Bank Marketing Campaign Data

Introduction:

The prediction model uses direct marketing campaign data from a banking institution. Phone calls were used in the marketing campaigns to contact customers in order to determine whether the customer would subscribe to a term deposit.

The objective of this project is to create a model that will predict whether or not a customer will sign up for the product (bank term deposit) based on the data at hand.

Data Specifications:

1. Age - Age of the customer.
2. Job - Profession of the customer.
3. Marital Status - Relationship status of the customer.
4. Education - Education level of the customer.
5. Default - / Having a previously broken credit.
6. Housing - Whether customer has a home loan.
7. Loan - Whether the customer has a personal loan.
8. Contact - Whether the customer was contacted on his home or mobile phone.
9. Month - The last month when the customer was contacted.
10. Day - The day when the customer was contacted.
11. Duration - The total time spent on talking to the customer.
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 result, whether successful or not.
16. Deposit: Whether customer has a term deposit or not.

Importing libraries

In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

Loading data

In [2]:

```
data = pd.read_csv('C:/Data Science Projects/Product Uptake Prediction/bank.csv')

data.head()
```

Out[2]:

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campa
0	59	admin.	married	secondary	no	2343	yes	no	unknown	5	may	1042	

1	56	admin.	married	secondary	no	45	no	no	unknown	5	may	1467
2	41	technician	married	secondary	no	1270	yes	no	unknown	5	may	1389
3	55	services	married	secondary	no	2476	yes	no	unknown	5	may	579
4	54	admin.	married	tertiary	no	184	no	no	unknown	5	may	673

Checking dataframe info

number of columns, column labels, column data types, memory usage, range index, and the number of cells in each column (non-null values)

In [3]:
```
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
```

Checking missing values

(In this case 'NA's as there are no null values as observed above).

In [4]:
```
data.isna().sum()
```

Out[4]:
```
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
```

Outlier detection

In [5]:
```
from collections import Counter

def detect_outliers(data,features):

    outlier_indices = []

    for f in features:

        # 1st quartile
        Q1 = np.percentile(data[f],25)

        # 3rd quartile
        Q3 = np.percentile(data[f],75)

        # IQR
        IQR = Q3 - Q1

        # Outlier size
        outlier_size = IQR * 1.5

        # detect outliers indices
        outlier_list = data[(data[f] < Q1 - outlier_size) | (data[f] > Q3 + outlier_size

        # store outlier indices
        outlier_indices.extend(outlier_list)

    outlier_indices = Counter(outlier_indices)

    multiple_outliers = list(i for i, v in outlier_indices.items() if v > 2)

    return multiple_outliers
```

Identify outliers based on the features (duration, campaign, and previous) directly linked to the marketing campaign.

In [6]:
```
data.loc[detect_outliers(data,['duration','campaign','previous'])]
```

Out[6]:

age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pda

No outlier detected.

NB\: Unless outliers are caused by data entry errors, usually outliers should not be removed as they represent the natural occurence of the data.

Descriptive statistics

Numerical variables

In [7]:
```
data.describe()
```

Out[7]:

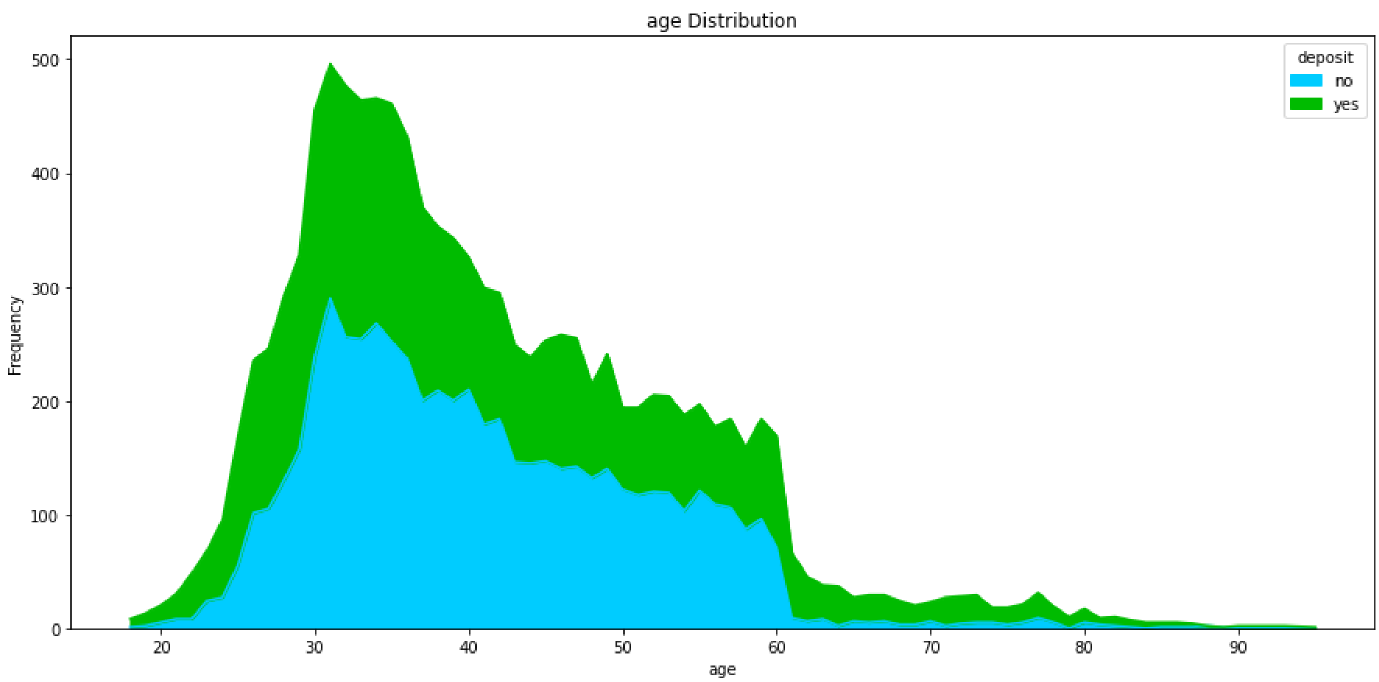
	age	balance	day	duration	campaign	pdays	previous
count	11162.000000	11162.000000	11162.000000	11162.000000	11162.000000	11162.000000	11162.000000
mean	41.231948	1528.538524	15.658036	371.993818	2.508421	51.330407	0.832557

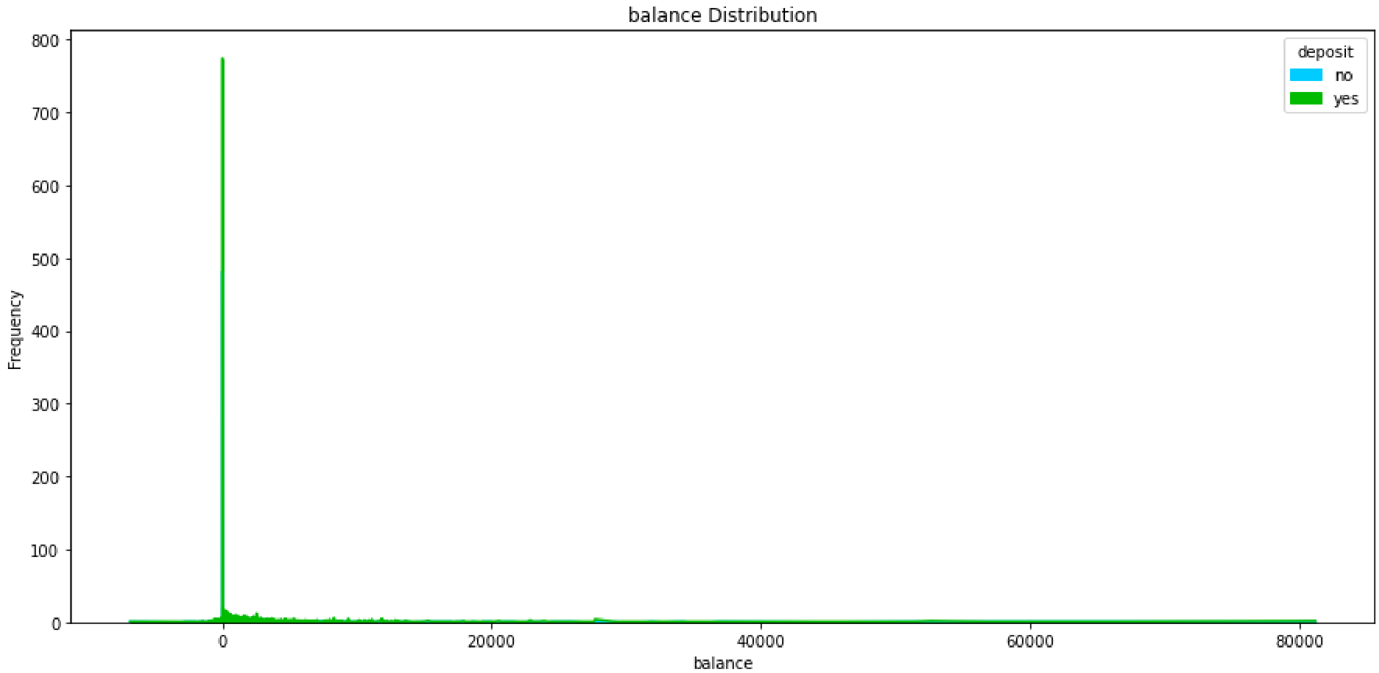
std	11.913369	3225.413326	8.420740	347.128386	2.722077	108.758282	2.292007
min	18.000000	-6847.000000	1.000000	2.000000	1.000000	-1.000000	0.000000
25%	32.000000	122.000000	8.000000	138.000000	1.000000	-1.000000	0.000000
50%	39.000000	550.000000	15.000000	255.000000	2.000000	-1.000000	0.000000
75%	49.000000	1708.000000	22.000000	496.000000	3.000000	20.750000	1.000000
max	95.000000	81204.000000	31.000000	3881.000000	63.000000	854.000000	58.000000

