To build a model to predict whether someone is going to make a deposit or not depending on some attributes.

For better marketing campaings in the future based on the previous(this) marketing campaign.

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

```
#To remove waarnings
import warnings
warnings.filterwarnings('ignore')
```

```
from google.colab import files
data= files.upload()
```

Choose Files No file chosen Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

```
Saving bank.csv to bank.csv
```

Input variables:

age (numeric)

job : type of job (categorical: 'admin.','blue-collar','entrepreneur','housemaid','management','retired','self-employed','services','student','technician','unemployed','unknown')

marital : marital status (categorical: 'divorced','married','single','unknown'; note: 'divorced' means divorced or widowed)

education (categorical: 'basic.4y','basic.6y','basic.9y','high.school','illiterate','professional.course','university.degree','unknown')

default: has credit in default? (categorical: 'no','yes','unknown') housing: has housing loan? (categorical: 'no','yes','unknown')

loan: has personal loan? (categorical: 'no','yes','unknown')

contact: contact communication type (categorical: 'cellular','telephone')

month: last contact month of year (categorical: 'jan', 'feb', 'mar', ..., 'nov', 'dec')

day_of_week: last contact day of the week (categorical: 'mon','tue','wed','thu','fri')

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.

campaign: number of contacts performed during this campaign and for this client (numeric, includes last contact)

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)

previous: number of contacts performed before this campaign and for this client (numeric)

poutcome: outcome of the previous marketing campaign (categorical: 'failure','nonexistent','success')

Output variable (desired target):

y. has the client subscribed a term deposit? (binary: 'yes','no') According to the dataset documentation, we need to remove the 'duration' column because in real-case the duration is only known after the label column is known. This problem can be considered to be 'data leakage' where predictors include data that will not be available at the time you make predictions.

```
df= pd.read_csv('bank.csv')
df.head()
```

In this case we want to focus on the recall value of our model because in our problem we should try to predict as many actual positive as we can. Because a misclassification of customer who actually wanted to make a deposit can mean a lose opportunity/revenue.

My thought process:

1)Understand problem statement: future campaign focus based on deposit classification. Where to focus(which feature)? 2) ML problem: Binary classification 3)Understand data: read, features(which type), size, cols, describe, unique for categorical, data balance. 4)NUll(missing), duplicate, distribution of data (to get sense of feature and outliers).

```
#duration says how long customer had a conversation (time)
#because when we get new data or runtime, will don't know about that, so
#It can cause data leakage problem.
df= df.drop('duration', axis=1)
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11162 entries, 0 to 11161
Data columns (total 16 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  campaign   11162 non-null  int64
 12  pdays      11162 non-null  int64
 13  previous   11162 non-null  int64
 14  poutcome   11162 non-null  object
 15  deposit    11162 non-null  object
dtypes: int64(6), object(10)
memory usage: 1.4+ MB
```

```
df.describe() #it descibes your all numerical data type columns
```

	age	balance	day	campaign	pdays	previous
count	11162.000000	11162.000000	11162.000000	11162.000000	11162.000000	11162.000000
mean	41.231948	1528.538524	15.658036	2.508421	51.330407	0.832557
std	11.913369	3225.413326	8.420740	2.722077	108.758282	2.292007
min	18.000000	-6847.000000	1.000000	1.000000	-1.000000	0.000000
25%	32.000000	122.000000	8.000000	1.000000	-1.000000	0.000000
50%	39.000000	550.000000	15.000000	2.000000	-1.000000	0.000000
75%	49.000000	1708.000000	22.000000	3.000000	20.750000	1.000000
max	95.000000	81204.000000	31.000000	63.000000	854.000000	58.000000

```
df.describe(include='all') #all columns details
```

