xgboost Classifier']=f1

cohen_kappa = cohen_kappa_score(y_test, prediction)*100
print('Cohen Kappa score: ',cohen_kappa)
kappaScores['Xgboost Classifier']=cohen_kappa
```

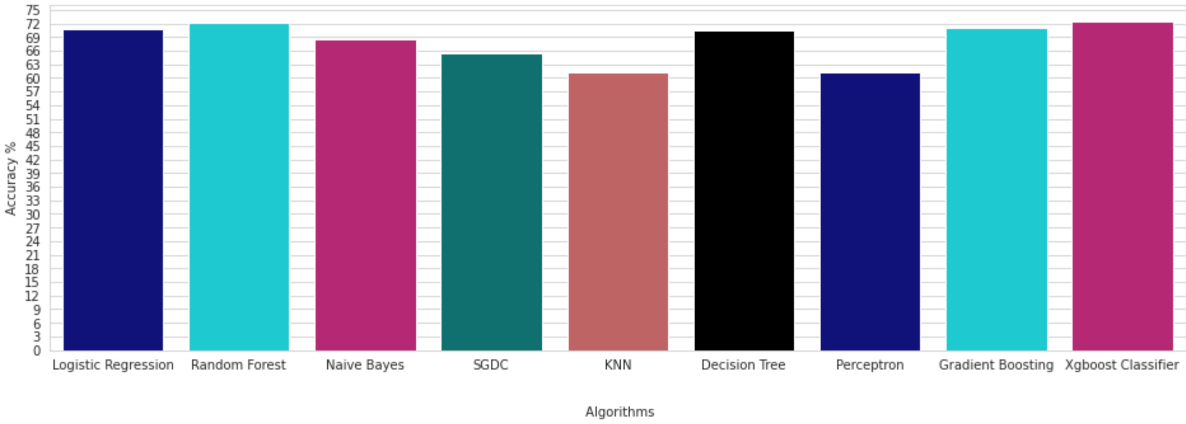
```
Xgboost Classifier accuracy: 72.50335871025526
F1 Score:  67.5475687103594
Cohen Kappa score:  44.25775091212313
```

Comparison of accuracies

Accuracy is a metric used to measure the success of a model but is not sufficient by itself.

In [57]:
```
colors = ["#00008b", "#00e5ee", "#cd1076", "#008080","#cd5555",'bla

sns.set_style("whitegrid")
plt.figure(figsize=(16,5))
plt.yticks(np.arange(0,100,3))
plt.ylabel("Accuracy %")
plt.xlabel("\n\n Algorithms")
sns.barplot(x=list(accuracies.keys()), y=list(accuracies.values()),
plt.show()
```



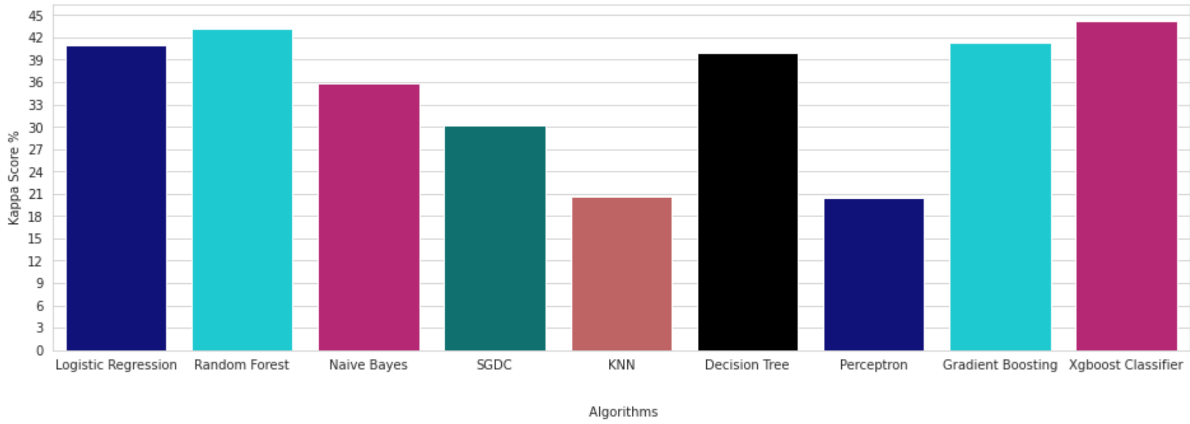
Comparison of Kappa Scores

Cohen's kappa, (7), symbolized by the lowercase Greek letter, is a powerful statistic useful for testing reliability. Similar to the correlation coefficients, between -1 and +1; where 0 represents the availability that can be expected from random chance, and 1 represents the perfect match between raters.

- 0 indicates no information agreement
- 0.01-0.20 **Slight agreement**
- 0.21-0.40 **Fair agreement**
- 0.41-0.60 **Moderate agreement**
- 0.61-0.80 **Substantial agreement**
- 0.81-1.00 **Almost perfect agreement**

In [58]:
```
colors = ["#00008b", "#00e5ee", "#cd1076", "#008080","#cd5555",'bla

sns.set_style("whitegrid")
plt.figure(figsize=(16,5))
plt.yticks(np.arange(0,100,3))
plt.ylabel("Kappa Score %")
plt.xlabel("\n\n Algorithms")
sns.barplot(x=list(kappaScores.keys()), y=list(kappaScores.values()
plt.show()
```



Comparison of F1 Scores

The F1 Score value shows us the harmonic mean of the Precision and Recall values.

The main reason for using the F1 Score value instead of Accuracy is not to make an incorrect model selection in non-uniform data sets.

In [59]:
```
colors = ["#00008b", "#00e5ee", "#cd1076", "#008080","#cd5555",'bla

sns.set_style("whitegrid")
plt.figure(figsize=(16,5))
plt.yticks(np.arange(0,100,3))
plt.ylabel("F1 Score %")
plt.xlabel("\n\n Algorithms")
sns.barplot(x=list(f1scores.keys()), y=list(f1scores.values()), pal
plt.show()
```