In [8]:
```
num_features = ['age','balance','day','duration','campaign','pdays','previous']
```

In [9]:
```
def area_plot(feature):
    var = data[feature]

    pd.crosstab(var,data.deposit).plot(kind="area",figsize=(15,7),color=['#00ccff','#00b
    plt.title("{} Distribution".format(feature))
    plt.xlabel("{}".format(feature))
    plt.ylabel('Frequency')
    plt.show()
```

In [10]:
```
# Considering only age and balance

num_features1 = ['age','balance']

for f in num_features1:
    area_plot(f)
```





Age:

From the age distribution graph above, we can note that the highest number of customers with term deposits range between the ages 30 - 35 years. Also, within the same age range, there are many customers who have not subscribed to a term deposit, hence there is still a huge opportunity to sell this product others customers within this age range.

Balance

From the balance distribution graph above, we note that majority of the customers who have subscribed to term deposits have a nearly zero balance. we may observe this more clearly by grouping the customers based on their balances.

In [11]:
```
# Categorizing the customers by balance

data1 = data.copy()

data1.loc[data1['balance'] >= 10000, 'bal_cat'] = "High_bal"
data1.loc[(data1['balance'] > 2000) & (data1['balance'] < 10000),'bal_cat'] = "Average_b
data1.loc[(data1['balance'] >= 0) & (data1['balance'] < 2000), 'bal_cat'] = "Low_bal"
data1.loc[data1['balance'] < 0, 'bal_cat'] = "Negative_bal"

table_bal_cat = pd.crosstab(data1['deposit'], data1['bal_cat']).apply(lambda x: x/x.sum(
table_bal_cat
```

Out[11]:

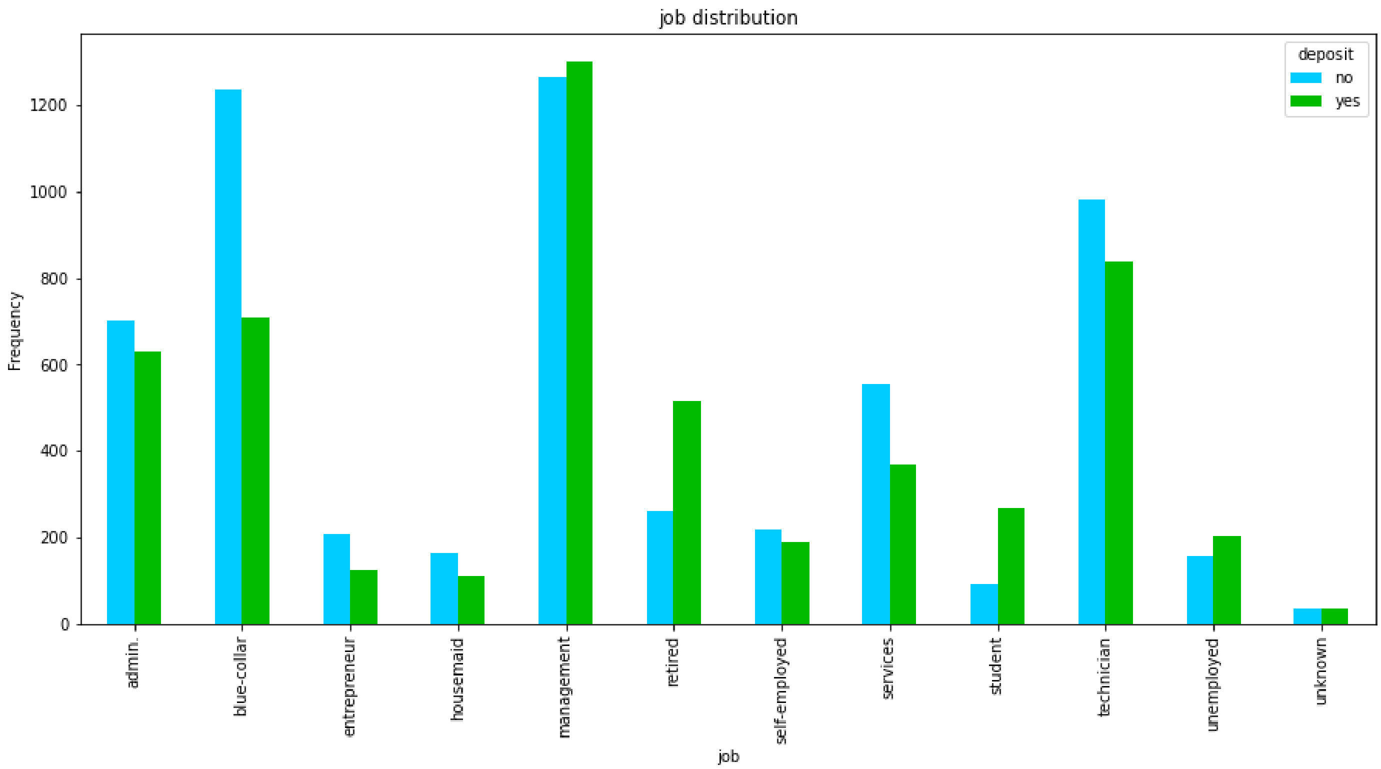
bal_cat	Average_bal	High_bal	Low_bal	Negative_bal
deposit				
no	42.0	41.0	54.0	69.0
yes	58.0	59.0	46.0	31.0

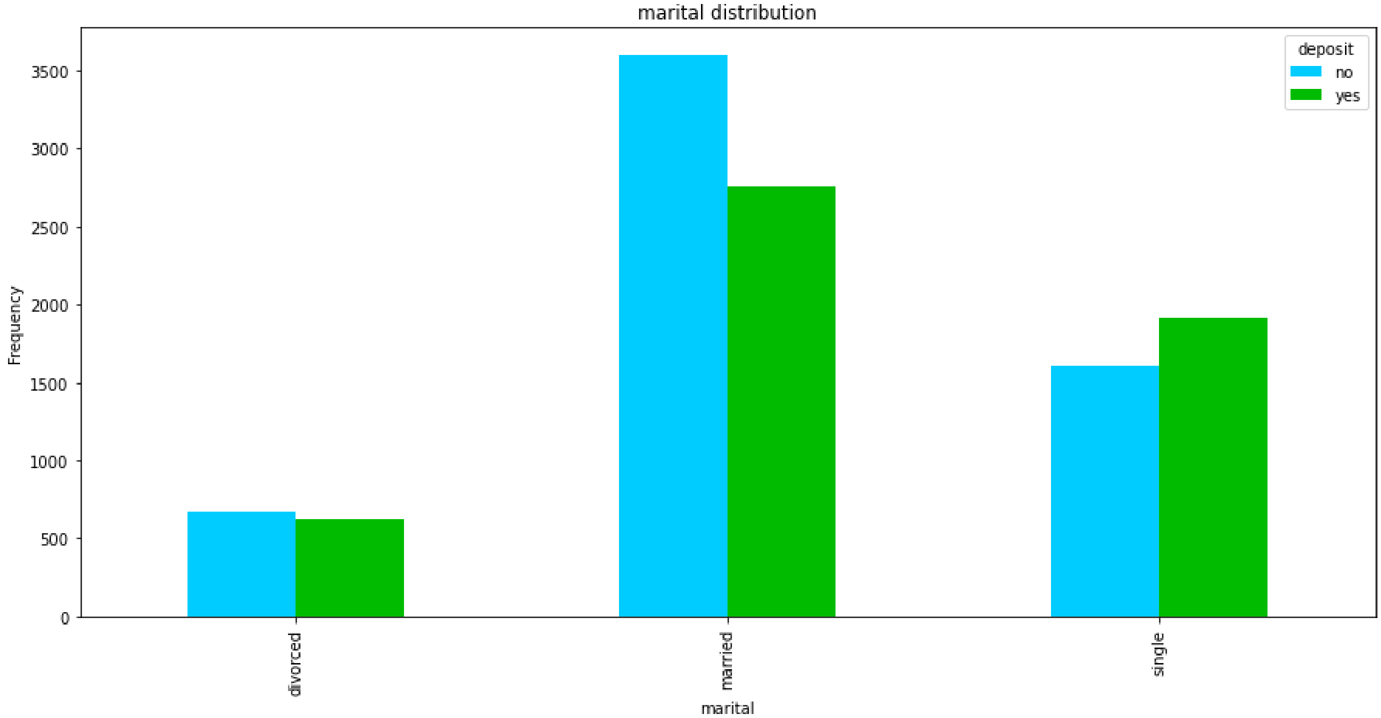
From table above we can note that nearly 60% of those customers having average and high balances (over 2,000) have a term deposit. Important to note is that quite a significant proportion of customers with low and negative balances also have a term deposit. This indicates that the marketing team can target customers with any balance amount.