	age	job	marital	education	default	balance	housing	loan	contact	day	month	campaign
count	11162.000000	11162	11162	11162	11162	11162.000000	11162	11162	11162	11162.000000	11162	11162.000000
unique	NaN	12	3	4	2	NaN	2	2	3	NaN	12	NaN
top	NaN	management	married	secondary	no	NaN	no	no	cellular	NaN	may	NaN
freq	NaN	2566	6351	5476	10994	NaN	5881	9702	8042	NaN	2824	NaN

check unique values in the categorical dtype

```
#checking null values
df.isnull().sum()
```

```
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
deposit      0
dtype: int64
```

```
df.nunique()
```

```
age            76
job            12
marital         3
education       4
default         2
balance      3805
housing         2
loan            2
contact         3
day            31
month          12
campaign       36
pdays         472
previous       34
poutcome        4
deposit         2
dtype: int64
```

```
print(list(df['job'].unique()))
```

```
['admin.', 'technician', 'services', 'management', 'retired', 'blue-collar', 'unemployed', 'entrepreneur', 'housemaid', 'unknown', 'self
```

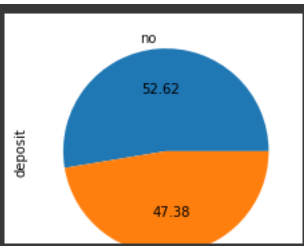
```
df.duplicated().sum()   #there is no duplicate rows, if we got, we will drop those rows
```

```
1
```

```
df.value_counts('deposit')
```

```
deposit
no     5873
yes    5289
dtype: int64
```

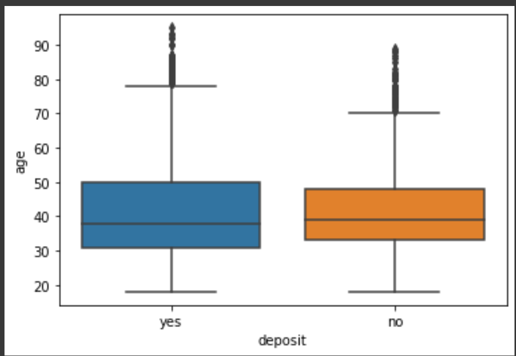
```
plt.figure(figsize=(20,12))

plt.subplot(3,3,1)
df['deposit'].value_counts().plot(kind='pie',autopct='%.2f')
plt.show()
```



Its almost balanced. so we treat as a balanced dataset.

You should do numeric standardized

```
#I want to know the distribution of data. To getting sense of data spread, outliers etc.
sns.boxplot(x='deposit',y='age', data=df)
plt.show()
```



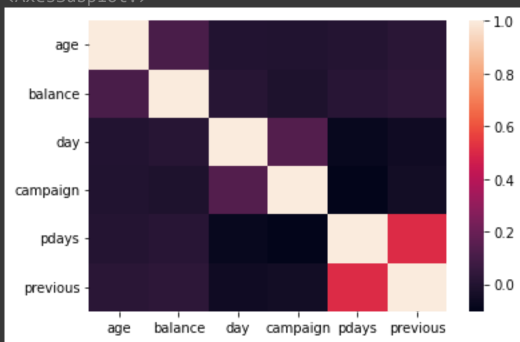

```
plt.figure(figsize=(18,14))

plt.subplot(3,3,1)
sns.boxplot(x='deposit',y='age', data=df)
plt.subplot(3,3,2)
sns.boxplot(x='deposit',y='balance', data=df)
plt.subplot(3,3,3)
sns.boxplot(x='deposit',y='day', data=df)
plt.subplot(3,3,4)
sns.boxplot(x='deposit',y='campaign', data=df)
plt.subplot(3,3,5)
sns.boxplot(x='deposit',y='pdays', data=df)
plt.subplot(3,3,6)
sns.boxplot(x='deposit',y='previous', data=df)
plt.show()
```

To see distribution of data of each input feature with target variable. Found some insights of featr as well, for example: I can say that between 8th to 22nd 'day' of every month, by using day boxplot. People generally respond and buy. for checking outliers. Apart from Iqr, we can consider out but not getting how to read.