Categorical variables

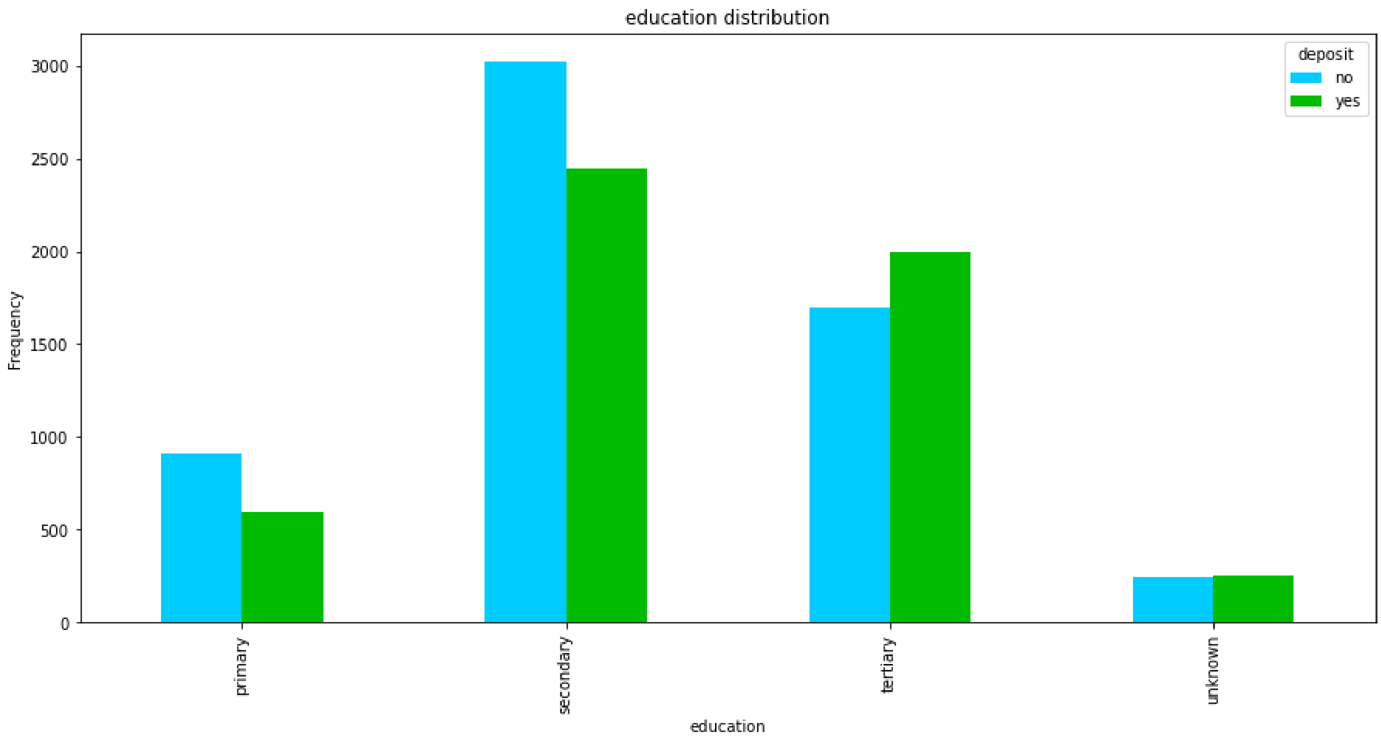
In [12]:
```
def bar_plot(feature):
    var = data[feature]

    pd.crosstab(var,data.deposit).plot(kind="bar",figsize=(15,7),color=['#00ccff','#00bb
    plt.title("{} distribution".format(feature))
    plt.xlabel("{}".format(feature))
    plt.ylabel('Frequency')
    plt.show()
```

In [13]:
```
cat_features = ['job', 'marital', 'education', 'default', 'housing', 'loan','contact', '

for f in cat_features:
    bar_plot(f)
```

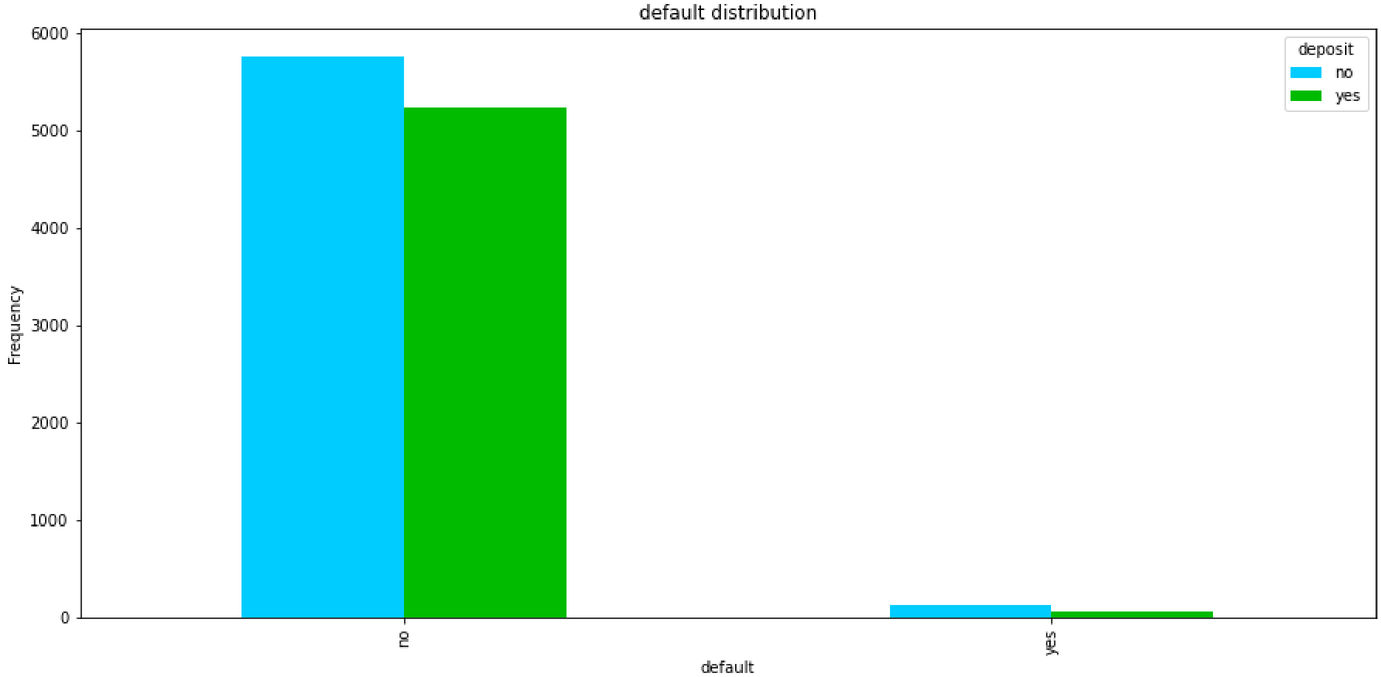


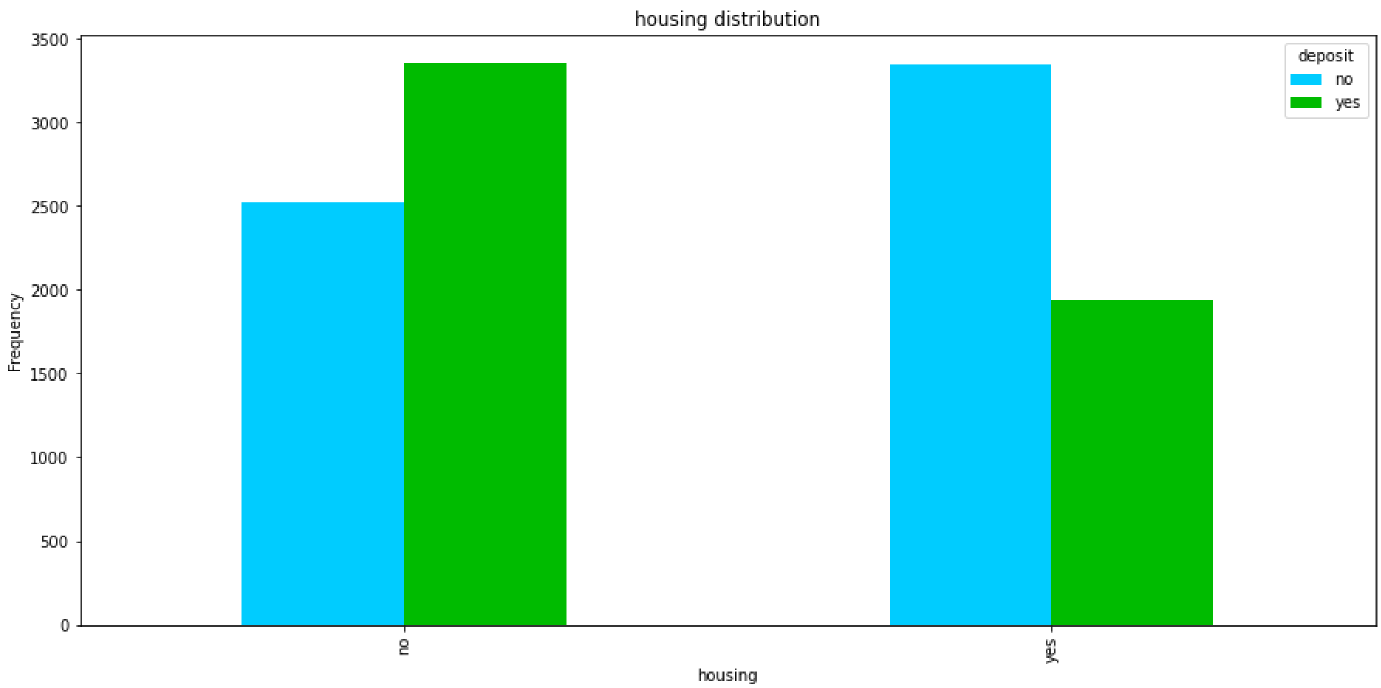


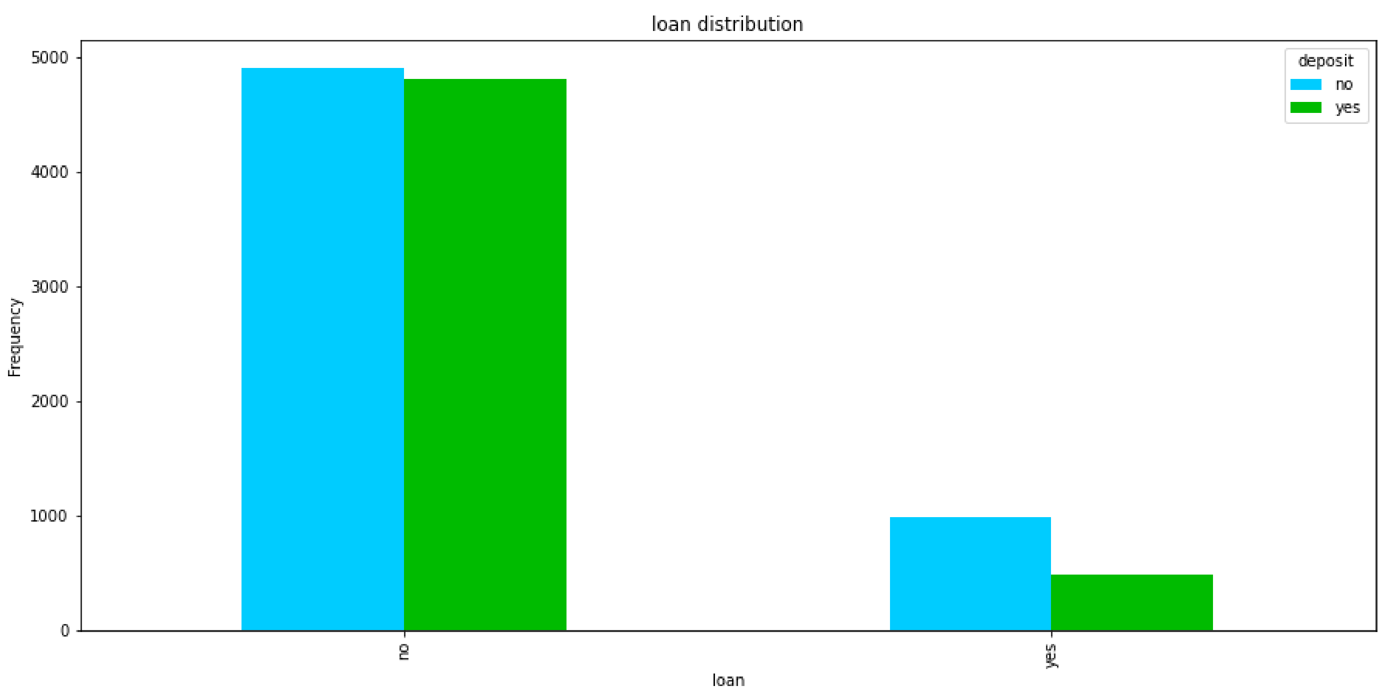
marital distribution
deposit
no
yes
Frequency
3500
3000
2500
2000
1500
1000
500
0
divorced
married
single
marital