Here, we are not saying about outliers r8 now

```
sns.heatmap(df.corr())
```

<AxesSubplot:>




```
#checking correlation between columns,continous(numerical)
df.corr()
```

	age	balance	day	campaign	pdays	previous
age	1.000000	0.112300	-0.000762	-0.005278	0.002774	0.020169
balance	0.112300	1.000000	0.010467	-0.013894	0.017411	0.030805
day	-0.000762	0.010467	1.000000	0.137007	-0.077232	-0.058981
campaign	-0.005278	-0.013894	0.137007	1.000000	-0.102726	-0.049699
pdays	0.002774	0.017411	-0.077232	-0.102726	1.000000	0.507272
previous	0.020169	0.030805	-0.058981	-0.049699	0.507272	1.000000

No corr b/w columns except pdays and previous has some corr (50%). So there's no multi-colinearity. Multicollinearity can also cause instability in the model, leads to affect model performance.

1) Remove one of the correlated variables: If two or more variables are highly correlated, then removing one of the variables can help reduce the multicollinearity.

2) Combine the correlated variables: If two or more variables are highly correlated, then you can create a new variable by taking a linear combination of those variables. For example, if two variables x1 and x2 are highly correlated, then you can create a new variable x3 = ax1 + bx2, where a and b are constants.

3) Use regularization techniques: Regularization techniques like Ridge Regression and Lasso Regression can help reduce the impact of multicollinearity on the model.

4) Use dimensionality reduction techniques: Techniques like Principal Component Analysis (PCA) and Factor Analysis can help reduce the number of variables in the dataset by combining the correlated variables into new variables, called principal components or factors.

```
df.groupby('deposit').mean()
```

deposit	age	balance	day	campaign	pdays	previous
no	40.837391	1280.227141	16.108122	2.839264	35.685340	0.528350
yes	41.670070	1804.267915	15.158253	2.141047	68.702968	1.170354

Here, the diff of 0 & 1 of each category will tell us about the feature that it will help us to classify or not. Here, balance,pdays are important. But, cant say about feture importance.

```
df1= df
df1
```

	age	job	marital	education	default	balance	housing	loan	contact	day	month	campaign	pdays	previous	poutcome	depo
0	59	admin.	married	secondary	no	2343	yes	no	unknown	5	may	1	-1	0	unknown	
1	56	admin.	married	secondary	no	45	no	no	unknown	5	may	1	-1	0	unknown	
2	41	technician	married	secondary	no	1270	yes	no	unknown	5	may	1	-1	0	unknown	
3	55	services	married	secondary	no	2476	yes	no	unknown	5	may	1	-1	0	unknown	
4	54	admin.	married	tertiary	no	184	no	no	unknown	5	may	2	-1	0	unknown	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
11157	33	blue-collar	single	primary	no	1	yes	no	cellular	20	apr	1	-1	0	unknown	
11158	39	services	married	secondary	no	733	no	no	unknown	16	jun	4	-1	0	unknown	
11159	32	technician	single	secondary	no	29	no	no	cellular	19	aug	2	-1	0	unknown	
11160	43	technician	married	secondary	no	0	no	yes	cellular	8	may	2	172	5	failure	
11161	34	technician	married	secondary	no	0	no	no	cellular	9	jul	1	-1	0	unknown	

11162 rows × 16 columns

```
df1['deposit'] = df1['deposit'].replace({'yes': 1, 'no': 0})
#df1['deposit'] = df1['deposit'].apply(lambda x: 1 if x == 'yes' else 0)   can use Lambda function as well
df1
```