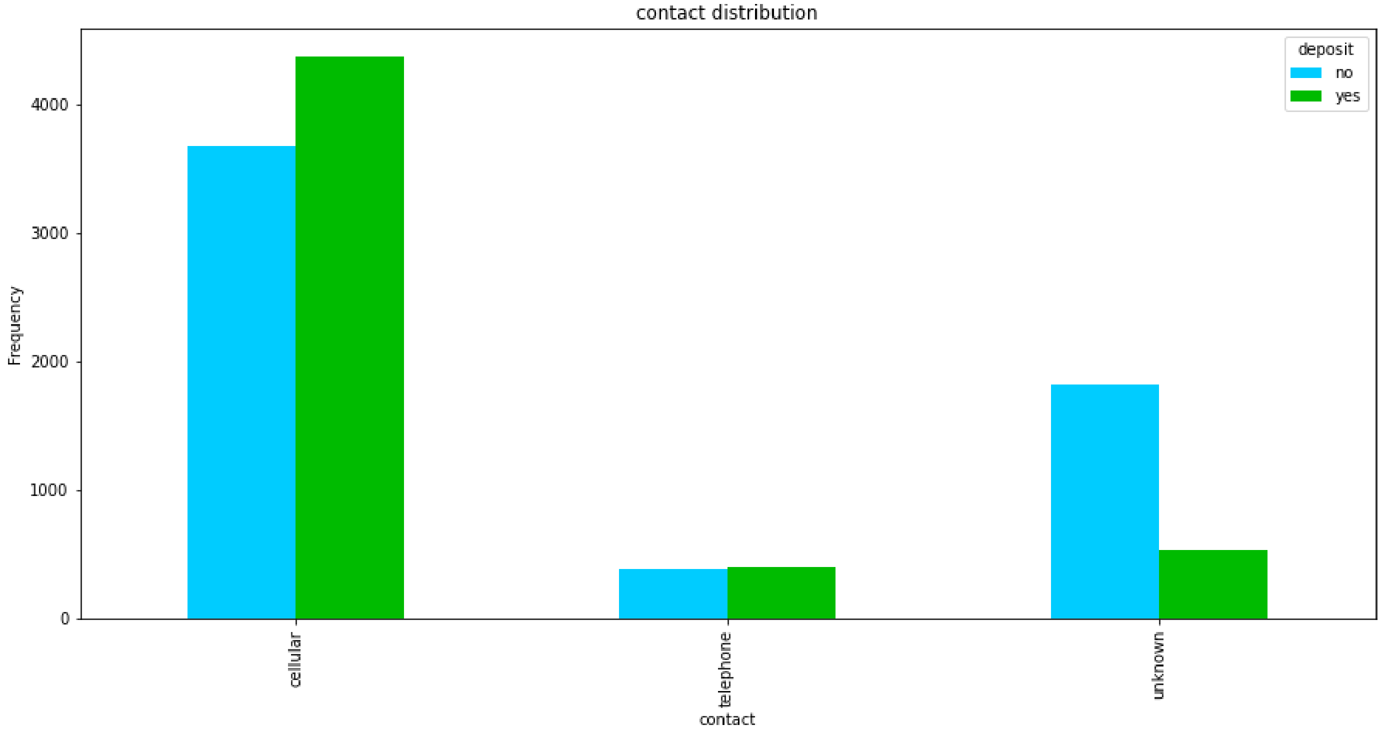


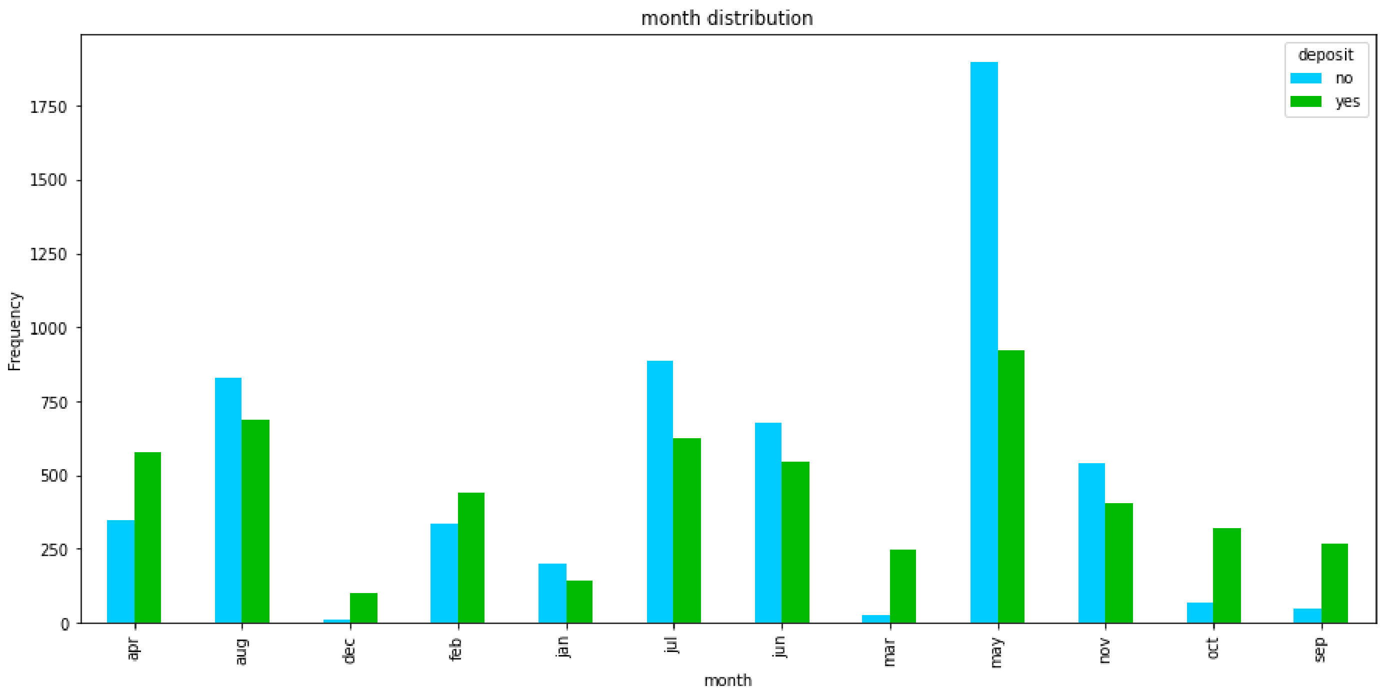
education distribution
deposit
no
yes
Frequency
3000
2500
2000
1500
1000
500
0
primary
secondary
tertiary
unknown
education

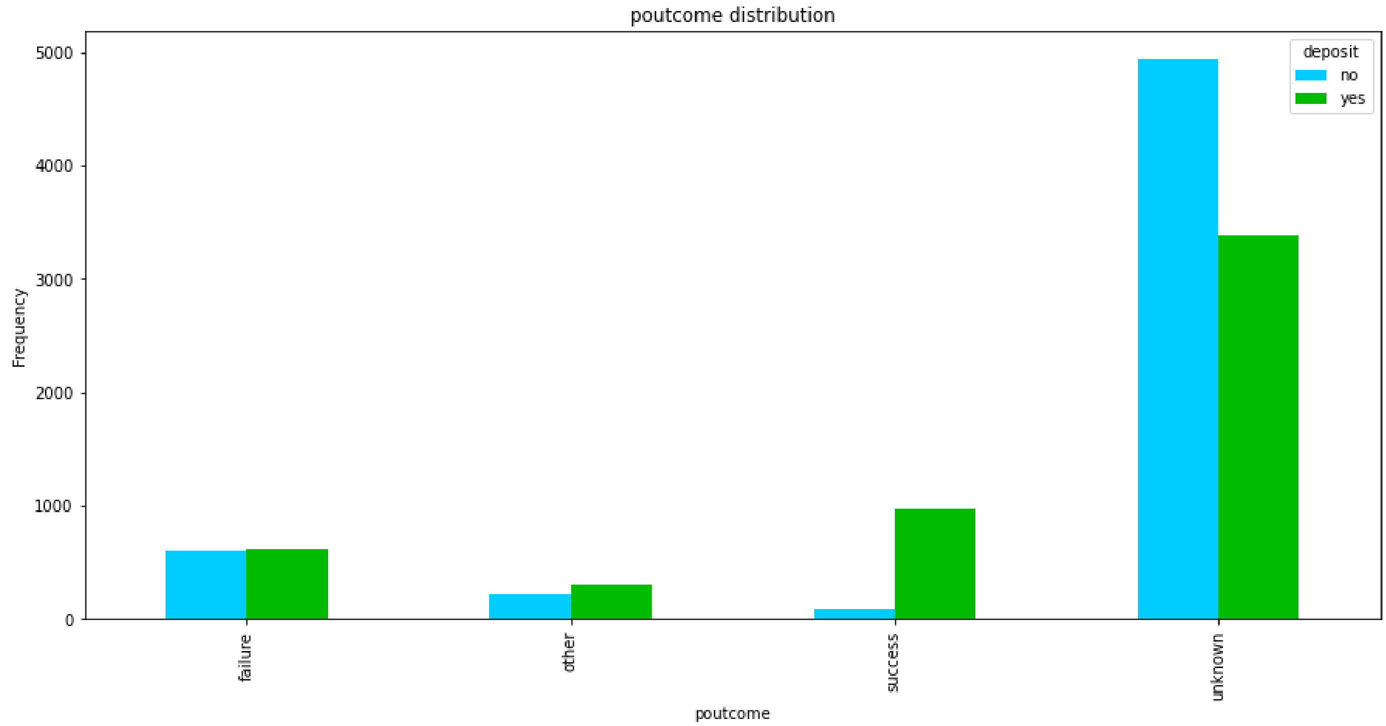

default distribution
deposit
no
yes
Frequency
6000
5000
4000
3000
2000
1000
0
no
yes
default


housing distribution
deposit
no
yes
Frequency
3500
3000
2500
2000
1500
1000
500
0
no
yes
housing


loan distribution
deposit
no
yes
Frequency
5000
4000
3000
2000
1000
0
no
yes
loan


contact distribution
deposit
no
yes
Frequency
0
1000
2000
3000
4000
cellular
telephone
unknown
contact


month distribution
deposit
no
yes
Frequency
0
250
500
750
1000
1250
1500
1750
apr
aug
dec
feb
jan
jul
jun
mar
may
nov
oct
sep
month



The graphs above can provide an overview of the characteristics of customers with high number of term deposits. For example, from the first graph, we can note that customers with a management job have the highest number of term deposits and so on. For a detailed summary of the exact numbers and subscription proportions of each variable see below.