	age	job	marital	education	default	balance	housing	loan	contact	day	month	campaign	pdays	previous	poutcome	depo
0	59	admin.	married	secondary	no	2343	yes	no	unknown	5	may	1	-1	0	unknown	
1	56	admin.	married	secondary	no	45	no	no	unknown	5	may	1	-1	0	unknown	
2	41	technician	married	secondary	no	1270	yes	no	unknown	5	may	1	-1	0	unknown	
3	55	services	married	secondary	no	2476	yes	no	unknown	5	may	1	-1	0	unknown	
4	54	admin.	married	tertiary	no	184	no	no	unknown	5	may	2	-1	0	unknown	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
11157	33	blue-collar	single	primary	no	1	yes	no	cellular	20	apr	1	-1	0	unknown	
11158	39	services	married	secondary	no	733	no	no	unknown	16	jun	4	-1	0	unknown	
11159	32	technician	single	secondary	no	29	no	no	cellular	19	aug	2	-1	0	unknown	
11160	43	technician	married	secondary	no	0	no	yes	cellular	8	may	2	172	5	failure	
11161	34	technician	married	secondary	no	0	no	no	cellular	9	jul	1	-1	0	unknown	

11162 rows × 16 columns

```
df1.corr()['deposit']
```

```
age         0.034901
balance     0.081129
day        -0.056326
campaign   -0.128081
pdays       0.151593
previous    0.139867
deposit     1.000000
Name: deposit, dtype: float64
```

from these, I can say that theres no high corr with deposit. Correlation is not right for knowing feature impo. (in general)

```
#To know feature importance but later realised that's not the way to know fetr impo
X=df1[['age', 'balance', 'day', 'pdays', 'campaign', 'previous']]
y=df1['deposit']

from sklearn.linear_model import SGDClassifier
#model= LogisticRegression(SGDClassifier)
```

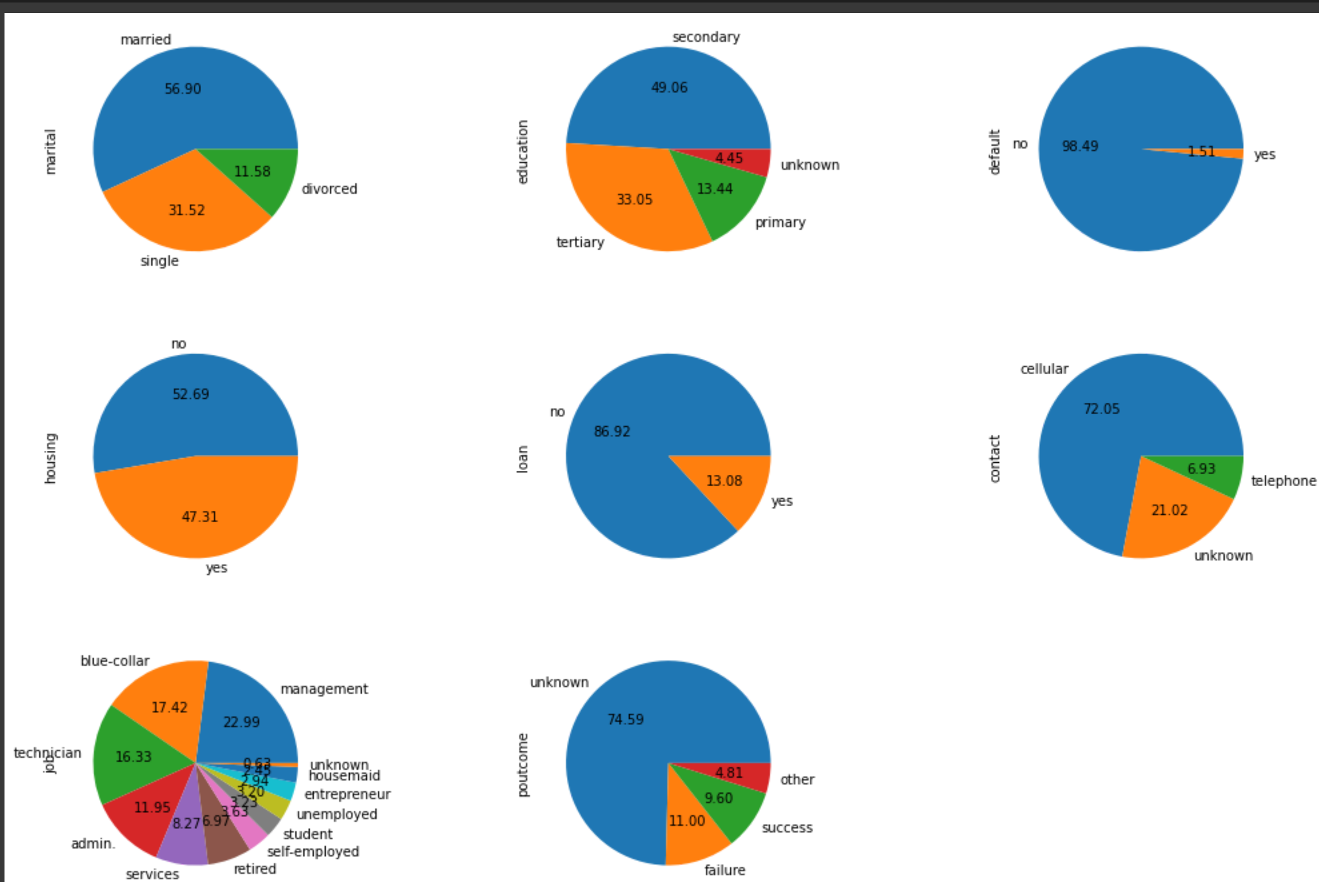
```
model= SGDClassifier(loss='log', random_state= 42)
#random_state(typically 42)- consistent result & to shuffle the data,
#improves model performance on test data
model.fit(X, y)
print(model.coef_)
```

```
[[  24.68009285 -540.59239992  -70.26319891   19.40800526 -783.69089265
   374.32336656]]
```

By this, age, day, campaign impacts much on model. But cant say about feature impo

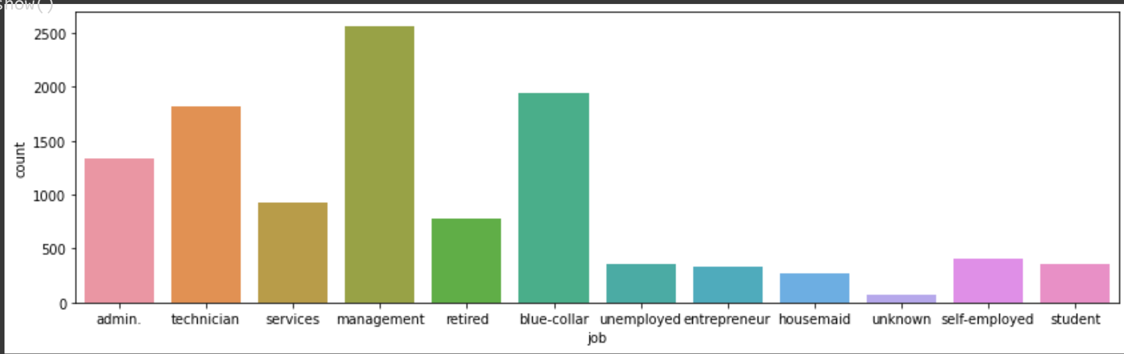
By examining the coefficients, we can infer which independent variables are most strongly associated with the dependent variable and in which direction.

```
#understanding categorical features
plt.figure(figsize=(18,12))

plt.subplot(3,3,1)
df['marital'].value_counts().plot(kind='pie',autopct='%.2f')
plt.subplot(3,3,2)
df['education'].value_counts().plot(kind='pie',autopct='%.2f')
plt.subplot(3,3,3)
df['default'].value_counts().plot(kind='pie',autopct='%.2f')
plt.subplot(3,3,4)
df['housing'].value_counts().plot(kind='pie',autopct='%.2f')
plt.subplot(3,3,5)
df['loan'].value_counts().plot(kind='pie',autopct='%.2f')
plt.subplot(3,3,6)
df['contact'].value_counts().plot(kind='pie',autopct='%.2f')
plt.subplot(3,3,7)
df['job'].value_counts().plot(kind='pie',autopct='%.2f')
plt.subplot(3,3,8)
df['poutcome'].value_counts().plot(kind='pie',autopct='%.2f')

plt.show()
```