In [14]:
```
for f in cat_features:
    print(pd.crosstab(data['deposit'], data[f]).apply(lambda x: x/x.sum() * 100).round()
    print(data.groupby(f).size().sort_values(ascending=False), '\n')
```

```
job      admin.  blue-collar  entrepreneur  housemaid  management  retired  \
deposit
no         53.0         64.0          62.0       60.0        49.0     34.0
yes        47.0         36.0          38.0       40.0        51.0     66.0

job      self-employed  services  student  technician  unemployed  unknown
deposit
no                54.0      60.0     25.0        54.0        43.0     51.0
yes               46.0      40.0     75.0        46.0        57.0     49.0

job
management       2566
blue-collar      1944
technician       1823
admin.           1334
services          923
retired           778
self-employed     405
student           360
unemployed        357
entrepreneur      328
housemaid         274
unknown            70
dtype: int64

marital  divorced  married  single
deposit
no           52.0     57.0    46.0
yes          48.0     43.0    54.0
```

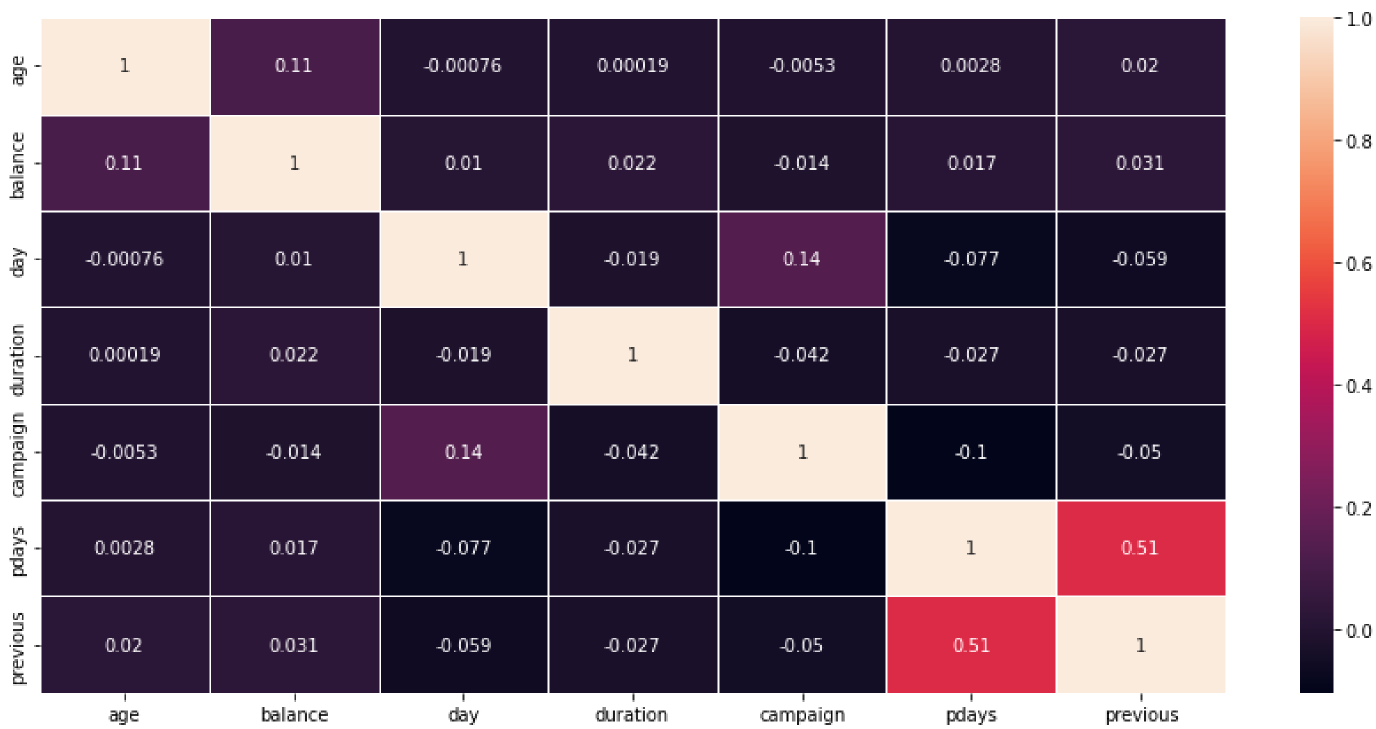
```
marital
married     6351
single      3518
divorced    1293
dtype: int64

education  primary  secondary  tertiary  unknown
deposit
no            61.0       55.0      46.0     49.0
yes           39.0       45.0      54.0     51.0

education
secondary    5476
tertiary     3689
primary      1500
unknown       497
dtype: int64

default    no   yes
deposit
no       52.0  69.0
yes      48.0  31.0

default
no     10994
yes      168
dtype: int64

housing    no   yes
deposit
no       43.0  63.0
yes      57.0  37.0

housing
no     5881
yes    5281
dtype: int64

loan       no   yes
deposit
no       50.0  67.0
yes      50.0  33.0

loan
no     9702
yes    1460
dtype: int64

contact  cellular  telephone  unknown
deposit
no           46.0       50.0     77.0
yes          54.0       50.0     23.0

contact
cellular     8042
unknown      2346
telephone     774
dtype: int64

month     apr   aug   dec   feb   jan   jul   jun   mar   may   nov   oct  \
deposit
no       37.0  55.0   9.0  43.0  59.0  59.0  55.0  10.0  67.0  57.0  18.0
yes      63.0  45.0  91.0  57.0  41.0  41.0  45.0  90.0  33.0  43.0  82.0

month     sep
```

```
deposit
no       16.0
yes      84.0

month
may    2824
aug    1519
jul    1514
jun    1222
nov     943
apr     923
feb     776
oct     392
jan     344
sep     319
mar     276
dec     110
dtype: int64

poutcome  failure  other  success  unknown
deposit
no           50.0   43.0      9.0     59.0
yes          50.0   57.0     91.0     41.0

poutcome
unknown    8326
failure    1228
success    1071
other       537
dtype: int64
```

Correlations

In [15]:
```python
fig, ax = plt.subplots(figsize=(15,7))         # Sample figsize in inches
sns.heatmap(data.corr(), annot=True, linewidths=.5, ax=ax)
```

Out[15]:
```
<AxesSubplot:>
```



Majority of the variables have weak positive or negative correlations except the relationship between the 'pdays' and 'previous' variables (r=0.51).

Data Pre-processing before Modelling

One hot encoding

In [16]:
```
# Converting deposit column values to numerical values

data['deposit'].replace(['yes', 'no'],[1, 0], inplace=True)

# Removing negative values for pdays

data['pdays'].replace([-1],[0], inplace=True)

data.head()
```

Out[16]:

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campa
0	59	admin.	married	secondary	no	2343	yes	no	unknown	5	may	1042	
1	56	admin.	married	secondary	no	45	no	no	unknown	5	may	1467	
2	41	technician	married	secondary	no	1270	yes	no	unknown	5	may	1389	
3	55	services	married	secondary	no	2476	yes	no	unknown	5	may	579	
4	54	admin.	married	tertiary	no	184	no	no	unknown	5	may	673	

In [17]:
```
# Encoding the categorical values only

new_cat_features = pd.get_dummies(data[cat_features], drop_first=False)

new_cat_features.head()
```

Out[17]:

	job_admin.	job_blue-collar	job_entrepreneur	job_housemaid	job_management	job_retired	job_self-employed	job_services
0	1	0	0	0	0	0	0	0
1	1	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	1
4	1	0	0	0	0	0	0	0

5 rows × 44 columns

In [18]:
```
# Combining numerical and categorical independent variables

df2 = pd.concat([data, new_cat_features], axis=1)

data_main = df2.drop(['job', 'marital', 'education', 'default', 'housing', 'loan','conta

data_main.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11162 entries, 0 to 11161
Data columns (total 52 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
```

```
 0   age                  11162 non-null  int64
 1   balance              11162 non-null  int64
 2   day                  11162 non-null  int64
 3   duration             11162 non-null  int64
 4   campaign             11162 non-null  int64
 5   pdays                11162 non-null  int64
 6   previous             11162 non-null  int64
 7   deposit              11162 non-null  int64
 8   job_admin.           11162 non-null  uint8
 9   job_blue-collar      11162 non-null  uint8
 10  job_entrepreneur     11162 non-null  uint8
 11  job_housemaid        11162 non-null  uint8
 12  job_management       11162 non-null  uint8
 13  job_retired          11162 non-null  uint8
 14  job_self-employed    11162 non-null  uint8
 15  job_services         11162 non-null  uint8
 16  job_student          11162 non-null  uint8
 17  job_technician       11162 non-null  uint8
 18  job_unemployed       11162 non-null  uint8
 19  job_unknown          11162 non-null  uint8
 20  marital_divorced     11162 non-null  uint8
 21  marital_married      11162 non-null  uint8
 22  marital_single       11162 non-null  uint8
 23  education_primary    11162 non-null  uint8
 24  education_secondary  11162 non-null  uint8
 25  education_tertiary   11162 non-null  uint8
 26  education_unknown    11162 non-null  uint8
 27  default_no           11162 non-null  uint8
 28  default_yes          11162 non-null  uint8
 29  housing_no           11162 non-null  uint8
 30  housing_yes          11162 non-null  uint8
 31  loan_no              11162 non-null  uint8
 32  loan_yes             11162 non-null  uint8
 33  contact_cellular     11162 non-null  uint8
 34  contact_telephone    11162 non-null  uint8
 35  contact_unknown      11162 non-null  uint8
 36  month_apr            11162 non-null  uint8
 37  month_aug            11162 non-null  uint8
 38  month_dec            11162 non-null  uint8
 39  month_feb            11162 non-null  uint8
 40  month_jan            11162 non-null  uint8
 41  month_jul            11162 non-null  uint8
 42  month_jun            11162 non-null  uint8
 43  month_mar            11162 non-null  uint8
 44  month_may            11162 non-null  uint8
 45  month_nov            11162 non-null  uint8
 46  month_oct            11162 non-null  uint8
 47  month_sep            11162 non-null  uint8
 48  poutcome_failure     11162 non-null  uint8
 49  poutcome_other       11162 non-null  uint8
 50  poutcome_success     11162 non-null  uint8
 51  poutcome_unknown     11162 non-null  uint8
dtypes: int64(8), uint8(44)
memory usage: 1.1 MB
```