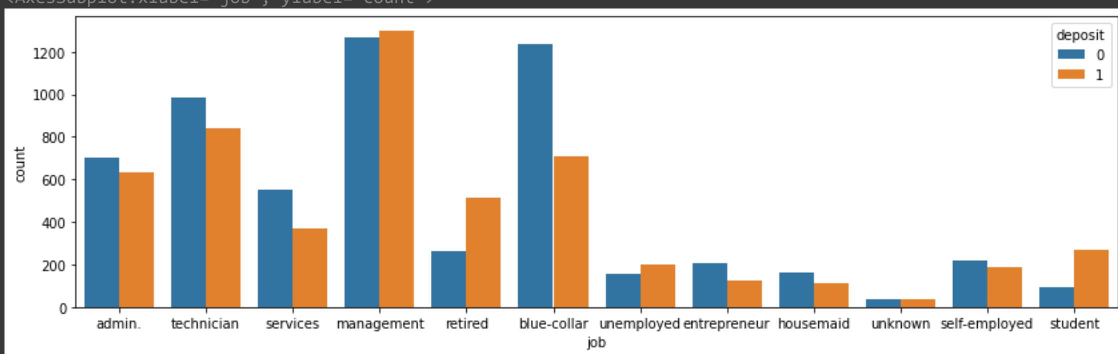

```
plt.figure(figsize=(14,4))
plt.subplot(1,1,1)
sns.countplot(x=df1['job'])
```

```
plt.show()
```



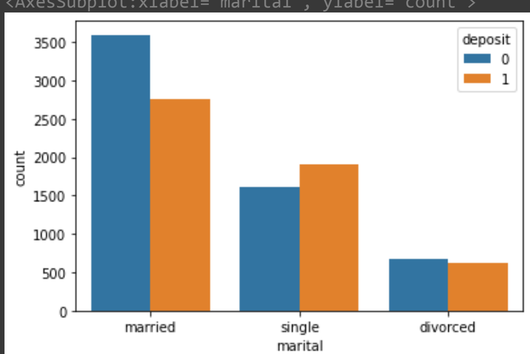

```
plt.figure(figsize=(14,4))
sns.countplot(x='job', hue='deposit', data=df)
```

```
<AxesSubplot:xlabel='job', ylabel='count'>
```



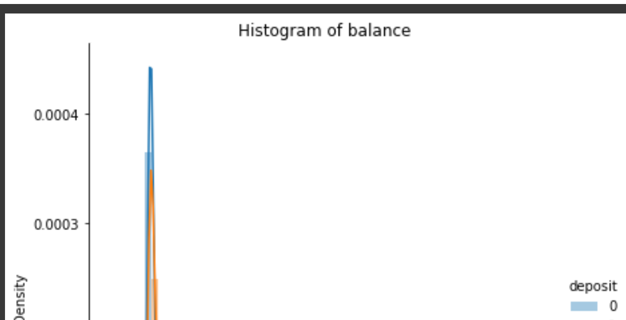

```
plt.figure(figsize=(6,4))
sns.countplot(x='marital', hue='deposit', data=df)
```

```
<AxesSubplot:xlabel='marital', ylabel='count'>
```

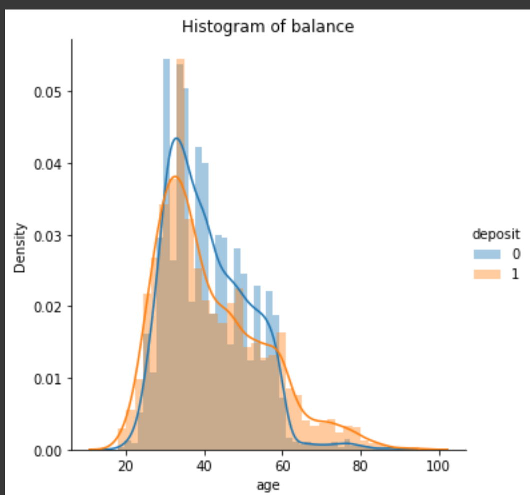


Important eda step, will tell about distribution as well as split of classification. We can do for all features using loop & we should do.

```
# plotting histogram (smooth line is pdf)
sns.FacetGrid(df, hue="deposit", size= 6) \
   .map(sns.distplot, "balance") \
   .add_legend();
plt.title('Histogram of balance')
plt.show();
```




```
# plotting histogram (smooth line is pdf)
sns.FacetGrid(df, hue="deposit", size= 5) \
   .map(sns.distplot, "age") \
   .add_legend();
plt.title('Histogram of balance')
plt.show();
```




```
#Plot CDF of age

sns.set_style('whitegrid')
counts, bin_edges = np.histogram(df['balance'], bins=10,
                                 density = True)
pdf = counts/(sum(counts))
print(pdf);
print(bin_edges)
#compute CDF
cdf = np.cumsum(pdf)
plt.plot(bin_edges[1:],pdf)
plt.plot(bin_edges[1:], cdf)

plt.title('Pdf & Cdf of balance')
plt.legend(['PDF plot', 'CDF plot'])
plt.xlabel("balance")
plt.show();
```

```
[7.77011288e-01 2.05697904e-01 1.21841964e-02 3.31481813e-03
 1.07507615e-03 8.95896793e-05 2.68769038e-04 8.95896793e-05
```

```
#Encoding

df.head()
```

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

0 10000 20000 30000 40000 50000 60000 70000 80000

```
one_hot_data = pd.get_dummies(df, columns = ['job', 'marital', 'education', 'default', 'housing', 'loan', 'contact', 'month', 'poutcome'])
one_hot_data.head()
```

	age	balance	day	campaign	pdays	previous	deposit	job_admin.	job_blue-collar	job_entrepreneur	...	month_jun	month_mar	month_may
0	59	2343	5	1	-1	0	1	1	0	0	...	0	0	1
1	56	45	5	1	-1	0	1	1	0	0	...	0	0	1
2	41	1270	5	1	-1	0	1	0	0	0	...	0	0	1
3	55	2476	5	1	-1	0	1	0	0	0	...	0	0	1
4	54	184	5	2	-1	0	1	1	0	0	...	0	0	1