Spliting the dataset

In [19]:
```
# Spliting dataset into independent (X) and dependent (y) variables

X=data_main.drop(['deposit'], axis=1)

y=data_main['deposit']
```

Test Train Split

In [20]:
```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state
```

Feature scaling

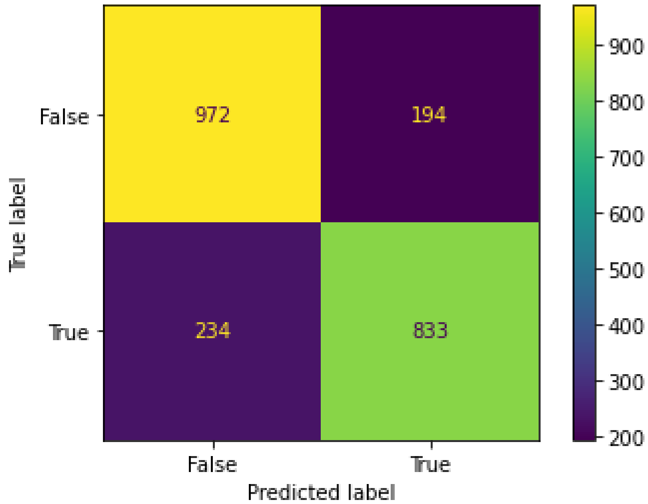
In [21]:
```
from sklearn.preprocessing import StandardScaler

sc = StandardScaler()

X_train = sc.fit_transform(X_train)

X_test = sc.transform(X_test)
```

Modeling

In [40]:
```
from sklearn.model_selection import train_test_split
from sklearn.metrics import cohen_kappa_score
from sklearn.metrics import classification_report
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import ConfusionMatrixDisplay
from sklearn.metrics import f1_score
```

Logistic Regression

In [41]:
```
from sklearn.linear_model import LogisticRegression

lr_model = LogisticRegression()

lr_model.fit(X_train,y_train)

y_pred = lr_model.predict(X_test)

confusion_matrix = confusion_matrix(y_test, y_pred)

cm_display = ConfusionMatrixDisplay(confusion_matrix = confusion_matrix, display_labels

cm_display.plot()
plt.show()

print(classification_report(y_test,y_pred))

acc = accuracy_score(y_test,y_pred)*100
print("Logistic Regression accuracy: ",acc.round(2))

f1=f1_score(y_test,y_pred)*100
print("F1-Score: ",f1.round(2))

cohen_kappa = cohen_kappa_score(y_test, y_pred)*100
print('Cohen Kappa score: ',cohen_kappa.round(2))
```

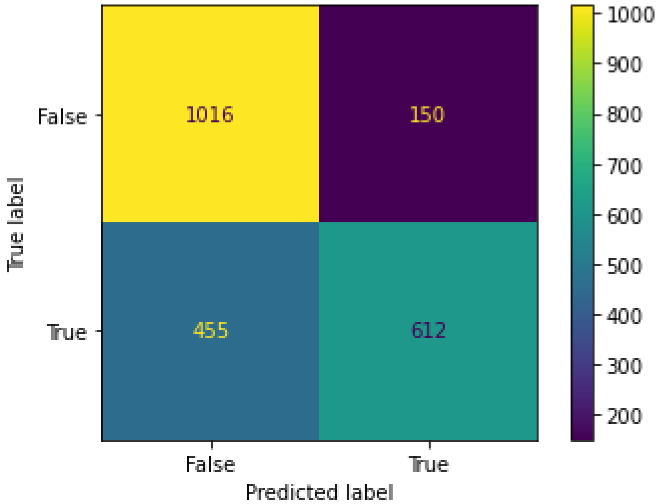



```
              precision    recall  f1-score   support

           0       0.81      0.83      0.82      1166
           1       0.81      0.78      0.80      1067

    accuracy                           0.81      2233
   macro avg       0.81      0.81      0.81      2233
weighted avg       0.81      0.81      0.81      2233

Logistic Regression accuracy:  80.83
F1-Score:  79.56
Cohen Kappa score:  61.53
```

Naive Bayes

In [27]:

```
from sklearn.naive_bayes import GaussianNB

nb_model = GaussianNB()

nb_model.fit(X_train,y_train)

y_pred = nb_model.predict(X_test)

confusion_matrix = confusion_matrix(y_test, y_pred)

cm_display = ConfusionMatrixDisplay(confusion_matrix = confusion_matrix, display_labels

cm_display.plot()
plt.show()

print(classification_report(y_test,y_pred))

acc = accuracy_score(y_test,y_pred)*100
print("Naive Bayes accuracy: ",acc.round(2))

f1=f1_score(y_test,y_pred)*100
print("F1-Score: ",f1.round(2))


cohen_kappa = cohen_kappa_score(y_test, y_pred)*100
print('Cohen Kappa score: ',cohen_kappa.round(2))
```

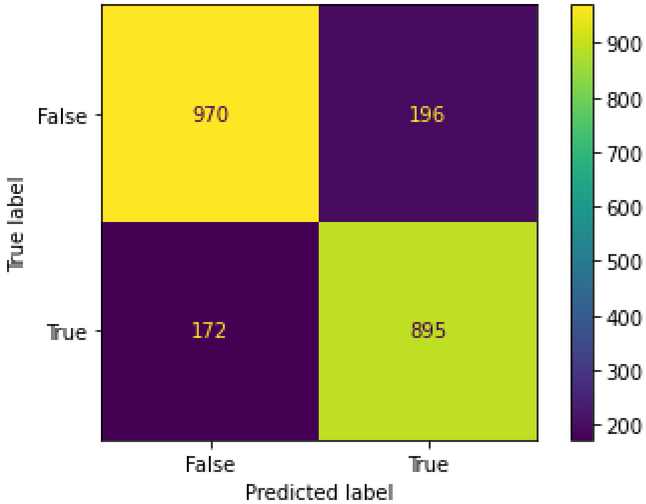



```
              precision    recall  f1-score   support

           0       0.69      0.87      0.77      1166
           1       0.80      0.57      0.67      1067

    accuracy                           0.73      2233
   macro avg       0.75      0.72      0.72      2233
weighted avg       0.74      0.73      0.72      2233

Naive Bayes accuracy:  72.91
F1-Score:  66.92
Cohen Kappa score:  45.04
```

Support Vector Machine (SVM)

In [29]:

```
from sklearn.svm import SVC

svc_model = SVC(kernel = 'rbf', random_state = 0)

svc_model.fit(X_train, y_train)

y_pred = svc_model.predict(X_test)

confusion_matrix = confusion_matrix(y_test, y_pred)

cm_display = ConfusionMatrixDisplay(confusion_matrix = confusion_matrix, display_labels

cm_display.plot()
plt.show()

print(classification_report(y_test,y_pred))

acc = accuracy_score(y_test,y_pred)*100
print("SVM accuracy: ",acc.round(2))

f1=f1_score(y_test,y_pred)*100
print("F1-Score: ",f1.round(2))


cohen_kappa = cohen_kappa_score(y_test, y_pred)*100
print('Cohen Kappa score: ',cohen_kappa.round(2))
```

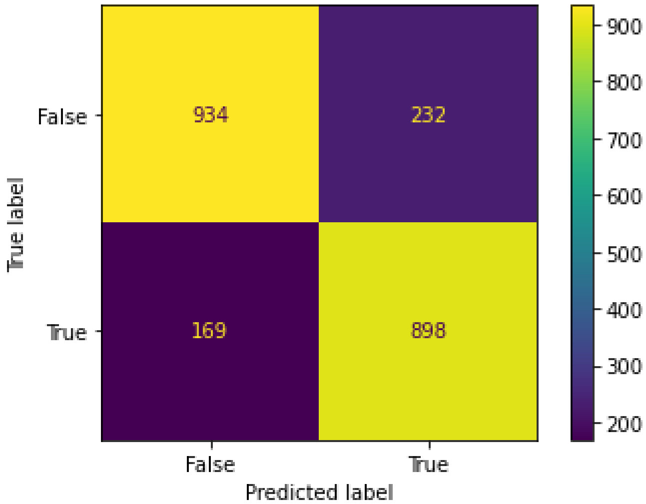



```
              precision    recall  f1-score   support

           0       0.85      0.83      0.84      1166
           1       0.82      0.84      0.83      1067

    accuracy                           0.84      2233
   macro avg       0.83      0.84      0.84      2233
weighted avg       0.84      0.84      0.84      2233

SVM accuracy:  83.52
F1-Score:  82.95
Cohen Kappa score:  67.01
```