5 rows × 51 columns

```
from sklearn.model_selection import train_test_split

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

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state= 10)
```

```
from sklearn.metrics import accuracy_score
from sklearn.linear_model import LogisticRegression
model= LogisticRegression()
#random_state(typically 42)- consistent result & to shuffle the data, improves model performance on test data
model.fit(X_train, y_train)
```

```
LogisticRegression()
```

```
y_pred= model.predict(X_test)
acc = accuracy_score(y_test, y_pred)
print(acc)

0.7694834278889221
0.767990444908928
```

```
0.6757240967452971
0.767990444908928
```

```
from sklearn.metrics import log_loss
model = LogisticRegression()
model.fit(X_train, y_train)
y_pred = model.predict(X_test)

logloss = log_loss(y_test, model.predict_proba(X_test)[:, 1])
print("Log loss:", logloss)
```

```
Log loss: 0.6240731714250114
```

```
one_hot_data = one_hot_data.drop(one_hot_data.columns[-1], axis=1)
X= one_hot_data
```

```
y
```

```
0        1
1        1
2        1
3        1
4        1
        ..
11157    0
11158    0
11159    0
11160    0
11161    0
Name: deposit, Length: 11162, dtype: int64
```

```
from sklearn.model_selection import train_test_split

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

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state= 10)
```

```
from sklearn.metrics import accuracy_score
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model= LogisticRegression()
#random_state(typically 42)- consistent result & to shuffle the data, improves model performance on test data
model.fit(X_train, y_train)
```

```
LogisticRegression()
```

```
y_pred= model.predict(X_test)
acc = accuracy_score(y_test, y_pred)
print(acc)
```

```
0.6700507614213198
```

```
from sklearn.metrics import log_loss
model = LogisticRegression()
model.fit(X_train, y_train)
y_pred = model.predict(X_test)

logloss = log_loss(y_test, model.predict_proba(X_test)[:, 1])
print("Log loss:", logloss)
```

```
Log loss: 0.6294125520323491
```

```
X= one_hot_data.drop(['deposit', 'age', 'day'], axis=1)
y= one_hot_data['deposit']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state= 10)
```

```
model= LogisticRegression()
#random_state(typically 42)- consistent result & to shuffle the data, improves model performance on test data
model.fit(X_train, y_train)
```

```
LogisticRegression()
```

```
y_pred= model.predict(X_test)
acc = accuracy_score(y_test, y_pred)
print(acc)
```

```
0.6888623469692445
```

```
model = LogisticRegression()
model.fit(X_train, y_train)
y_pred = model.predict(X_train)

logloss = log_loss(y_train, model.predict_proba(X_train)[:, 1])
print("Log loss:", logloss)
```

```
Log loss: 0.6003881383142997
```

```
model = LogisticRegression()
model.fit(X_train, y_train)
```

```
y_pred = model.predict(X_test)

logloss = log_loss(y_test, model.predict_proba(X_test)[:, 1])
print("Log loss:", logloss)
```

```
Log loss: 0.6077395811972804
```

After dropping age & day column, performance increases

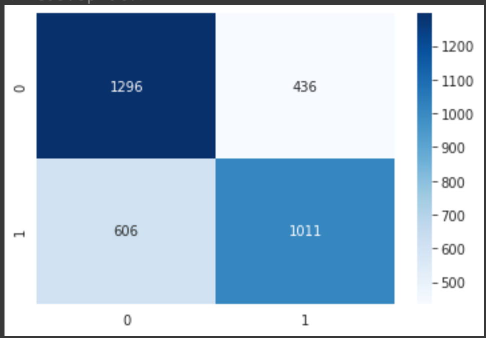
There is no overfitting & underfitting in the data

```
from sklearn.metrics import roc_auc_score
auc = roc_auc_score(y_test, y_pred)
print('AUC:', auc)
```

```
AUC: 0.6867499046647842
```

```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred)
sns.heatmap(cm, annot=True, cmap='Blues', fmt='g')
```

<AxesSubplot:>




```
#Linear SVM
from sklearn.svm import LinearSVC
model = LinearSVC()

# Train the model on the training data
model.fit(X_train, y_train)

# Predict the target variable for the test data
y_pred = model.predict(X_test)

# Evaluate the model's performance
accuracy = model.score(X_test, y_test)
print(accuracy)
```

```
0.5753956404896984
```

SVM has less acc than LR

```
#Random forest: Random forest or Random Decision Forest is a method that
#operates by constructing multiple decision trees during training phases.
#The decision of the majority of the trees is chosen as final decision.
from sklearn.ensemble import RandomForestClassifier
rf = RandomForestClassifier(n_estimators=30, random_state=42)

rf.fit(X_train, y_train)

# Evaluate the classifier on the test data
accuracy = rf.score(X_test, y_test)

print("Accuracy: {:.2f}".format(accuracy))
```

```
Accuracy: 0.68
```

```
rf = RandomForestClassifier(n_estimators=100, random_state=42)
rf.fit(X_train, y_train)
y_pred = rf.predict(X_test)
```

```
logloss = log_loss(y_test, rf.predict_proba(X_test)[:, 1])
print("Log loss:", logloss)
```

```
Log loss: 0.6398147695530514
```

Random Forest gives better performance (accuracy & loss) than LR