Decision Trees

In [33]:

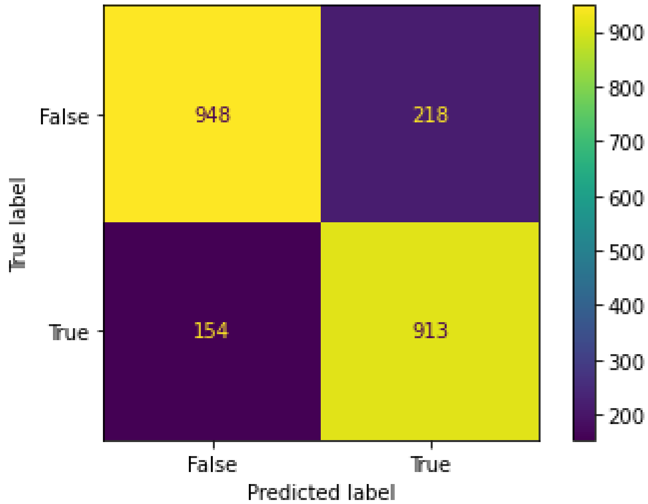
```
from sklearn.tree import DecisionTreeClassifier

dt_model= DecisionTreeClassifier(criterion='gini', max_depth=10, random_state=0, min_sam

dt_model.fit(X_train, y_train)

y_pred = dt_model.predict(X_test)

confusion_matrix = confusion_matrix(y_test, y_pred)

cm_display = ConfusionMatrixDisplay(confusion_matrix = confusion_matrix, display_labels

cm_display.plot()
plt.show()

print(classification_report(y_test,y_pred))

acc = accuracy_score(y_test,y_pred)*100
print("Decision tree accuracy: ",acc.round(2))

f1=f1_score(y_test,y_pred)*100
print("F1-Score: ",f1.round(2))


cohen_kappa = cohen_kappa_score(y_test, y_pred)*100
print('Cohen Kappa score: ',cohen_kappa.round(2))
```




```
              precision    recall  f1-score   support

           0       0.85      0.80      0.82      1166
           1       0.79      0.84      0.82      1067

    accuracy                           0.82      2233
   macro avg       0.82      0.82      0.82      2233
weighted avg       0.82      0.82      0.82      2233

Decision tree accuracy:  82.04
F1-Score:  81.75
Cohen Kappa score:  64.1
```

Random Forest

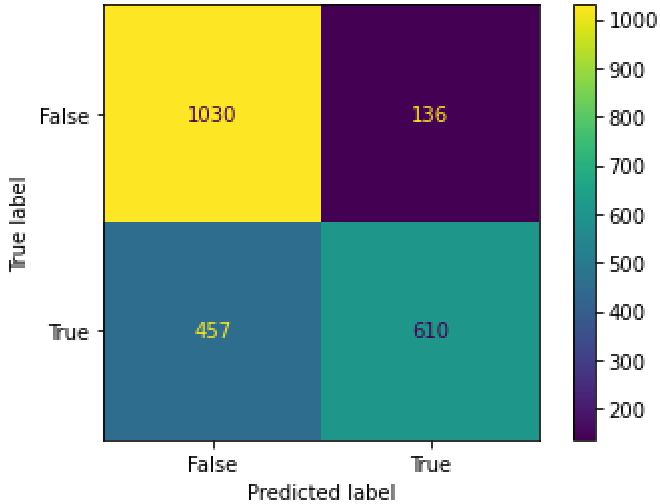
In [31]:
```
from sklearn.ensemble import RandomForestClassifier

rf_model = RandomForestClassifier(n_estimators=100, max_depth=10, random_state=0)

rf_model.fit(X_train, y_train)

y_pred = rf_model.predict(X_test)

confusion_matrix = confusion_matrix(y_test, y_pred)

cm_display = ConfusionMatrixDisplay(confusion_matrix = confusion_matrix, display_labels

cm_display.plot()
plt.show()

print(classification_report(y_test,y_pred))

acc = accuracy_score(y_test,y_pred)*100
print("Random Forest accuracy: ",acc.round(2))

f1=f1_score(y_test,y_pred)*100
print("F1-Score: ",f1.round(2))

cohen_kappa = cohen_kappa_score(y_test, y_pred)*100
print('Cohen Kappa score: ',cohen_kappa.round(2))
```




```
              precision    recall  f1-score   support

           0       0.86      0.81      0.84      1166
           1       0.81      0.86      0.83      1067

    accuracy                           0.83      2233
   macro avg       0.83      0.83      0.83      2233
weighted avg       0.83      0.83      0.83      2233

Random Forest accuracy:  83.34
F1-Score:  83.08
Cohen Kappa score:  66.7
```

K-Nearest Neighbors

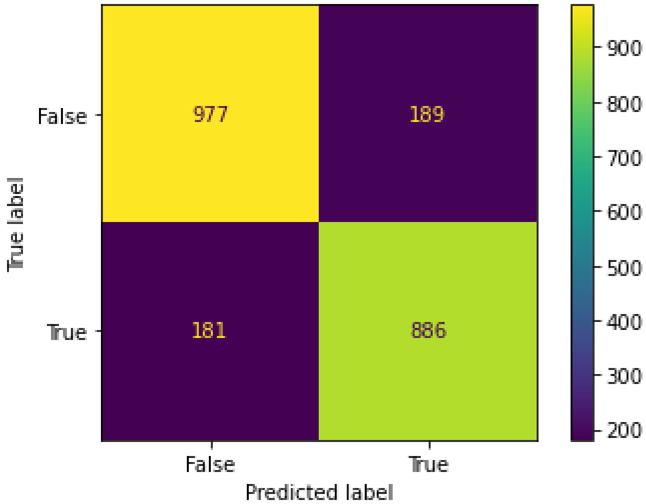
In [35]:
```python
from sklearn.neighbors import KNeighborsClassifier

knn_model = KNeighborsClassifier(n_neighbors = 4, algorithm='ball_tree')

knn_model.fit(X_train, y_train)

y_pred = knn_model.predict(X_test)

confusion_matrix = confusion_matrix(y_test, y_pred)

cm_display = ConfusionMatrixDisplay(confusion_matrix = confusion_matrix, display_labels

cm_display.plot()
plt.show()

print(classification_report(y_test,y_pred))

acc = accuracy_score(y_test,y_pred)*100
print("KNN accuracy: ",acc.round(2))

f1=f1_score(y_test,y_pred)*100
print("F1-Score: ",f1.round(2))

cohen_kappa = cohen_kappa_score(y_test, y_pred)*100
print('Cohen Kappa score: ',cohen_kappa.round(2))
```




```
              precision    recall  f1-score   support

           0       0.69      0.88      0.78      1166
           1       0.82      0.57      0.67      1067

    accuracy                           0.73      2233
   macro avg       0.76      0.73      0.72      2233
weighted avg       0.75      0.73      0.73      2233

KNN accuracy:  73.44
F1-Score:  67.29
Cohen Kappa score:  46.09
```

Gradient Boosting Classifier

In [37]:
```
from sklearn.ensemble import GradientBoostingClassifier

gbc_model = GradientBoostingClassifier(n_estimators=100, learning_rate=0.8, max_depth=2,

gbc_model.fit(X_train, y_train)

y_pred = gbc_model.predict(X_test)

confusion_matrix = confusion_matrix(y_test, y_pred)

cm_display = ConfusionMatrixDisplay(confusion_matrix = confusion_matrix, display_labels

cm_display.plot()
plt.show()

print(classification_report(y_test,y_pred))

acc = accuracy_score(y_test,y_pred)*100
print("GBC accuracy: ",acc.round(2))

f1=f1_score(y_test,y_pred)*100
print("F1-Score: ",f1.round(2))

cohen_kappa = cohen_kappa_score(y_test, y_pred)*100
print('Cohen Kappa score: ',cohen_kappa.round(2))
```




```
              precision    recall  f1-score   support

           0       0.84      0.84      0.84      1166
           1       0.82      0.83      0.83      1067

    accuracy                           0.83      2233
   macro avg       0.83      0.83      0.83      2233
weighted avg       0.83      0.83      0.83      2233

GBC accuracy:  83.43
F1-Score:  82.73
Cohen Kappa score:  66.81
```

SVM model produced the highest accuracy score of 83.52 but K-Nearest neighbors had the lowest number of false positives at 136.

Depending on the business strategy model, the marketing department could select the most ideal model based on the results of the accuracy, f1 score, and Cohen-Kappa score.

```
In [ ]:
```